

**Steunpunt Welzijn, Volksgezondheid en Gezin**

**Towards a projection model for the Flemish social protection**

**Part I**

**An overview of literature**

**Part II**

**A projection model for residential care for the older persons and for home care**

**Part III**

**A first step to projecting future needs, service use, and costs in ambulatory mental health care and psychosocial rehabilitation**

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**Towards a projection model for the Flemish social protection [Naar een projectiemodel voor de Vlaamse Sociale Bescherming].**

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**Samenvatting**

In 2016, bij de uitvoering van de zesde staatshervorming, werden de Vlaamse bevoegdheden inzake gezondheids- en zorgbeleid aanzienlijk verruimd. Vóór 2016 was Vlaanderen reeds bevoegd voor (een deel van) de geestelijke gezondheidszorg en voor (een deel van) de gezondheidspreventie. Met de verruiming kwam de langdurige residentiële zorg onder de bevoegdheid van de gewesten en werden de bevoegdheden inzake geestelijke gezondheidszorg en revalidatie uitgebreid. Deze nieuwe competenties werden vervolgens gecombineerd met reeds bestaande Vlaamse competenties, zoals gezinszorg en aanvullende thuiszorg, in de Vlaamse Sociale Bescherming (VSB).

Om een coherent beleid te kunnen formuleren en de kosten van zorg en sociale hulp te integreren in de globale Vlaamse begroting, rekening houdend met toekomstige behoeften, zijn budgettaire projecties op lange termijn nodig. Het doel van dit onderzoek is de constructie van een voorspellingsmodel voor de kost van de VSB. De eerste noodzakelijke stap hiervoor is natuurlijk het verzamelen van relevante data en dat bleek verre van triviaal. Het ontbreken van adequate gegevens voor sommige onderdelen van de VSB is te wijten aan de vrij recente wijziging in de Vlaamse bevoegdheden. Voor sommige onderdelen van de VSB (residentiële zorg en thuiszorg) leverde het samenvoegen van gegevens die op federaal niveau door het Intermutualistisch Agentschap (IMA) en op het niveau van de Vlaamse overheid worden verzameld (VESTA-gegevens), een dataset op die voldoende rijk is voor de opbouw van een projectiemodel. Voor andere onderdelen van de VSB (geestelijke gezondheidszorg en revalidatie) zijn de beschikbare gegevens echter onvolledig. Voor deze onderdelen waren we dus genoodzaakt minder ambitieus te zijn en ons te beperken tot een beschrijvende analyse.

Deel I van het rapport bevat een inleiding tot enkele methodologische problemen, een overzicht van bestaande modellen voor langdurige zorg en een korte beschrijving van de Vlaamse Sociale Bescherming.

Deel II beschrijft de constructie van een projectiemodel van het gebruik en de kosten voor de overheid van de residentiële zorg voor de ouderen en de thuiszorg. Simulaties illustreren op welke wijze het model kan gebruikt worden ter ondersteuning van het beleid.

Deel III bevat een kwantitatieve beschrijving van de sector van de geestelijke gezondheidszorg en de revalidatie, met een voorstel voor toekomstige dataverzameling in deze sectoren.

## **Deel I**

### *De Vlaamse Sociale Bescherming*

In deel I geven we een beknopte beschrijving van de inhoud en de doelstellingen van de Vlaamse Sociale Bescherming. Sinds de zesde staatshervorming is de Vlaamse Gemeenschap bevoegd geworden voor het beleid inzake de verstrekking van geestelijke gezondheidszorg in instellingen buiten ziekenhuizen, inclusief de Psychiatrische Verzorgingstehuizen (PVT) en de Initiatieven voor Beschut Wonen. De financiering van de psychiatrische ziekenhuizen zelf is nog steeds een federale bevoegdheid. Organisaties en diensten in de geestelijke gezondheidszorg die onder de VSB ressorteren zijn de Centra voor Ambulante Revalidatie (CAR), de Centra voor Geestelijke Gezondheidszorg (CGG), de Revalidatiecentra voor Verslaving, de Psychosociale Revalidatiecentra voor Volwassenen, de Centra voor Vroegtijdige Stoornissen in de Interactie ouders-kinderen, de Referentiecentra voor Autisme en de Centra voor Kinderpsychiatrische Aandoeningen. Daarnaast zijn de volgende organisaties voor lichamelijke revalidatie opgenomen in de VSB: Revalidatievoorzieningen voor Locomotorische en Neurologische Revalidatie, de Centra voor Visuele Revalidatie, de Centra voor Revalidatie van Kinderen met Respiratoire en Neurologische aandoeningen en de Eenheden voor Respijtzorg. De Vlaamse Gemeenschap is tenslotte ook bevoegd voor de (grote) sectoren van de aanvullende gezinszorg en de residentiële ouderenzorg.

### *Een bondig overzicht van bestaande prognosemodellen*

De zorgplanning moet anticiperen op toekomstige langdurige zorgbehoeften. Daartoe moeten de factoren die de vraag naar zorg en hulp beïnvloeden geïdentificeerd worden en, indien mogelijk, geïntegreerd in een coherent prognosemodel. Hierbij worden de statistische tijdspatronen op lange termijn geschat op basis van beschikbare (historische) gegevens. Bij de prognose wordt dan verondersteld dat deze historische tendensen zich in de toekomst zullen doorzetten.

Indien mogelijk, is het aangewezen om bij de constructie van het model te vertrekken van gegevens op het niveau van de individuele personen. Dat vereist een grote hoeveelheid gegevens over alle relevante individuele kenmerken in een steekproef die representatief is voor de hele populatie. Vaak worden gegevens uit verschillende databestanden verzameld en zijn er geavanceerde statistische technieken nodig om die verschillende databases te standaardiseren en met elkaar te linken. Bij de projectie worden de individuele gegevens geaggregeerd om groepen van mensen te kunnen onderscheiden (bv. de aantallen in verschillende leeftijdsgroepen) waarvan de evolutie in de toekomst kan geprojecteerd worden.

Om prognoses te kunnen maken, moeten determinanten van lange-termijn uitgaven in de modellen worden opgenomen. Afhankelijk van de beschikbaarheid van gegevens, worden in alle modellen in de literatuur ongeveer dezelfde verklarende factoren opgenomen: demografische verschuivingen in de

bevolking, evolutie van de gezondheidstoestand van de bevolking, inkomen, gedrag van cliënten, technische wijzigingen, prijzen en productiviteit en organisatie van de zorg.

Voor het literatuuroverzicht werden in totaal 26 studies geselecteerd, waarvan 13 modellen in verschillende landen meer in detail worden toegelicht. We bespreken steeds bondig de methodologie en de prognoseresultaten. Voor België is het meest relevante model geconstrueerd door het Federaal Kenniscentrum voor de Gezondheidszorg en het Federaal Planbureau. Dit model voorspelde het aantal bedden in de residentiële zorg voor ouderen voor de periode 2011-2025. Determinanten in het model waren de bevolkingsopbouw in termen van geslacht en leeftijd, de gezinssamenstelling, de beschikbaarheid van mantelzorgers en de trends in de gezondheidstoestand van de bevolking. Bij de constructie van het model werd gebruik gemaakt van de Gezondheidsenquête (HIS) voor de jaren 2004 en 2008 en van de Permanente Steekproef (EPS), opgezet door het Intermutualistisch Agentschap (IMA). Het model verklaart de verdeling van de bevolking over verschillende zorgcategorieën: geen zorg; twee thuiszorgsituaties 'laag' en 'hoog'; vijf niveaus van residentiële zorg - categorieën O, A, B, C en Cd; ziekenhuisopname; en, ten slotte, de dood. Met het geconstrueerde model worden verschillende alternatieve scenario's gesimuleerd. Het prognosemodel dat wij voorstellen in deel II maakt eveneens gebruik van EPS-data en vertoont gelijkenissen met dit KCE-FPB model.

In een ideale wereld zouden alle zorguitgaven die onder de Vlaamse Sociale Bescherming vallen, geïntegreerd moeten worden in één samenhangend prognosemodel. Voor de sectoren van de geestelijke gezondheidszorg en van de revalidatie zijn er echter onvoldoende individuele gegevens beschikbaar om een volwaardig prognosemodel te construeren. Voor residentiële zorg en thuiszorg (inclusief verpleegkundige zorg, een federale bevoegdheid), hebben we de individuele gegevens in de Permanente Steekproef (EPS) van IMA gekoppeld aan de VESTA-databank, die gegevens over het gebruik van thuiszorgdiensten bevat op individueel niveau. Dit maakt het mogelijk om voor deze sectoren een model te schatten dat perfect vergelijkbaar is met de modellen voor andere landen die in deel I beschreven worden.

## ***Deel II***

In deel II beschrijven we de ontwikkeling van een projectiemodel om het gebruik van thuiszorg en het aantal dagen in residentiële zorg te voorspellen. Voor de schatting maken we gebruik van individuele gegevens en we gebruiken het model om toekomstige uitgaven en beleidsscenario's te simuleren.

### *Afhankelijke en verklarende variabelen*

De structuur van deel II volgt de voornaamste stappen die bij de opbouw van een projectiemodel moeten gezet worden. Eerst beschrijven we in detail de beschikbare databanken: de Permanente Steekproef (EPS) van het Intermutualistisch Agentschap en het VESTA-platform met data over de gezinszorg. Zoals reeds gezegd, werden deze twee databanken aan elkaar gekoppeld. We schetsen de evolutie doorheen de tijd van de afhankelijke variabelen: het aantal dagen residentiële zorg, uitgesplitst naar de verschillende zorgcategorieën (O, A, B, C, Cd en kortverblijf), het aantal prestaties in de thuisverpleging, het aantal uren gezinszorg en logistieke hulp. De uitgaven voor de psychiatrische verzorgingstehuizen (PVT) worden niet in detail bestudeerd. Het model concentreert zich op de verklaring van het zorggebruik, niet op de evolutie van eenheidskosten en prijzen. We beschikken niet over de nodige informatie om daarvoor een behoorlijk model te schatten. We berekenen daarom de

uitgaven door de geprojecteerde gebruiksvolumes te vermenigvuldigen met de meest recent beschikbare eenheidskosten. Het spreekt echter vanzelf dat in de beleidssimulaties verschillende veronderstellingen over de kostenevolutie kunnen geïmplementeerd worden.

De verklarende variabelen komen grotendeels overeen met de variabelen die in soortgelijke modellen in andere landen worden gebruikt, zoals beschreven in deel I. Het belang van leeftijd en geslacht is evident, en in het licht van de vergrijzing, een belangrijke factor in de projecties. We introduceren ook een variabele voor de aanwezigheid van een handicap: hierbij wordt gebruik gemaakt van de definitie zoals die op federaal niveau en in de EPS wordt gehanteerd. Dataproblemen maakten het onmogelijk om te werken met de definitie van "handicap" die door de Vlaamse Gemeenschap wordt gehanteerd. De socio-economische achtergrond van de individuen wordt benaderd met een variabele die aangeeft of ze al dan niet een laag inkomen hebben. Binnen de EPS is, op basis van de samenstelling van de huishoudens, ook een variabele geconstrueerd, die de potentiële beschikbaarheid van een mantelzorger weergeeft. De morbiditeit (cardiovasculaire problemen, COPD, diabetes, Parkinson) wordt benaderend gemeten aan de hand van het geneesmiddelengebruik in de EPS. De variabele voor Alzheimer schiet echter duidelijk tekort omdat het geneesmiddelengebruik voor die aandoening in het verleden onvolledig en variabel is. De aanwezigheid van Alzheimer is nochtans evident een essentieel kenmerk voor onze doelstellingen: we hebben daarom een imputatieprocedure toegepast zodat we de globale prevalentiecijfers voor Alzheimer in de populatie en in de residentiële zorg, die bekend zijn uit andere bronnen, zo goed mogelijk benaderen. Tenslotte gaan we ook na of het regionale aanbod van gezinszorg en de regionale beschikbaarheid van bedden in de residentiële zorg invloed hebben op het zorggebruik.

De beschikbare gegevens zijn zeker niet perfect, maar ze zijn wel goed vergelijkbaar met de voorbeelden voor andere landen die wij in het eerste deel hebben beschreven. Ook het door ons voorgestelde projectiemodel kan de toets van een vergelijking met die internationale voorbeelden doorstaan.

### *Methodologische keuzes*

We gaan uitvoerig in op onze methodologische keuzes. Uiteindelijk hebben wij geopteerd voor de meest eenvoudige en meest gebruiksvriendelijke benadering waarin een lineair model wordt geschat met gewone kleinste kwadraten (OLS) op basis van een gepoolde dataset, waarin alle gegevens voor alle jaren (2009-2017) worden samengebracht. Voor 2018 en 2019 zijn ook reeds globale administratieve gegevens beschikbaar. Wij hebben met de verschillende voor de periode 2009-2017 geschatte modellen het gebruik in 2018-2019 voorspeld en die geprojecteerde waarden vergeleken met de werkelijke data. Voor de simulaties hebben we dan verder gewerkt met de specificatie die bij deze oefening de beste predicties opleverde. Gezien projectie van de toekomstige uitgaven de eerste bedoeling is van deze oefening, leek ons dat veruit het beste criterium.

De keuze voor de eenvoudige benadering betekent niet dat wij niet geëxperimenteerd hebben met meer gesofistikeerde benaderingen. We hebben hiërarchische modellen geschat, waarbij eerst de bevolking in verschillende categorieën wordt ingedeeld (geen zorg, thuiszorg, overgang van thuiszorg naar residentiële zorg, residentiële zorg) en dan het specifieke zorggebruik binnen elke categorie wordt geanalyseerd. Terwijl in het door ons verkozen model met een variabele "gestorven in het jaar" wordt gewerkt, hebben wij ook de alternatieve benadering geëxploreerd, waarbij de data geannualiseerd worden. Ten slotte hebben we om beter rekening te kunnen houden met een hele reeks niet observeerbare individuele kenmerken, van de panelstructuur van de gegevens gebruik gemaakt om een model met "fixed effects" te schatten. Al deze resultaten worden samengebracht in een appendix,

waaruit blijkt dat de voorspellende prestatie van het eenvoudige OLS-model minstens even goed en meestal beter was dan die van de meer gesofistikeerde modellen.

In hoofdstuk 4 van deel II worden de schattingsresultaten voorgesteld. Deze liggen perfect in de lijn van de verwachtingen. Leeftijd en morbiditeit hebben de verwachte effecten. Een laag inkomen en een handicap hebben een positief effect op het zorggebruik. Zeer belangrijk is de beschikbaarheid van mantelzorg. Ondanks de onnauwkeurige meting van deze variabele, is ze significant voor alle zorgcategorieën. De beschikbaarheid van mantelzorg houdt mensen inderdaad langer weg uit de residentiële zorg. Wij vinden ook interessante aanbodeffecten: wanneer het aanbod van gezinszorg in een zorgregio toeneemt, daalt het aantal dagen in de categorieën O en A van de residentiële zorg en in kortverblijf.

### *Projecties en beleidssimulaties*

Met het geschatte model simuleren we vervolgens de toekomstige zorgvolumes en kosten voor de periode van 2019 tot 2035. Bij deze projecties worden de bevolkingsvooruitzichten van Statbel gebruikt. Voor de andere verklarende variabelen worden de trends uit het verleden naar de toekomst geëxtrapoleerd.

In hoofdstukken 6 en 7 wordt geïllustreerd hoe verschillende scenario's kunnen worden geconstrueerd en gesimuleerd om het effect van relevante beleidsbeslissingen op het zorggebruik en de kosten te laten zien. Het uiteindelijke doel van een projectiemodel is de mogelijkheid te creëren om dergelijke beleidssimulaties uit te voeren. 'Projecties' mogen niet worden beschouwd als 'voorspellingen', aangezien het duidelijk is dat er in de toekomst maatschappelijke veranderingen zullen optreden die wij in de gegevens over het verleden niet konden ontdekken. Vergelijking van de referentieprojectie met de simulatieresultaten voor alternatieve veronderstellingen geeft echter nuttige inzichten in het relatieve belang van de verschillende verklarende variabelen en in de waarschijnlijke effecten van beleidsveranderingen. Ter illustratie van deze mogelijkheid hebben wij de budgettaire gevolgen getoond van de omzetting van ROB in RVT-bedden en van de financiering van meer "boven norm"-personeel. Een andere simulatie suggereert dat een verhoging van het aanbod van gezinszorg het aantal personen dat beroep doet op residentiële zorg doet afnemen en dat het zelfs mogelijk is dat deze verschuiving op lange termijn een positief effect heeft op de overheidsuitgaven, omdat de besparingen in de residentiële zorg groter worden dan de meeruitgaven in de gezinszorg. We tonen ook hoe belangrijk de afnemende beschikbaarheid van mantelzorg is voor de toekomstige evolutie van het gebruik van formele zorg.

Deze simulatieresultaten zijn slechts illustraties van het nut van het prognosemodel. Er zijn nog vele andere mogelijkheden en de belangrijkste output van dit werk is niet het overzicht van enkele simulatieresultaten, maar wel het model zelf dat door beleidsmakers kan gebruikt worden voor de analyse van de effecten van een hele reeks van beleidsmaatregelen. Aangezien het model wordt geschat met gegevens tot 2017, is daarvoor echter een regelmatige actualisering noodzakelijk. Dit is des te meer het geval omdat we mogen aannemen dat de covid-19-crisis tot een aantal structurele veranderingen in het systeem en in het gedrag heeft geleid, die niet kunnen worden geanalyseerd op basis van de gegevens van vóór de covid-19-crisis.

### ***Deel III***

In Deel III wordt een beeld geschetst van de behoeften, het huidige gebruik en de kosten in de ambulante geestelijke gezondheidszorg en de psychosociale revalidatiesector. Omwille van de beperkte beschikbaarheid van gegevens was het niet mogelijk een projectiemodel uit te werken voor de voorzieningen in deze sectoren. Wij hebben ons dan ook beperkt tot een gedetailleerde beschrijving van het huidige gebruik, met bijzondere aandacht voor de wijze waarop de beschikbare gegevens in de toekomst zouden kunnen worden verbeterd. Voorzieningen waarvoor voldoende gebruiksgegevens beschikbaar zijn, beschrijven we in afzonderlijke hoofdstukken, waarbij telkens dezelfde structuur gevolgd wordt:

- Eerst wordt een beschrijving gegeven van de doelgroep, de doelstellingen en de organisatiestructuur van de voorziening.
- Ten tweede bespreken wij de financiering en de kosten, zowel voor de cliënten als voor de overheid.
- Ten derde introduceren wij de beschikbare gegevens met betrekking tot het gebruik van diensten en de daaraan verbonden kosten.
- Tenslotte wordt alle informatie gebundeld in een poging om de toekomstige behoeften en kosten te ramen, rekening houdend met externe informatie zoals demografische gegevens en prevalentiegegevens en met bijzondere nadruk op de leemten in de beschikbare gegevens.

#### *Beschikbare gegevens*

De Permanente Steekproef van de IMA-databank (EPS), die we gebruikten voor de ontwikkeling van het model van de residentiële ouderenzorg en de thuiszorg, is ontoereikend voor de analyse van het gebruik van diensten in de geestelijke gezondheidszorg en revalidatiesector, vooral wegens het beperkte aantal relevante gevallen in de steekproef. Ook de informatie in de volledige IMA-databank zou ontoereikend zijn om een volledig beeld te schetsen, aangezien de Centra voor Geestelijke Gezondheidszorg nooit deel uitmaakten van de federale ziekteverzekering en de geleverde diensten dus niet in de IMA-databank geregistreerd zijn. Voor andere diensten, die vóór de zesde staatshervorming wel deel uitmaakten van de federale ziekteverzekering, zijn de nomenclatuurcodes vrij algemeen, zodat er weinig details beschikbaar zijn over de behandelde aandoeningen of de eigenlijke zorgactiviteiten waarop zij betrekking hebben.

De Centra voor Geestelijke Gezondheidszorg maken gebruik van hun eigen specifieke registratiesysteem. Veel belangrijke variabelen voor het beschrijven van cliëntprofielen en het gebruik van diensten zijn opgenomen in dit elektronisch patiëntendossier of EPD. Afgezien van de jaarlijkse samenvattende rapporten op de website van het Agentschap Zorg en Gezondheid, wordt de schat aan informatie die sinds 2008 in het EPD is geregistreerd echter weinig gebruikt in onderzoek en is er weinig informatie beschikbaar met betrekking tot de standaardisatie van de registratie en de betrouwbaarheid van de gegevens. Voor het huidige rapport verkregen we een aantal geaggregeerde datasets. Hoewel deze informatie te beperkt is voor de constructie van een projectiemodel, blijkt uit de beschrijvende statistieken het potentieel van de EPD-databank, indien de informatie op individueel niveau toegankelijk zou kunnen worden gemaakt voor onderzoeksdoeleinden.

Voor de Centra voor Ambulante Revalidatie vormden de jaarverslagen die jaarlijks naar het Vlaams Agentschap voor Personen met een Handicap (VAPH) werden gestuurd een mogelijke bron van nuttige



informatie, zij het niet op individueel niveau, maar op het niveau van het centrum en in afzonderlijke documenten. In het kader van dit project werden deze gegevens gedigitaliseerd in een kleine databank, waaruit bleek dat een aanzienlijk deel van de gegevens ontbrak en de kwaliteit ervan variabel was.

Voor de beschrijving van het gebruik van diensten in de Revalidatiecentra voor Verslaving, hebben wij gebruik gemaakt van een geaggregeerde dataset die is afgeleid van de Treatment Demand Indicator databank (TDI). Omdat door Sciensano belangrijke inspanningen zijn geleverd om de registratie te standaardiseren, is de betrouwbaarheid van deze dataset sinds 2011 aanvaardbaar. Het in kaart brengen van het gebruik van de diensten en de zorgverlening is echter niet het hoofddoel van de verzameling van TDI-gegevens. Als gevolg daarvan zijn veel relevante behandelingsvariabelen niet opgenomen en zijn de gegevens beperkt tot nieuw opgestarte zorgperiodes, waardoor de dataset beperkt bruikbaar is voor de doeleinden van dit onderzoek.

Een bijkomend aandachtspunt is de substantiële overlapping in het profiel van de cliënten van de verschillende diensten. Personen met psychische aandoeningen ontvangen zorg in de Centra voor Geestelijke Gezondheidszorg, maar vormen ook de belangrijkste doelgroep van de Centra voor Psychosociale Revalidatie en de Initiatieven voor Beschut Wonen. Kinderen en jongeren met ontwikkelingsstoornissen en comorbide psychische problemen worden bij voorkeur geholpen door de Centra voor Ambulante Revalidatie en de Centra voor Geestelijke Gezondheidszorg in een gezamenlijk zorgtraject, enz. Koppeling van gegevens tussen voorzieningen is daarom noodzakelijk voor het beschrijven van zorggebruik en het voorspellen van toekomstige trends.

De ideale dataset moet dus bestaan uit rijen die groepen op basis van hun zorgbehoefte onderscheiden en kolommen die de verschillende diensten van geestelijke gezondheidszorg en revalidatie vertegenwoordigen. Niet alleen het gebruik van een gemeenschappelijk identificatienummer is hiervoor cruciaal. Tevens is het noodzakelijk dat belangrijke cliënt- en behandelvariabelen die behoeftengroepen identificeren, consequent op een gestandaardiseerde manier in de hele sector worden geregistreerd. Met de introductie van BelRAI in de geestelijke gezondheidszorg en revalidatiesector zijn de eerste stappen gezet in het implementeren van een beoordelingsinstrument met het potentieel om een dergelijke uniforme, allesomvattende dataset op te leveren.

### *Aanbodbeperkingen*

Naast het probleem van de beschikbaarheid van gegevens doet zich een fundamenteel conceptueel probleem voor bij de beschrijving van het gebruik van diensten in de geestelijke gezondheidszorg en de psychosociale revalidatiesector. Voor de meeste van deze diensten leiden capaciteitsrestricties tot onvoldoende aanbod voor de zorgbehoeften in sommige of alle Vlaamse provincies. De wachtlijsten zijn lang en nemen toe, wat ertoe leidt dat cliënten gebruikmaken van diensten die niet helemaal op hun behoeften zijn afgestemd of dat potentiële cliënten helemaal niet worden behandeld.

In deze context zijn gegevens over het gebruik van diensten onvoldoende informatief voor het in kaart brengen van de behoeften. Toekomstprognoses die uitsluitend gebaseerd zijn op waarnemingen over het gebruik in het verleden, kunnen dan zeer misleidend zijn als indicator voor toekomstige tendensen. Bijgevolg is het noodzakelijk prevalentiegegevens in de analyse op te nemen als een middel om de behoeften aan geestelijke gezondheidszorg of revalidatie te beoordelen, onafhankelijk van het feitelijke gebruik van diensten. Een samenvatting van informatie in verband met de prevalentie van enkele belangrijke geestelijke gezondheidsproblemen en ontwikkelingsstoornissen toont echter aan dat de

Vlaamse prevalentiegegevens momenteel ontoereikend zijn. Ten slotte is ook andere aanvullende informatie nodig voor de constructie van een volledig model voor het gebruik van diensten in de geestelijke gezondheidszorg en revalidatiesector. Aangezien de specifieke zorg die wordt geboden door de gespecialiseerde diensten niet altijd geïndiceerd is voor alle mensen die dat probleem melden, is informatie over het verband tussen probleem (bv. ernst, comorbiditeiten, enz.) en passende dienst noodzakelijk. Gegevens met betrekking tot cliëntprofielen van alle voorzieningen in het zorgtraject van cliënten zijn derhalve belangrijk, met inbegrip van gegevens van huisartsen en andere verwijzende instanties.

### *Aanbevelingen voor toekomstige gegevensverzameling*

De implementatie van BelRAI als basis voor zorgplanning en financiering in de sector van de geestelijke gezondheidszorg en psychosociale revalidatie is een belangrijke stap in de ontwikkeling van een uniform systeem van gegevensverzameling. De definitieve invoering zal echter nog een aanzienlijk aantal jaren in beslag nemen, en het zal nog langer duren voordat tijdreeksen een voldoende lange periode bestrijken om trends in het gebruik van de diensten te kunnen schatten. Bij het formuleren van aanbevelingen moet dus enerzijds rekening worden gehouden met de BelRAI als basis voor toekomstige gegevensverzameling, zonder anderzijds de rijkdom aan informatie uit het verleden verloren te laten gaan.

In een eerste fase kunnen de resultaten in dit rapport helpen om (de evolutie in) cliëntprofielen in verband te brengen met (de evolutie in) behandelingskenmerken, en zo cruciale cliënt- en behandelingsvariabelen te bepalen die moeten worden opgenomen in BelRAI of in om het even welk systeem van gegevensverzameling in de sector van de geestelijke gezondheidszorg en psychosociale revalidatie.

Gezien het geschetste probleem van het beperkte aanbod, is voor de ontwikkeling van modellen voor de beschrijving en voorspelling van het gebruik van diensten bovendien aanvullende interne en externe informatie nodig, waaronder:

- Interne gegevens over wachttijden en wachtlijsten, die continu en op uniforme wijze worden geregistreerd in de gehele sector van de geestelijke gezondheidszorg en de revalidatie.
- Externe informatie betreffende de toegangspoorten tot de gespecialiseerde diensten voor geestelijke gezondheidszorg en revalidatie, met de mogelijkheid om gegevens op cliëntniveau te koppelen door middel van het gebruik van de INSZ-code.
- Betrouwbare en voldoende frequent verzamelde externe prevalentiegegevens voor de ontwikkelingsgerelateerde, psychosociale en fysieke gezondheidsproblemen die behandeld worden in de gespecialiseerde ambulante geestelijke gezondheidszorg en psychosociale revalidatiesector. Hoewel prevalentiegegevens bij voorkeur worden verzameld bij de algemene bevolking, onafhankelijk van het zorggebruik, zou het informatief zijn om in de gebruikte enquêtes vragen over het zorggebruik op te nemen voor alle zorgvoorzieningen. Op die manier wordt het mogelijk om kenmerken van de onderzochte aandoeningen en stoornissen (bv. ernst, comorbiditeit, enz.) te koppelen aan specifiek dienstengebruik. Bovendien is het aangewezen dezelfde definities te hanteren voor het bepalen van de prevalentie van stoornissen in de algemene bevolking als voor de registratie van diagnostische informatie in de geestelijke gezondheidszorg en revalidatiediensten.

Gezien het lange traject dat nog voor de boeg ligt voor de implementatie van BelRAI, kunnen onder-tussen de bestaande databanken die in dit rapport worden beschreven efficiënter gebruikt worden. Vooral het EPD-systeem in de Centra voor Geestelijke Gezondheidszorg bevat uitgebreide en gedetailleerde informatie op het niveau van de individuele cliënt en de zorgperiode. Het is echter noodzakelijk om de bruikbaarheid en de kwaliteit van deze gegevens in kaart te brengen en zo nodig te verbeteren.

Voor de andere geestelijke gezondheidszorg- en revalidatiediensten blijft de IMA-databank de belangrijkste gegevensbron voor informatie over het gebruik van diensten in het verleden. Er moet evenwel gebruik worden gemaakt van de volledige dataset, gezien het geringe aantal relevante gevallen in de Permanente Steekproef (EPS). Vooral voor de Centra voor Ambulante Revalidatie zou het de moeite waard zijn de IMA-dataset verder te onderzoeken, gezien het gebruik van diagnosespecifieke nomenclatuurcodes voor het factureren van behandelingssessies. Daarnaast kan voor de Revalidatie-centra voor Verslaving koppeling met de TDI-database worden gerealiseerd via de INSZ.

Hoewel de codes voor facturering gewijzigd zijn, is de financiering van de diensten die na de zesde staatshervorming naar de Vlaamse overheid zijn overgegaan, op dit ogenblik nog steeds in grote lijnen op dezelfde manier gestructureerd als vroeger onder de federale ziekteverzekering. Dit betekent dat het voor nu en in de nabije toekomst mogelijk en dus raadzaam is de registratie op dezelfde wijze voort te zetten om tijdreeksen te produceren die naadloos aansluiten op de federale gegevens die in de IMA-databank worden verzameld.



# Content

- Part I    An overview of literature** ➔
- Part II    A projection model for residential care for the older persons and for home care** ➔
- Part III    A first step to projecting future needs, service use, and costs in ambulatory mental health care and psychosocial rehabilitation** ➔



**Steunpunt Welzijn, Volksgezondheid en Gezin**

**Towards a projection model for the Flemish Social Protection**

**Part I**  
**An overview of literature**

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# Introduction

Before 2016 Flanders was already responsible for (a part of) public mental health care policies and for (a part of) health prevention. In 2001 the Flemish care insurance system was set up as an insurance for long term care expenditures. In 2016, with the Sixth State Reform, the Flemish responsibilities with regard to health and care policy were considerably broadened. While traditional health care remained largely a federal responsibility, long-term residential care became a responsibility of the regions, and the regional competences with respect to mental care and revalidation care were also extended. These new competences were then combined with already existing Flemish competences, such as family and supplementary home care (social care, logistic help and surveillance help) into the Flemish Social Protection (FSP) scheme.

Long-term projections of needs and costs are needed to formulate coherent policies and to integrate the costs of the FPS into the overall Flemish budget. The objective of the research on which we report here, is the construction of a long-run forecasting model for the FPS. The first necessary step is then of course the collection of relevant data and this turned out to be far from trivial. The lack of adequate data for some parts of the FPS is easily explained in the light of the rather recent change in Flemish competencies. For some parts of the FPS (residential care for the elderly and home care), merging data that are collected at the Federal Level by IMA (Intermutualistic Agency) and at the level of the Flemish Administration, yielded a dataset that is sufficient for the construction of a projection model. However, for other parts of the FPS (mental and revalidation care), the available data are much poorer. For these parts we therefore had to be less ambitious and to restrict ourselves to a descriptive analysis.

This explains why our report consists of three parts:

1. An introduction to some methodological issues, an overview of existing long-term care models, and a short description of the Flemish Social Protection program.
2. The presentation of a projection model, including simulations, for home care and residential care for the elderly. For this model we will use data at the level of the individual (micro data), but in the projections these will of course be aggregated according to age-groups or groups with specific health or disability problems, akin to what can be called a component-based model.
3. A quantitative description of the sector of mental healthcare and rehabilitation care, with a proposal for future data collection in this sector.

Chapter 1 in this first part contains an overview of existing models. Chapter 2 describes the main features of the Flemish Social Protection. We conclude by making the link between the two and suggesting which parts of the Flemish Social Protection program will be covered by the projection models in parts 2 and 3 of this report.



# Chapter 1

## Overview of forecasting methods for long-term care expenditures

### 1 Introduction

Anticipating future long-term care needs presents a challenge for health planners, both in terms of (the lack of) available data on population needs and in terms of the prediction of factors affecting the demand for care services. In order to project future long-term care expenditures, forecasting models can be applied at different levels of data. In this chapter, we make an overview of forecasting methods to make projections of long-term care needs and expenditures. We introduce some basic methodological issues and then give an overview of existing forecasting models for long-term care (LTC) expenditures, which may be inspiring for constructing a model of the Flemish social care sector in the context of the Flemish Social Protection.

### 2 Forecasting models

According to Makridakis et al. (2003), Diebold (2007) and Hyndman and Athanasopoulos (2018), statistical forecasting is a commonly used technique to plan into the future and to guide decision making. The idea is to identify long-run statistical time patterns in currently available (historical) data that are assumed to continue into the future. Forecasting therefore starts by building a statistical model and then estimates the parameters of the model by using observed historical data. A model can be defined as an analytical representation or quantification of a real-world system, used to make projections or to assess the behavior of the system under specified conditions. It represents the current state of knowledge about the concerned economic, environmental, social or health system. A model is a simplification of reality usually developed to address a specific issue. Great care must be taken when models are used for policy to make sure that they are fit for the purpose. Maximum quality, transparency and coherence are required. Notably, model results should be reproducible and available for scrutiny.

Forecasting models for care expenditures may include only spending on personal care, public spending, or total spending. The variable of interest may be projected per se or as an aggregation of different components (component-based models); as part of the overall economy (macro-level models); or as an aggregation of individual expenditure profiles (microsimulation models). We now provide an overview of the types of forecasting models, their features and data requirements (based on Astolfi et al., 2012).

#### 2.1 Types of forecasting models

##### 2.1.1 Macro models

Macro models focus on forecasting total health and wellbeing expenditure at an aggregated level. The analysis is restricted to health or wellbeing expenditures focusing on total budgets. They are most appropriate for projections in the presence of clear and constant trends and do not consider changes in policies or in consumers' choices or behavior. Therefore, macro models are more suitable for projections in the short run, where health systems can be considered more stable. On the other hand, computable general equilibrium models (CGE) are macro models which can account for reactions from consumers

and sectors to changing relative prices and other indicators. There are not many CGE models for the social care sector however.

### 2.1.2 Component-based models

Component-based models forecast health expenditure by stratifying the analysis into groups. The most often used type of component-based model is the cohort-based model in which individuals are grouped into cells according to key attributes such as age. Further refinements can be performed by sub-dividing the groups by gender and/or health status. These models are often referred to as actuarial models or cell-based models, where the term cell identifies the sub-categories into which each cohort is divided.

Cohort-based models have been very common over the years, probably because their implementation and maintenance tend to be simple, as the model requires a limited amount of data, generally including only a few parameters. Many of these parameters can be found in the literature, rather than being estimated. Secondly, the impact of policy changes can be assessed by simply modifying the policy parameters.

### 2.1.3 Micro models

Microsimulation models focus on individuals as the unit of analysis and they require large amounts of data to effectively build a sample that adequately represents the whole population of interest and includes all relevant characteristics. Data are often gathered from a variety of sources, and sophisticated statistical techniques are often required to standardize the various databases so that they can be used to populate all of the desired attributes of individuals included in the sample. For dynamic microsimulation, the model has to contain a realistic description of the behavior for all of the individuals. This may be estimated through econometric regressions based on the individuals' past experiences and choices or may be taken from a review of the health and economic literature (Ringel et al., 2010).

Micro models offer flexibility to test a range of policy scenarios related to the organization and financing of care. The forecast results can be shown by attributes included in the model, such as by disease-groups, age-groups, treatments (Zucchelli et al., 2010). In the case of dynamic microsimulation models, certain characteristics and behaviors can evolve over the life course. Progression of disabilities, as well as diseases, can all be associated to simulated individuals with attributions based on risks or probabilities. Individual life trajectories are then simulated until death. Costs are assigned to services associated with the life events that have been simulated to forecast a future trend in LTC spending.

Figure 1 represents the different approaches graphically.

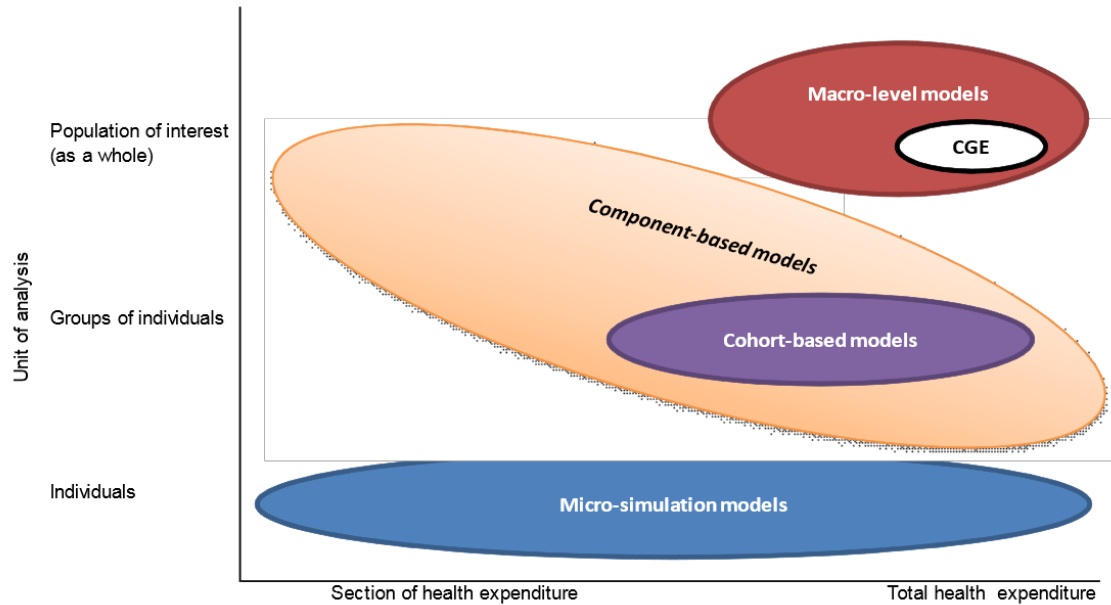


Figure 1 Types of forecasting models

Source: Astolfi et al. (2012)

## 2.2 Time span of the models

As the time window expands, many drivers that influence the trend in health expenditures can change and become more difficult to forecast. The degree of uncertainty increases over time in long-run forecasts and should be considered when valuing the information provided (Lee and Miller, 2002). While short-term forecasts are more accurate and should be performed when the structure of the system can be considered unchanged, medium-to-long-term projections have the ability to support policy planning and decision-making by incorporating changes or considering several scenarios. Macro models are suitable for projections in the short-run, while component-based and micro models can be applied for medium-to-long-term forecasts. The latter bring the opportunity to policy makers to investigate future trends and to predict the course of events and act on it, if necessary.

## 2.3 Combining models

As mentioned before, forecasting models can project health and wellbeing expenditure using data at the level of individuals (micro), groups of individuals or the nation as a whole. At the same time, some models can focus on specific sections of health or wellbeing expenditure, such as public expenditure, social security, private insurance or out-of-pocket payments by individuals. Anderson (1990) reports the following reasons to link different types of forecasting models:

- to align the predictions of the micro model with the macroeconomic predictions;
- to take up general equilibrium feedbacks and interactions among variables in the micro model;
- to provide a microeconomic basis for aggregate behavior in a macro model.

In addition, combining models can provide a more detailed description of the use of health and wellbeing services by individual agents and have the potential to capture externalities from the provision and use of these services, such as evolution in labor productivity or in labor supply (Peichl A., 2016).

Recent decision-support models offer enhanced opportunity to test policy scenarios and to understand the broader social and economic implications of policy changes. For example, the U.S. Congressional Budget Office (CBO) is combining microsimulation and component-based approaches within a platform for health expenditure projections. In Australia, a microsimulation approach has been combined with a computable general equilibrium approach to project the impact of chronic disease prevention efforts.

## **2.4 Scenario analysis of forecasting models**

When creating forecasting models, it is useful to show the primary results as well as the results with the impact of different scenarios. Scenario analysis provides several outcomes: the first outcome is the most likely one, based on the data and baseline information in the model. After manipulation of the data or the assumptions of the model, a series of outcome scenarios can be constructed, for example, the most favorable outcome (best-case scenario) and the most unfavorable outcome (worst-case scenario). In addition, the results from the more sophisticated forecasting models usually show a prediction interval in which the outcome value lies between an upper and a lower bound (interval).

Interpretation of the scenarios and their prediction interval enables users to:

- assess future uncertainty;
- plan different strategies for the range of possible outcomes indicated by the prediction interval;
- compare forecasts from different methods more thoroughly.

While uncertainty analysis aims at quantifying the uncertainty in model output due to the uncertainty in model inputs, sensitivity analysis establishes how the quantified uncertainty in the model results can be attributed to the different sources of uncertainty in the model inputs (Saltelli et al., 2004). The difference between sensitivity analysis and scenario analysis is that sensitivity analysis changes only one input at a time in order to assess the sensitivity of the projection to that variable. With scenario analysis, all inputs changes are made at the same time with the purpose of assessing the effect on the results of a complete change in circumstances.

## **2.5 Model determinants and cost drivers**

In order to make projections, determinants of LTC expenditure have to be included in the models. Almost all forecasting models take into consideration demographic shifts in the population, which is likely the result of the generally accepted impact of population aging on health spending and the availability of credible demographic projections. A plethora of empirical studies provided evidence that suggests correlation between LTC health expenditure and demand factors related to demography and health conditions. Particularly, the relationship between demographic change and LTC spending is generally accepted, given that a majority of LTC patients is 65 or older (Yang et al. (2003), Marino et al. (2017)). Evidence shows a positive relationship between residential healthcare spending and age (Oliveira Martins and de la Maisonneuve (2006), Jin et al. (2020), Gianino et al. (2017)).

However, other influences on the upward trend in health expenditures have been identified, including the introduction of new health technologies; increases in the intensity of treatments provided to persons in need of care; increases in labor costs; overall growth in national income (as rising wealth enables health and care spending); changes in the organization and delivery of care; the productivity of



the care system; trends in key diseases and their treatment costs; and changes in health-seeking behaviors.

In a comparative review of forecasting methods for care spending in de OECD countries, Astolfi et al. (2012) identified seven commonly used determinants:

- demographic factors (also including health status)
- income
- consumer/patient behaviors
- treatment practices
- technological progress
- (health)care prices and productivity
- organization of care

Figure 2 (taken from Bartosz, 2010) gives a useful overview of the determinants of healthcare expenditures by type and classified between demand or supply side factors.

	<b>Demographic factors</b>	<b>Health factors</b>	<b>Economic and social factors</b>	<b>Public policy factors</b>
<b>Demand side factors</b>	<ul style="list-style-type: none"> <li>• Size and structure of the population</li> </ul>	<ul style="list-style-type: none"> <li>• Health status of the population, in particular of elderly cohorts</li> <li>• Death-related costs</li> </ul>	<ul style="list-style-type: none"> <li>• National/ individual income</li> <li>• Income elasticity of demand for health care</li> <li>• Social determinants of health (environment, living conditions) and health-related behaviour</li> <li>• Public expectations and real convergence in living standards</li> </ul>	<ul style="list-style-type: none"> <li>• Health promotion and disease prevention policy</li> </ul>
<b>Supply side factors</b>			<ul style="list-style-type: none"> <li>• Development of new technologies and medical progress</li> <li>• Unit costs in health care sector relative to the other sectors of economy</li> <li>• Resource inputs, both human and capital</li> </ul>	<ul style="list-style-type: none"> <li>• Contribution of public and private budgets to the financing of health care</li> <li>• Insurance schemes</li> <li>• Remuneration schemes in health care</li> <li>• Regulation and/or liberalisation of the market for health care services and pharmaceuticals</li> </ul>

Figure 2 Determinants of LTC expenditure

Source: Bartosz (2010)

### **3 Overview of forecasting models for LTC expenditures**

To get a better idea about forecasting models and their projections, it is useful to have some concrete examples of what type of determinants they use and of how to interpret the results of the projections. In this section, we give an overview of forecasting models, which can give inspiration to build a model for the Flemish social care needs and expenses.

#### **3.1 Inclusion criteria of forecasting models**

The following criteria were used to identify in the scientific literature forecasting models which can be appropriate for the use in Flanders:

1. The model includes health and also wellbeing or social services/care outcomes;
2. The variables and the methodology of the model are well described;
3. The model is preferably a micro-level or component-based model.

Table 1 gives an overview of forecasting models for LTC spending. Models based on the total LTC expenditures are scarce since not all models include expenditures on wellbeing or social services. Only component-based models and micro models were included in the table due to their relevance for the Flemish model which we wish to build. The models in the table indicated with an \* will be further explained in this chapter.

Table 1 Overview of forecasting models for LTC expenditures

Country	Institution	Type	Explanatory variables in the model	Residual factor (1)	Projection years	Outcomes
Australia	Australian Institute for Health and Welfare (AIHW)	Component	<ul style="list-style-type: none"> <li>- Demographic changes and age structure</li> <li>- Relative prices</li> <li>- Technological change</li> <li>- Expenses near death</li> <li>- Obesity</li> </ul>	Changes in use of services to capture changes in technologies	30	Private and public expenses by gender, age and some diagnoses
Australia	Australian Treasury	Component and Macro	<ul style="list-style-type: none"> <li>- Hospital use (patient days)</li> <li>- Medical use (visits)</li> <li>- Pharmaceutical use (subsidized drugs)</li> <li>- Private insurance</li> <li>- Other health expenses (small healthcare delivery projects)</li> </ul>	Non-demographic factors	40	Public expenses for hospital and medical use by age groups
Canada	Statistic Canada / Population Health Model (POHEM)	Micro	<ul style="list-style-type: none"> <li>- Demographic changes</li> <li>- Risk factors such as smoking, obesity, hypertension and cholesterol problems</li> <li>- Prevalence of diseases</li> <li>- Use of diagnostic tests and therapies</li> <li>- Cost of diagnostic tests and therapies</li> </ul>		25	Public cost of the incidence and prevalence of diseases (pulmonary diseases, breast cancer, cardio diseases, diabetes, and others)
Canada	Ontario study	Component	<ul style="list-style-type: none"> <li>- Demographic changes</li> <li>- Age structure</li> <li>- Inflation</li> </ul>		20	Public expenses per age and gender for hospital costs, physicians, use of medicines and other institutions and services

Country	Institution	Type	Explanatory variables in the model	Residual factor (1)	Projection years	Outcomes
France	Direction de la recherché, de l'évaluation et des études statistiques (DRESS)	Component	<ul style="list-style-type: none"> <li>- Income elasticity (2)= 0.9</li> <li>- Demographic changes and age structure</li> <li>- Excess growth of economy</li> </ul>	Non-demographic factors	40	Public and private expenses per gender and age
Italy	Regioneria Generale dello Stato (RGS)	Component	<ul style="list-style-type: none"> <li>- Relative prices</li> <li>- Income elasticity=1.1 converging to 1 at the end of the projection</li> <li>- Demographic changes</li> <li>- PIB per capita</li> <li>- Consumption per age and gender</li> </ul>	-	50	Public expenses per gender and age
Italy	Department of Economics and Law, Sapienza-University of Rome *	Component	<ul style="list-style-type: none"> <li>- Demographic factors (share of older people with 2 or more disabilities, number of healthy life years at 65, life expectancy at 65 years old)</li> <li>- Household (living alone)</li> <li>- Unemployment rate of women (15-64)</li> <li>- Dummy variables for region characteristics</li> </ul>	-	No projections were shown, but the methodology of the model is useful	Regional expenditure on residential LTC as a ratio of over-65 residents
The Netherlands	Institute for Social Research/SCP *	Micro	<ul style="list-style-type: none"> <li>- Demographic changes and age structure</li> <li>- Social factors</li> <li>- Illness level (chronic diseases or dementia)</li> <li>- Physical disabilities</li> </ul>	-	16	Public funded long-term care: household care, nursing and personal care and support, both at home and in a residential setting

Country	Institution	Type	Explanatory variables in the model	Residual factor (1)	Projection years	Outcomes
						(homes for the elderly and nursing homes)
The Netherlands	Bureau for Economic Policy Analysis (CPB)	Component	<ul style="list-style-type: none"> <li>- Demographic changes and age structure</li> <li>- Changes in health expenses due to increase in life expectancy</li> <li>- Fiscal impact of macro-economic policies</li> </ul>	Non-demographic factors and prices	5	Public and private expenses per age, gender and function (hospital, specialists, home physicians), dentists, paramedics, psychiatric care and medication use)
New Zealand	Ministry of Health Treasury	Component	<ul style="list-style-type: none"> <li>- Demographic data</li> <li>- Health status near death</li> </ul>	Technological changes, policies, inflation, productivity	50	Public expenses per capita per gender, age
Sweden SESIM/LEV	Ministry of Health and Social affairs *	Micro	<ul style="list-style-type: none"> <li>- Demographic changes and age structure</li> <li>- Social data (census)</li> <li>- Health profile</li> <li>- Demand for health and social services</li> <li>- Epidemiology: cancer, dementia, diabetes, CVA and acute heart attack</li> </ul>	-	40	Public expenses per age, gender and diagnoses
Belgium	Belgian Healthcare Knowledge Center *	Micro	<ul style="list-style-type: none"> <li>- Demographic changes and age structure</li> <li>- Social data</li> <li>- Availability of informal carers</li> <li>- Health status (cognitive and physical health)</li> <li>- Use of residential care.</li> </ul>	Policies	15	Number of beds in residential care

Country	Institution	Type	Explanatory variables in the model	Residual factor (1)	Projection years	Outcomes
United Kingdom	Office for Budgetary Responsibility	Component	<ul style="list-style-type: none"> <li>- Demographic data and age structure</li> <li>- Health status and life expectancy</li> <li>- Service volume and improvements in decreasing waiting lists and in reassuring specific treatments</li> <li>- New medical technologies</li> <li>- Productivity gains</li> </ul>	-	20	Public expenses per age and gender and diagnoses
United Kingdom	Personal Social Services Research Unit (PSSRU)/London School of Economics *  PSSRU updated in 2015. *	Micro	<ul style="list-style-type: none"> <li>- Demographic changes and age structure</li> <li>- Informal care</li> <li>- Home tenure and household</li> <li>- Physical disability (IADL / ADL)</li> <li>- Use of home care, residential care, hospital care and social care</li> <li>- Staff needed to provide care</li> </ul>	Factors affecting demand and supply such as staff needed and availability of informal care;  Several scenarios	40	Use of services by age, gender and household; Estimated levels of long-term care services demanded by type of service and total expenditure by funding source
USA	The Future Older People Model (CMS/RAND)	Micro	<ul style="list-style-type: none"> <li>- Demographic data</li> <li>- Health status</li> <li>- Medical innovations</li> <li>- Risk factors</li> <li>- Prevalence of chronic diseases</li> <li>- Annual costs of treatment of diseases</li> </ul>		30	Medical costs, also Medicaid and Medicare and medicine costs for people older than 51
USA	Department of Veterans Affairs	Component	<ul style="list-style-type: none"> <li>- Clients</li> <li>- Rate of service utilization</li> <li>- Costs of services</li> <li>- Degree of dependency of clients</li> </ul>		20	Total number of clients, utilization of services and operational costs

Country	Institution	Type	Explanatory variables in the model	Residual factor (1)	Projection years	Outcomes
USA	Comprehensive Assessment of Reform Efforts (Compare) (RAND/USDL/USDHHS)	Micro	<ul style="list-style-type: none"> <li>- Total clients still working and benefiting from Medicaid</li> <li>- Subsidies for government insurance and for mixed insurance</li> <li>- Fiscal policies</li> </ul>	-	40	Changes in public expenses due to transfers in insurances by working clients after fiscal policy changes
OECD forecasts	OECD	Component	<ul style="list-style-type: none"> <li>- Demographical changes based of use of health services for survivals and non-survivals</li> <li>- Income elasticity=1</li> <li>- Technology changes and relative prices effect</li> <li>-</li> </ul>	Several non-demographical factors	45	Public expenses per gender and age as % of GDP
OECD model for 40 countries	OECD *	Component	<ul style="list-style-type: none"> <li>- Share of old-age dependent people</li> <li>- Share of young dependent people</li> <li>- Life expectancy at birth</li> <li>- Income</li> <li>- Productivity</li> </ul>	Evolution of health prices and technology index	50	LTC care spending
Model for 31 countries from OECD.	OECD *	Component	<ul style="list-style-type: none"> <li>- Share of older persons (65 plus) and young people (under 15)</li> <li>- Death related costs and age specific cost curves</li> <li>- Medical prices</li> <li>- Wages in excess of general productivity, GDP per capita</li> <li>- Index of hospital-country characteristics, infant mortality, Life expectancy, share of R&amp;D, share of patents</li> <li>-</li> </ul>	Index of policies and institutional characteristics of countries	No projections were shown, but the methodology of the model is useful.	LTC care spending, mostly residential care



Country	Institution	Type	Explanatory variables in the model	Residual factor (1)	Projection years	Outcomes
Europe	ANCIEN *	Micro	<ul style="list-style-type: none"> <li>- Demographic data</li> <li>- Social data</li> <li>- Prevalence of chronic diseases, cognitive problems</li> <li>- Disability</li> <li>- Formal and informal care, residential care</li> <li>- Supply of formal and informal care</li> </ul>	<p>Supply factors</p> <p>Several scenarios</p>	50	Formal and informal care use, as well as residential care; supply and demand
28 European countries	Università di Torino, Italy *	Component	<ul style="list-style-type: none"> <li>- Percentage of population aged 65 and older</li> <li>- Self-perceived health (bad and very bad): Is auto-evaluation of the general health state by the surveyed, with six categories, including very good, good, fair, bad, very bad. It is measured by the percentage of whole population of aged 65 years and older.</li> <li>- Self-perceived long-standing limitations in usual activities: it is self-assessment of the interviewees of the degree of limitation of daily activities dues to health problems over the last 6 months. It is measured by percentage of whole population of aged 65 years and older</li> </ul>		No projections were shown, but the methodology of the model is useful.	<p>Benefits per inhabitant for 65 years and older;</p> <p>the number of beds in institutions;</p> <p>the proportion of LTC recipients in institutions and at home;</p> <p>the healthcare expenditure on long-term nursing care services and on LTC social services</p>

Country	Institution	Type	Explanatory variables in the model	Residual factor (1)	Projection years	Outcomes
Turkey		micro	<ul style="list-style-type: none"> <li>- Age dependency ratio</li> <li>- GDP per capita</li> <li>- Female labor force participation rate (as a proxy for informal care provision)</li> </ul>	45		LTC expenditures
Japan INAHSIM model	Institution for future welfare, Tokyo *	micro	<ul style="list-style-type: none"> <li>- Events such as birth, death, marriage, divorce, changes of household situations generated by those events, and the merger of aged parent(s) with the child's household and other movements of households.</li> <li>- Death rates</li> <li>- Dependency index of older people</li> </ul>	-	40	<p>Number of the elderly according to dependency and/or living situations</p> <p>Relative parents/children ratio</p> <p>A 1-year transition matrix by household type</p> <p>LTC expenditures</p>
China	OECD *	Component	<ul style="list-style-type: none"> <li>- Demographic factors: changes in the number of dependent people in the population. These changes depend on the age of the population and the</li> <li>- Income</li> <li>- GDP per capita</li> <li>- cost-disease (relative productivity or Baumol effect)</li> <li>- Life expectancy</li> <li>- Income elasticity of LTC expenditures</li> </ul>	-	15	LTC expenditures

Country	Institution	Type	Explanatory variables in the model	Residual factor (1)	Projection years	Outcomes
China	Center for Aging Health Research, School of Public Health, Xiamen University *	micro	<ul style="list-style-type: none"> <li>- Age</li> <li>- Total number of older people</li> <li>- Disability index and Katz scale levels</li> <li>- Care use</li> </ul>		30	Number of disabled older persons  LTC expenditures in urban and rural area

(1) Residual factors are factors which affect the projections but which are not explicitly included in the model (ex. technology, government policies, inflation, productivity levels, etc.) and are used in scenario analysis.

(2) The real income elasticity varies in empirical results depending on the assumption whether healthcare is a luxury good or a necessity. Empirical estimates of elasticity tend to increase with the degree of income aggregation. The OECD income elasticity is generally larger than elasticities estimated in national or regional levels. Results for the US and Canadian provinces, as well as national-level data for 16 OECD countries, confirm that the size of the income elasticity varies by the level of analysis.

Source: Table adapted from Astolfi et al. (2012) and Benavides et al. (2013)

### 3.1 Most appropriate forecasting models for use in Flanders

The following LTC models were selected for a more detailed description because of their comprehensiveness, as most of them include health and wellbeing outcomes, and their usefulness for the construction of a model for the Flemish Social Protection system.

#### 3.1.1 Gianino et al. (2017) - 28 European countries

Gianino et al. (2017) examined how an increase in the number of older people and a degradation in the self-evaluation of one's general health state, as well as in the performance of daily activities can affect the LTC service demand. The study used a pooled, cross-sectional, time series design on 28 European countries for the period of 2004-2015. Indicators considered in the study as explanatory variables were from Eurostat Statistics, including:

- Percentage of population aged 65 and older;
- Self-perceived health (bad and very bad): based on self-evaluation of the general health state by the surveyed, with six categories, including very good, good, fair, bad, very bad;
- Self-perceived long-standing limitations in usual activities: a self-assessment by the interviewees of the degree of limitation of daily activities due to health problems over the last 6 months.

The dependent variables included:

- Benefits per inhabitant of 65 years and older;
- The number of beds in institutions per 1000 population aged 65 years and older;
- The proportion of LTC recipients in institutions and at home aged 65 years and older out of the entire population;
- Healthcare expenditure on long-term nursing care services and on LTC social services.

The authors performed fixed effects linear regression models, as they considered that OLS regressions did not yield proper estimates on data containing repeated measures. An advantage of using fixed effects models is that they can control for time-invariant heterogeneity among countries, such as cultural and historical patterns that shape social institution and policy systems. The authors also controlled for the presence of exogenous time trends in both explanatory and response variables (i.e. time-fixed effects) by adding dummies to the model for each of the study years except for the first year.

The results showed that the percentage of the older population increased steadily over the period while the percentage of self-perceived bad health and long-standing limitations witnessed a stable decreasing trend. This demonstrates an improvement in healthy aging. Nevertheless, the number of the available beds did not increase as much as the number of potential users of LTC. This can be explained by technological innovations combined with new and modern forms of services delivery organization, a strong willingness of the older people to stay at home, and higher incomes and better living standards than in the past. Another potential explanation may lie in the welfare policies adopted. Specifically, European countries with a high level of coverage, tend to concentrate services on the most serious cases (Pavolini and Ranci, 2008).

Lastly, there was a positive correlation between the proportion of the older people and the expenditures on social services. This item consisted of home help and help with the instrumental activities of daily living (IADL). This may be in line with the cultural and social changes of the last decade in EU countries. Particularly, a decline in fertility rates and an increase in female employment rate, and in the share of older people living alone resulted in a decreasing availability of informal caregivers.

### 3.1.2 Cepparulo and Giuriato (2021) - Italian regions

Cepparulo and Giuriato (2021) employed a pooled OLS model for the data in different regions in Italy over the period 2010–2018 to investigate the demand factors, market forces and institutional drivers of the spatial distribution of residential healthcare for older people. They selected a set of driving factors of regional expenditure on residential LTC, shown in Table 2.

Table 2 Overview of driving factors of regional expenditure on residential LTC

		Variable
Demand factors	Demographic	Dependency index ( <i>dep_ind</i> )
		Share of people aged over-65 with two or more chronic diseases every 1000 persons ( <i>chronic</i> )
		Number of healthy life years at 65 ( <i>healthylife_exp_M</i> for men; <i>healthylife_exp_F</i> , for women)
		Life expectancy at age 65 ( <i>life_exp</i> )
	Social	Share of families of single persons aged over 65 ( <i>fam_single_ + 65</i> )
		Share of over-65 people who live alone ( <i>lonely_ + 65</i> )
		Gini index ( <i>gini</i> )
	Market	Unemployment rate of women aged 15–64 ( <i>unempw15_64</i> ), 45–54 ( <i>unempw45_54</i> ) and 55–64 ( <i>unempw55_64</i> )
Female participation rate in the labor market ( <i>part_rate</i> )		
Institutional factors	Decentralization	Dummy for regions with a recovery plan ( <i>pr</i> ) or a commissioner in charge of the recovery plan ( <i>prc</i> )
		Regional current revenues ( <i>curr_rev</i> )
		Regional own taxes ( <i>own_tax</i> )
		Special statute regions dummy ( <i>rss</i> )

Source: Cepparulo and Giuriato (2021)

The dependent variable of the model is the regional expenditure on residential LTC per resident older than 65. A log transformation of this variable is used to reduce the wide data ranges. The authors found that the life expectancy of older people had a significant positive impact on LTC spending and that regional expenditure in Italy seems to be mainly driven by market and institutional factors. They also found a significant association between formal regional assistance and informal help, as the unemployment rate of women (aged 15–64) is negatively associated with the use of residential care, supporting the idea that an increase in the share of unemployed potential carers reduces the demand of formal residential assistance.

### 3.1.3 Marino et al. (2017) - 31 countries from OECD

Marino et al. (2017) implemented cross-country forecasts of health expenditure for OECD countries, using a component-based model. First, they reviewed the literature to understand the main approaches used to forecast healthcare expenditure growth employed in OECD countries. They argue that despite methodological divergences between approaches, there is a common set of healthcare spending drivers, including demographic factors, income developments, technological progress, Baumol’s cost disease (which represents relative productivity), and associated healthcare policies. Secondly, they estimated the relative contribution of these key drivers to the growth of healthcare spending. For example, unlike other functions of healthcare such as inpatient and outpatient care, LTC spending has a stronger relationship with demographic change, given that a majority of LTC patients are 65 or older.

The variables that were used are shown in Table 3.

Table 3 Overview of driving factors of regional expenditure on residential LTC (OECD model – 31 countries)

Drivers of healthcare expenditure	Variables used in the models
Demographics	<ul style="list-style-type: none"> <li>- Share of older persons (65 plus)</li> <li>- Share of young people (under 15)</li> <li>- Death related costs and age specific cost curves</li> </ul>
Baumol's cost disease	<ul style="list-style-type: none"> <li>- Medical prices</li> <li>- Wages in excess of general productivity</li> </ul>
Income	<ul style="list-style-type: none"> <li>- GDP per capita</li> </ul>
Technology	<ul style="list-style-type: none"> <li>- Index of hospital-country characteristics</li> <li>- Infant mortality</li> <li>- Life expectancy</li> <li>- Share of R&amp;D</li> <li>- Share of patents</li> </ul>
Policies	<ul style="list-style-type: none"> <li>- Index of policies and institutional characteristics of countries</li> </ul>

Source: Marino et al. (2017)

The results of the forecast showed that:

- For demographics, time-to-death was the main factor behind increasing healthcare costs, with expenditure for non-survivors ranging between 2 and 15 times higher than for survivors. The impact of ageing on increased health expenditure comes predominantly in terms of the share of a country's population being close to death (non-survivors).
- For income, they found that the income elasticity in high-income countries is lower than one, with an average elasticity estimate of 0.75. At the same time, there is evidence that middle-income countries show higher elasticities. Low productivity in the health sector – commonly referred to as Baumol's cost disease – has been widely documented in high-income country settings.
- On average, the literature pointed to over half of productivity gains in the overall economy being translated to wages in the healthcare sector.
- Technology also showed to have, on aggregate, a positive impact on health spending. Estimates of its exact effect, though, vary widely. The proxy for technological advancements, such as life expectancy, infant mortality, share of the elderly, indexes of medical technologies, hospital research, coverage and general research and development were all found, at different times, to be significant at different levels and effect size.

#### 3.1.4 De la Maisonnette and Martins (2013) - OECD

De la Maisonnette and Martins (2013) modelled separately specific healthcare functions from the model for general public healthcare expenditure, especially focusing on public long-term care. The LTC model included dependency ratios, defined as number of dependent people by age groups, as the key cost driver of LTC. A measure for Baumol's cost disease, which represents productivity in the healthcare sector compared to the general economy, is included as a major driver of LTC rather than healthcare as a whole. Indeed, because the LTC sector is more labor intensive than healthcare, it is more sensitive to Baumol's wage increases in excess of general productivity growth (Marino et al., 2017).

The drivers of LTC spending are illustrated in the following figure:

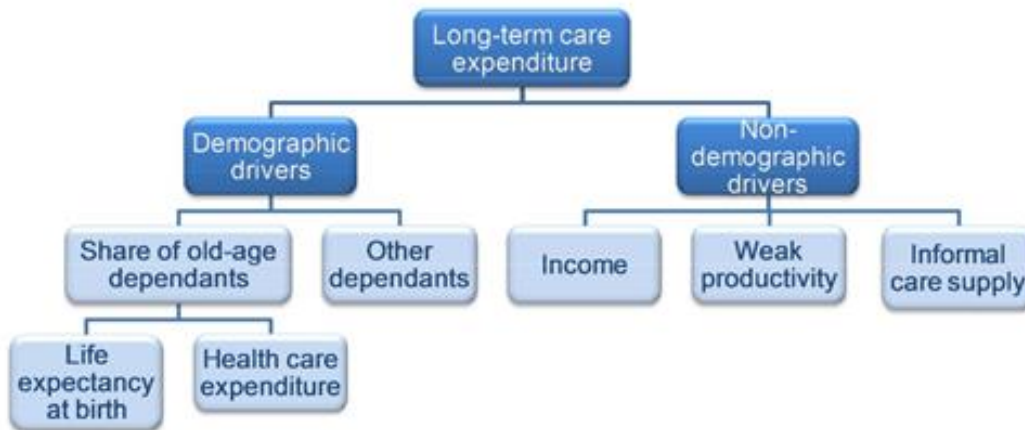


Figure 3 Determinants of LTC expenditure

Source: De la Maisonneuve and Martins (2013)

The authors argue that there is a sharp difference between long-term care and general healthcare. Particularly, healthcare services are used in the context of a changing health condition, while LTC aims at making the patient's current condition more bearable. Unlike the general healthcare, to which the whole population may have access, LTC is only beneficial to dependent persons.

De la Maisonneuve and Martins (2013) defined two kinds of determinants of public LTC expenditure: demographic and non-demographic drivers. The demographic factor refers to the number of dependent people in the population, measured by age-specific dependency ratios. This driver depends largely on the evolution of life expectancy and health conditions (see Figure 4, based on the Aging Report 2009). The authors show that these dependency ratios are broadly uniform across countries. For the projection of the evolution of dependency for 2010-2060, the age-specific dependency ratios are estimated based on historical data as a function of age, age-specific per-capita healthcare expenditures and life expectancy at birth.

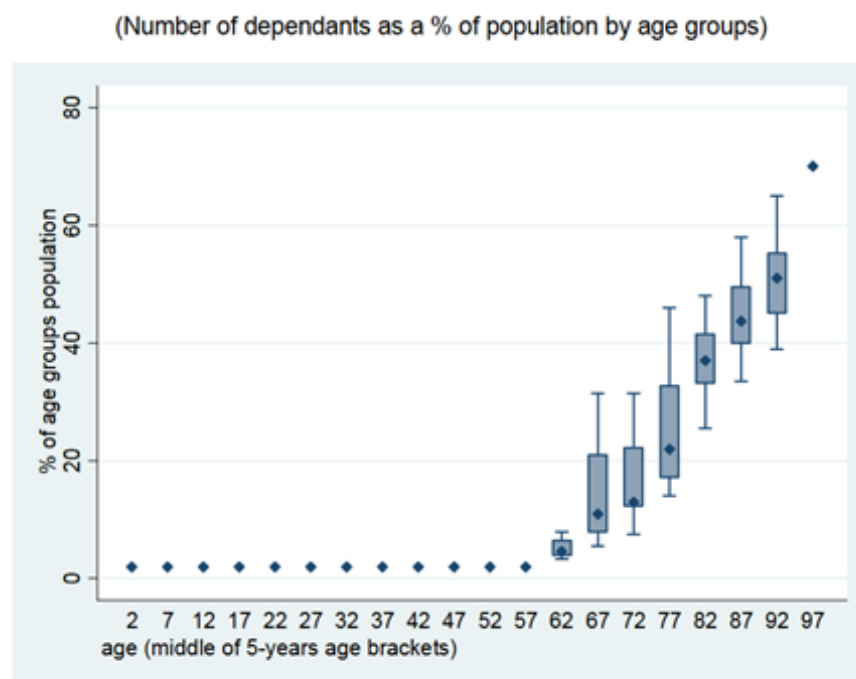


Figure 4 Determinants of LTC expenditure: number of dependents

Source: *Aging Report (2019)*

Non-demographic factors are related to rising incomes and changes in the demand for the public-financed LTC services. Income developments affect LTC expenditure directly via improvements in living standards (GDP per capita) and indirectly via the cost-disease effects (or relative productivity in the healthcare sector compared to the general economy), the so-called Baumol cost disease (Baumol, 1967; 1993). Since the LTC sector is labor-intensive, its relative price tends to rise with equalization of wages across sectors. Since it has a price inelastic demand, the share of LTC expenditure then tends to increase over time. A possible approach to capture the effect is to assume that unit costs increase with average earnings of care staff or a measure of wage inflation in the economy. It can be proxied by the productivity growth in the total economy.

The demand for the public-spending on LTC is assumed to depend on the availability of informal care, measured by the labor force participation of women aged 50-64.

Each determinant is projected separately and they are then combined to compute the future growth of total LTC expenditure. The authors distinguish a cost-pressure scenario and a cost-containment scenario. Both are based on a unitary income elasticity assumption and a healthy aging hypothesis. The healthy aging hypothesis postulates that with technological advancements, life expectancy increases, and time-to-death becomes less relevant. Under the cost-pressure scenario, a full Baumol effect is assumed, whereby the LTC unit labor costs increase fully in line with aggregate labor productivity. In the cost-containment scenario, the elasticity of LTC spending to productivity increases is set at half of the value in cost-pressure scenario. This possibly reflects possible policy actions aimed at mitigating relative wage increases of LTC providers.

The results showed that across OECD countries, LTC expenditure to GDP ratio is expected to more than double in the cost-pressure scenario, from 6.2% in 2010 to 13.6% of GDP in 2060. In the cost-containment scenario, the ratio is expected to rise by more than a half to 9.5% of GDP.



### 3.1.5 Ismail and Hussein (2021) - Turkey

Ismail and Hussein (2021) used the existing model from De la Maisonneuve and Martins (2013) for OECD countries to predict LTC cost in Turkey, based on different data sources, especially the World Bank and OECD. They regress the LTC spending in Turkey as a percentage of its GDP on GDP per capita (which represents the share of total productivity), female labor force participation rate (as a proxy for informal care provision), and age dependency ratio (the population aged 65 and above to the total population) as a control variable.

Results showed that the fast aging population in Turkey has increased the demand for LTC services. Reliance on the family support, especially from women, might not be a sustainable solution to the significantly rising LTC burden. Moreover, with low female labor participation rates, LTC expenditure in Turkey is estimated at 0.02% of GDP. This is a much lower level than that of the neighboring European countries, suggesting further expansion in LTC provision to prepare for the transition from an ageing to an aged society in a few decades.

### 3.1.6 Lorenzoni et al. (2015) - China

Lorenzoni et al. (2015) started from the model developed by De la Maisonneuve and Martins (2013) to project the long-term care spending until 2030 in China. The population projections are sourced from the United Nations Population database. As in De la Maisonneuve and Martins (2013), the demographic driver of government spending on LTC care is changes in the number of dependent people in the population. The non-demographic drivers are income and the demand for public-financed LTC services. Income is assumed to have a direct effect via increases in living standards (GDP per capita) and an indirect effect via cost-disease. While a full Baumol effect is assumed for OECD countries in the cost-pressure scenario, only half of the Baumol effect is incorporated in China, because excess labor supply especially in non-tradable sectors suggest weaker wage pressures. Demand for public spending on LTC is assumed to depend on changes in the availability of informal carers, which depends on changes in formal labor force participation. Under the healthy ageing assumption, the long-term care model postulates that there is a stability in disability levels, by shifting the years of disability in line with the gains of life expectancy.

The results from the model showed that, unlike OECD countries, demographic drivers account for the largest share of projected LTC expenditure increases in China. With the unit elasticity assumption, the income effect does not create any additional pressures on the expenditure share of GDP.

### 3.1.7 Zhang et al. (2020) - China

In the forecasting model of Zhang et al. (2020), the demographic data are projected based on the assumptions of other studies such as the Population Administration Decision Information System (PADIS) developed by China's Population and Development Research Center. They divided the different states of disability into the following three categories based on the Katz's Activities of Daily Living (ADL) Scale: mild disability, moderate disability, and severe disability.

The evidence showed that the older population is expected to rise sharply from 2020-2050 in China, and that the number of severely disabled people will increase faster than the numbers of mildly and moderately disabled people. Meanwhile the informal care is reducing due to the fast ageing population and slower fertility rate. Consequently, the costs of disabled elderly care and LTC are expected to rise dramatically over the projected period.

### 3.1.8 Brouwers et al. (2014) - SESIM-LEV model - Sweden

SESIM-LEV is a dynamic microsimulation model that estimates and projects the life course of the population of Sweden including key life events related to family formation, education, employment, retirement, health and aging. The model uses data from a representative sample of 300,000 individuals (3.5% of total population) from the Swedish Longitudinal Data register (LINDA). LINDA brings together data from Censuses, Income tax and other registries including longitudinal information on education, employment, income and pension. Other datasets key to the model included surveys of income and employment, living conditions and patient registries for health consumption other than primary care (HILDA/ULF) and consumption of medicines.

As the databases for SESIM did not contain information on health or utilization of health and social care services, such as home help services, initial values had to be inputted according to background characteristics of the individuals. Health status is a key variable in the model, influencing the consumption of health and social care. Health status is measured by an index ranging from 1 (severe illness) to 4 (full health) from the ULF survey. The model also included data on primary care derived from SHARE (Survey of Health, Ageing and Retirement in Europe), which is a European panel database on health, socio-economic status and social networks in which only persons aged 50 and more are included. A total of 1900 observations from the first wave (2004) are included in the analysis and 1100 individuals had follow-up data from the second wave (2006-2007).

Since the year 2000, simulations are used to model a number of events for all individuals – in the same way as in real life – such as getting married, having children, starting a job or retiring. Only events of significance to welfare systems are modelled. Projections cover a period of 40 years (2010-2050) and comprise several domains such as education, labor market, taxes and transfers, etc. They are carried out in a sequence represented in Figure 5. The figure also shows the determinants in each of the domains analyzed.

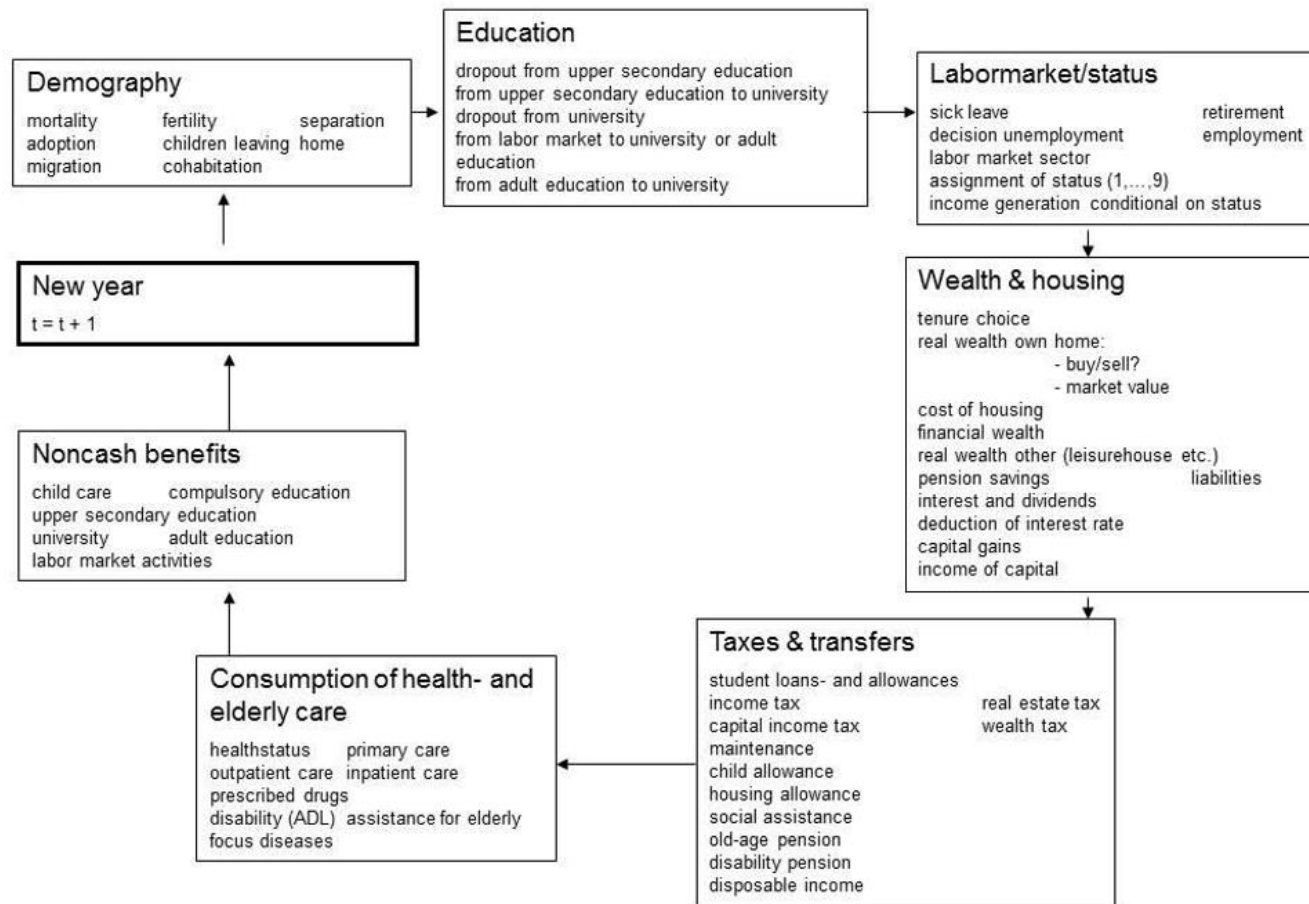


Figure 5 The sequential structure of SESIM/LEV model (Sweden)

Source: Brouwers et al. (2014)

Table 4 shows the categories of personal and social care consumption that were included in the model and the regression methods used. First initial consumption is determined and then consumption is estimated from one year to another (dynamic estimations). The estimation included the situation at the previous time as an explanatory variable. The total number of observations was 4302 but the number of observations used in the estimations varied from one estimation to another due to non-response. This problem was especially acute for the dementia diagnosis, for which the estimation of the binary logit model could only make use of 1612 observations.

The regression models included the following determinants: age, health status, and consumption of the same type of care in the previous period, consumption of other types of care in the current and previous period, education, sex, and region. The presence of dementia and dependence in ADL were also included in the model and both influenced demand for care assistance, which was captured as having two levels: home services (level 1) and special housing with 24-hour care (level 2). Because some diseases are associated with higher care costs, analyses by sub-groups were made for diagnosis of cancer, heart infarct, stroke and diabetes. Data on incidence, prevalence and healthcare use of patients were obtained from patient registers providing longitudinal histories for a six-year period.

To validate the model, the simulation results from the SISEM-LEV model for the years 2000-2008 were compared with observed values. The results were reasonable. For the long-run projections, the SESIM/LEV simulation results distinguish different scenarios for morbidity: expansion of morbidity (longer life but with more ill-years), dynamic equilibrium, or compression of morbidity (longer life in good health – most optimistic scenario). Some final results are shown in Figure 6.

Table 4 Types of econometric models used in the LTC estimations – disability and care assistance (SESIM/LEV)

Dependent variable	Econometric model		
	Population at risk	Static estimation	Dynamic estimation
Dementia	65+	Logit (binary)	---
ADL-dependence	65+	Proportional odds model (ordinal logistic regression)	---
Elderly care (assistance)	75+	Logit (binary) in 2 steps: 1. assistance? (1=yes/0=no) 2. level ? (1=home service, 2=special housing)	Logit (multinomial). Two models: one for persons with level 0 and one for level 1. Level 3 is irreversible.
ADL/DEM	65+ (last ADL/DEM = 0 or 2)	ADL    Dementia    Combined No      No              0	Logit (multinomial). Possible outcomes 0 - 3
	65+ (last ADL/DEM = 1)	No      Yes              1 Yes     No              2 Yes     Yes              3	Logit (binary). Possible outcomes: 1 and 3
Mortality	Elderly care > 0 and/or ADL/DEM > 0	---	Proportional hazard

Source: Brouwers et al. (2014)

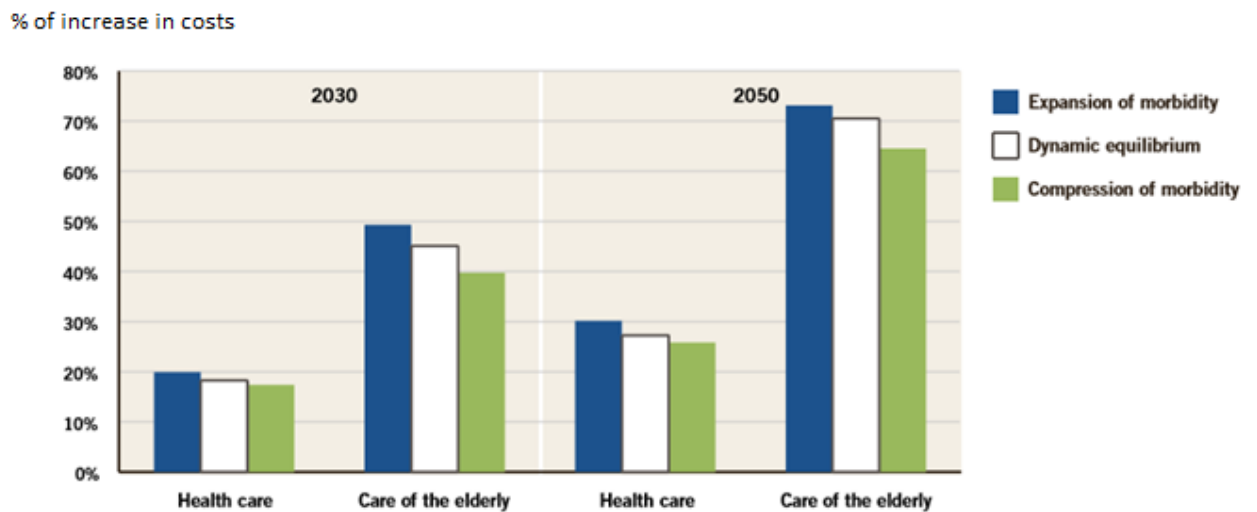


Figure 6 Percentage increase in costs of consumption of health and elderly care in 2030 and 2050 in relation to 2010 expressed in 2010 fixed prices

Source: Brouwers et al. (2014)

### 3.1.9 Eggink et al. (2016) - Netherlands Institute for Social Research - the Netherlands

The Dutch microsimulation model constructed by the SCP (Sociaal en Cultureel Planbureau) focuses on publicly funded LTC. It simulates expenditures for household help, nursing care and personal support, both at home and in a residential setting. According to Statistics Netherlands (2015), these types of care

count for two-thirds of long-term care expenditure and three-quarters of long-term care users. Simulations are made for the period of 2014 – 2030.

Figure 7 shows the model used to forecast public LTC expenditure. The model uses data at individual level about age, education, household type, chronic diseases and physical disabilities as determinants for the uptake rate. Population size and composition of the population influence total care use. No changes in preferences or in policies could be accounted for and income was not included in the model.

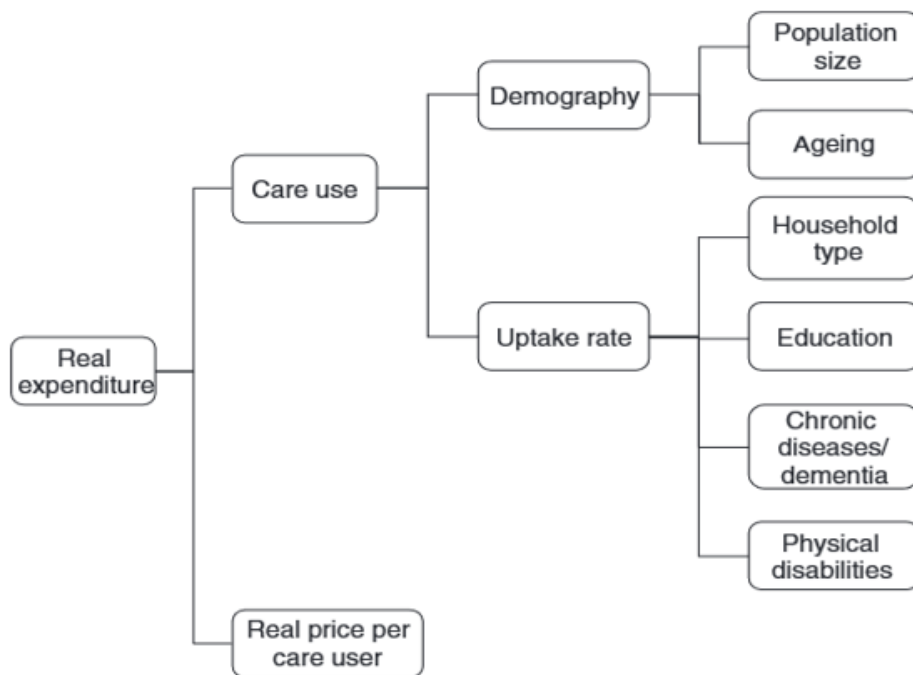


Figure 7 Model for public LTC expenditure (the Netherlands)

Source: Eggink et al. (2016)

As expected, care use increases with age, disabilities, co-morbidity and the prevalence of dementia. The public care use decreases with educational level. People living alone increase the use of long-term care more than others. An increase in the number of people without a partner leads to an increase in formal care use and a relatively lower increase in the use of residential care. As the number of chronic diseases (including dementia) rises, there is an increase in the use of formal care. On the other hand, the decrease in the prevalence of physical disabilities decreases the use of formal care in the future.

The results showed that the use of public LTC is expected to increase by 1.6% annually. Since real prices also increase, forecasted annual expenditure increases with 3.5%. The growth in use of public LTC in the model is lower than it would be by only considering demographic growth (2.2%) The reason is that the increase of ageing population does not imply an equally large increase in the number of years in bad health.

### 3.1.10 Wittenberg et al. (2001, 2015) - Personal Social Services Research Unit (PSSRU) / London School of Economics – England

Wittenberg et al. break down the official national statistics on the total numbers of people in residential care according to age-group, gender, previous household type (living alone, single living with others, living with partner or living with partner and others) and previous home tenure (own home or rented home) originating from PSSRU surveys. The main reason for the inclusion of housing tenure is that it is a proxy for socio-economic status and it is relevant for the division between privately funded and publicly funded residential care, as people who live alone and own a house are not eligible for fully publicly funded residential care. The information on non-residential care is very detailed and distinguishes local authority home help, private help, district nursing services, meals, day center services, chiropody, and others. Recently, the number of social care staff was added to the model to make projections about total amount of staff needed. The ratio social care staff to clients is maintained constant over the projection years. Figure 8 shows the determinants and the outcome variables in the model.

The model is suitable to analyze the demand for long-term care and informal care. Projections show an increase in the use of all services, depending on the disability assumptions. Measures to promote healthy ageing and to prevent disabilities in older adults could offset the demographic pressure of rising numbers of older people. The supply of informal care is a key aspect of the model. Projections for marital status show an increase in the number of married/cohabiting older people and an increase in 'spouse care' by more than double by 2041. However, the number of single people is also projected to rise, showing an increase in care by children (80% by 2041). This points to the need of motivating informal carers and to meeting their needs.

In 2015, the PSSRU model was updated to forecast the demand for social care and expenditures for older people (aged 65 and over) and younger adults (aged 18 to 64) until the year 2035. The model used the latest official population projections and projections of Gross Domestic Product (GDP) that were available in May 2015. Under the base case assumptions, the numbers of disabled older people, defined as those unable to perform at least one instrumental activity of daily living (IADL) or having problems with at least one activity of daily living (ADL), would rise by 65% between 2015 and 2035, from around 2.9 million to around 4.8 million.

In addition, the number of older people with more severe disability, defined as needing help with one or more ADL tasks, would increase by 74% from 1.15 million in 2015 to 2.0 million in 2035. Public expenditure on social services for older people, net of user charges, is projected to rise by 155% under the current funding system from around £6.9 billion (0.43% of GDP) in 2015 to £17.5 billion (0.69% of GDP) in 2035 at constant 2015 prices and under a set of base case assumptions about trends in the drivers of long-term care demand and in the unit costs of care services. The equivalent for social services for younger adults is a projected rise of 118% from 2015 to 2035 at constant 2015 prices. Total public expenditure on social services for older people and younger adults is projected to rise by 135% under the current funding system.

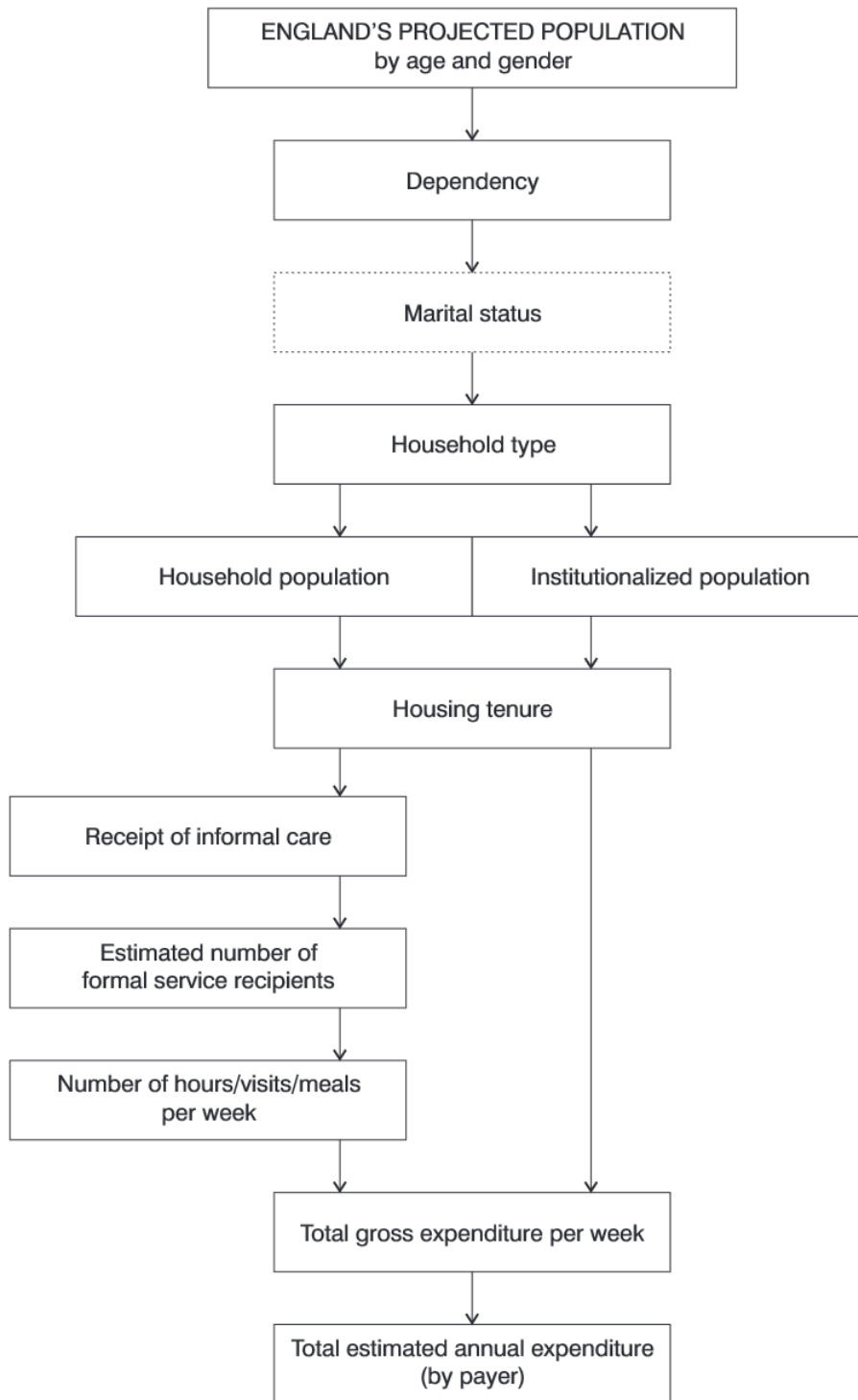


Figure 8 Model for public LTC expenditure (England)

Source: Wittenberg, R. et al. (2001)



3.1.11 Fukawa (2010) – INAHSIM -Japan

Fukawa (2010) used a dynamic micro-simulation model to project LTC expenditure in Japan from 2010 to 2050. Variables included in the model include events such as birth, death, marriage, divorce, changes of household situations generated by those events, the move of aged parent(s) to live with the child’s household and other movements of households. The dependency of the elderly aged 65 or older was classified into four levels.

As an application of the model, a projection of health and long-term care expenditures was made for the years 2010—2050. The death rate was assumed to decline gradually, resulting in an estimation for life expectancy at birth of 85 years for males and 91 years for females in 2065. The other estimated transition probabilities were assumed stable over the simulation period. The author combined the projected distribution of the age-group population by dependency level and the age-related expenditure profiles by dependency level to calculate the future elderly LTC expenditure. No future developments such as technology advance or price increase were considered.

As the population in Japan is projected to shrink from 127.1 million in 2015 to 88 million in 2065, if the rate of fertility stays at 1.4, the ageing rate is expected to rise from 26.6% to 39% in 2065. The LTC expenditure is projected to continue to rise until 2050 (see Table 5).

Table 5 LTC expenditure as percentage of the GDP

	Health		Long-Term Care			Total		
	A	B	D1	D2	D3	Case 1	Case 2	Case 3
2006	6.5		1.3	1.7		7.7		
2010	7.0	6.8	1.5	2.3	1.4	8.4	8.5	8.2
2020	7.6	7.4	2.0	3.0	1.8	9.6	9.7	9.3
2030	7.9	7.5	2.7	3.8	2.4	10.5	10.6	10.1
2040	7.6	7.3	3.3	3.8	3.0	10.9	11.1	10.5
2050	7.4	7.0	3.4	2.4	3.1	10.8	10.9	10.3
2025 <sup>a</sup>	7.9			3.0			10.3	
2025 <sup>b</sup>	8.8			2.7			11.7	
2050 <sup>c</sup>	9.4						12.1	

<sup>a</sup> MHLW (2006).

<sup>b</sup> NCSS (2008).

<sup>c</sup> OECD (2006).

Source: Fukawa (2010)

## 3.1.12 Geerts et al. (2012) - ANCIEN - Germany, the Netherlands, Spain and Poland

The ANCIEN model (Assessing Needs of Care in European Nations) makes forecasts for use and supply of LTC for older people in four countries representative of different long-term care systems: Germany, the Netherlands, Spain and Poland (Geerts et al., 2012). Table 6 shows the four country clusters according to combinations of levels of public or private spending, use of informal care and availability of support for informal carers.

Table 6 Typology of LTC systems

Cluster	Country	Public Spending	Private Spending	Informal Care Use	Informal Care Support
1	Belgium Czech Republic <i>Germany</i> Slovakia	Low	Low	High	High
2	Denmark <i>The Netherlands</i> Sweden	High	Low	Low	High
3	Austria England Finland France <i>Spain</i>	Medium	High	High	High
4	Hungary Italy <i>Poland</i>	Low	High	High	Low

Source: Kraus et al. (2010)

The projection models are based on survey data (SHARE) at the individual level. The variable of interest is the type of help older persons receive with personal care (ADL) for nursing care or informal care. The analysis does not include help with household tasks. The dependent variable 'help with personal care' has four categories: no care, informal care only, formal care only, formal and informal care. Clients were formal care users if they received professional or paid nursing or personal care, including private care, in the last 12 months before the survey. Clients were identified as having informal carers, if they had received informal personal care either from outside or from within their homes. Informal personal care is defined as help for dressing, bathing or showering, eating, getting in or out of bed, using the toilet, during the last 12 months.

The econometric approach distinguishes two stages (see Figure 9). At the first stage, all determinants were included in logit models for residential care use. Due to the unavailability of micro-level data for Germany and Poland, no logit models have been estimated for these countries. Instead, the prevalence of institutionalization by age, gender and disability have been calculated. At a second stage, multinomial models were constructed for home care use. Due to the unavailability of data on home care utilization for Poland, no projections for home care could be made for this country. Table 7 shows the significant factors in the models for Germany, the Netherlands and Spain.

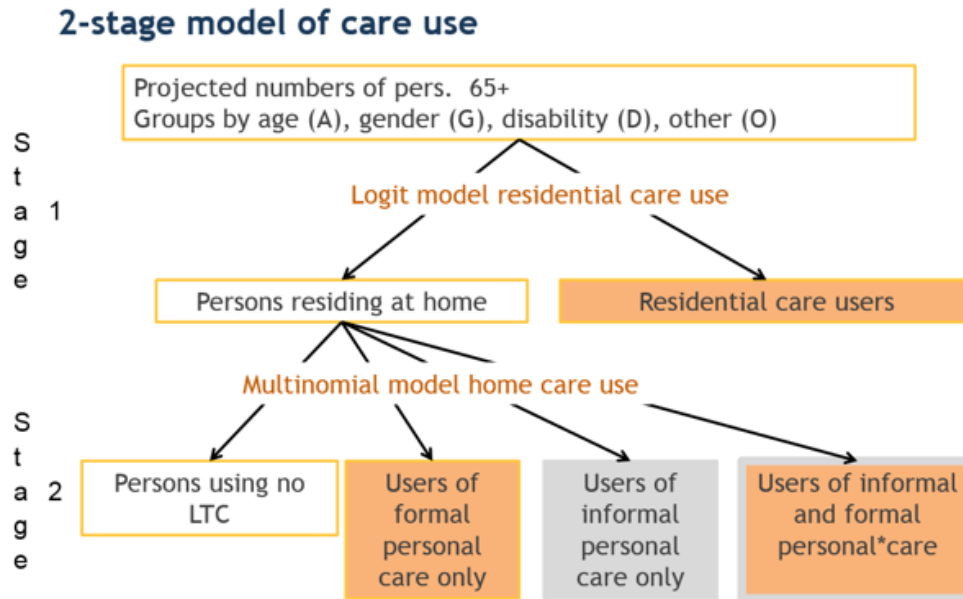


Figure 9 Model for public LTC expenditure in ANCIEN

Source: Geerts et al., 2012

Table 7 Significant explanatory variables in ANCIEN

Significant factors	Germany	The Netherlands	Spain
Age	X	X	X
Gender			
Education		X	X
Living alone	X	X	X
Children		X	
Income	X	X	
ADL limitations	X	X	X
IADL limitations	X	X	X
Chronic conditions		X	X
Cognitive functioning		X	X

Source: Geerts et al. (2012)

Projections were made for several alternative scenarios. The base scenario is the “DELAY” scenario in which disability incidence is delayed to older ages parallel with the delay of mortality. A pessimistic scenario assumes constant prevalence (PREV scenario) or constant incidence (CHRON scenario) of disability. The more radical optimistic scenario is called “BIOL”, which assumes a relative decline of disability incidence decline as the mortality is delayed. incidence decline. Table 8 shows the results of the projections for these three scenarios. Considering indicators of the supply of formal and informal care, it turned out that in none of the countries the supply of services will be enough to meet the demand of formal care services. In all these countries, the shares of the workforce in the LTC sector would at least have to double in order to meet the future demand.

Table 8 Results from ANCIEN model for disability scenarios

Projected increase in numbers of care users between 2010 and 2060				
		DELAY	BIOL "optimistic"	CHRON "pessimistic"
Germany	Res	+102%	+74%	+153%
	Home formal	+79%	+69%	+105%
	Informal	+51%	+46%	+59%
Netherlands	Res	+200%	+188%	+231%
	Home formal	+116%	+107%	+139%
	Informal	+66%	+55%	+94%
Spain	Res	+162%	+159%	+168%
	Home formal	+150%	+128%	+190%
	Informal	+140%	+115%	+183%
Poland	Res	+152%	+130%	+176%

Geerts, Willemé & Comas-Herrera (2012), Long-Term Care Use in Europe. ENEPRI Research Report No. 116, pp. 30-75

Source: Geerts et al. (2012)

### 3.1.13 Van den Bosch et al. (2011) - Belgian Healthcare Knowledge Center (KCE) and Federal Planning Bureau - Belgium

The purpose of the model constructed by the KCE and the Federal Planning Bureau was to calculate the number of beds in residential care for older people needed in the period 2011-2025 in Belgium. Determinants in the model were the population structure in terms of gender and age, family composition and the availability of informal carers and trends in population health status (cognitive and physical).

Two databases were used to make the projections:

- the database from the Health Interview Survey (HIS) for the years 2004 and 2008 which consists of a representative sample of the Belgian population reporting information on ADL and disabilities, chronic conditions and socio-economic characteristics. A total of 12,945 persons (2004) and 11,254 (2008) were interviewed.
- the "Permanent Sample" (EPS), designed by IMA-AIM (Intermutualistic Agency) and NIHDI (National Institute for Health and Disability Insurance) containing data for the years 2002-2009 on the reimbursement by health service procedure, admission, drug delivery, dates and cost allowing the estimation of transition rates between care levels and care settings.

The authors estimated a hierarchical model, as presented in Figure 10. The projection proceeded in five steps:

Step 1. Calculation of the distribution of the total population (65 years and older), by age, sex and projection year (2010 – 2025), in absolute numbers.

Step 2. Projection of the distribution of the population by living situation (living with a partner, son/daughter or other), for each age and sex category and projection year.

Step 3. Projection of the population by disability level (having at least one ADL limitation), for each age and sex category and projection year. The disability level was inputted using a model estimated on the HIS data. The independent variables are age, sex, selected chronic conditions (COPD, dementia, diabetes, hip fracture, Parkinson’s disease) and province.

Step 4. Projection of the distribution of the population across the LTC categories: no care; two home care situations ‘low’ and ‘high’; five levels of residential care - categories O, A, B, C and Cd; hospitalization; and, finally death, for each age and sex group and projection year. These distributions are derived from the transition probabilities that are estimated with the hierarchical model.

Step 5. Application of the proportions using long-term care as projected by the model (step 4) to the projected overall population numbers by age and sex obtained in step 1, and summation to aggregated results.

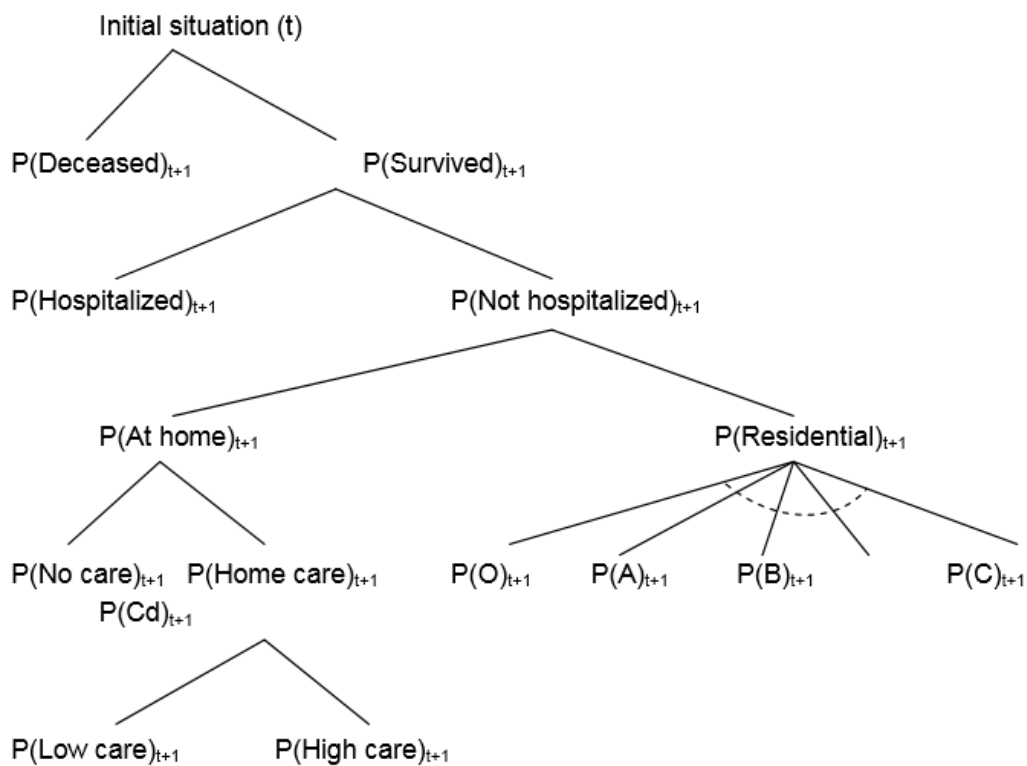


Figure 10 The hierarchical structure of the transition probability model KCE/BFP

Source: Van den Bosch et al. (2011)

Several alternative scenarios were applied to the model in order to show the sensitivity of the projections to possible developments. The “unchanged disability” (base scenario) refers to unchanged disability rates by sex-and-age group, only changed by demographic shifts. The scenario “better education” assumes a reduction in the prevalence of chronic conditions during the projection period as the result of the educational level of older persons being higher than it is now. The “disability compression” scenario assumes that a longer life is accompanied by a delayed onset of disability. The scenario “diabetes epidemic” implements the trend in diabetes that is observed for Belgium, i.e. a 7.9% rise in the use of diabetes medication between 1996 and 2006. In the "pure demographic" scenario it is assumed that the household situation within any sex-age group does not change over the projection period. The "fewer children" scenario assumes that fewer children will live in the same household as

their parents in the future. In the last scenario – “home care”, it was arbitrarily assumed that home care would be expanded by 50%, beyond what is already required because of the ageing of the population.

Figure 11 compares the projections from the various scenarios. Projections vary from about 149,000 people in residential care in the optimistic “home care” scenario, to almost 170,000 in the pessimistic “fewer children” and “diabetes epidemic” scenarios. The expected ageing of the population will not only push up the residential care use, but will put substantial upward pressure on the demand for home care as well.

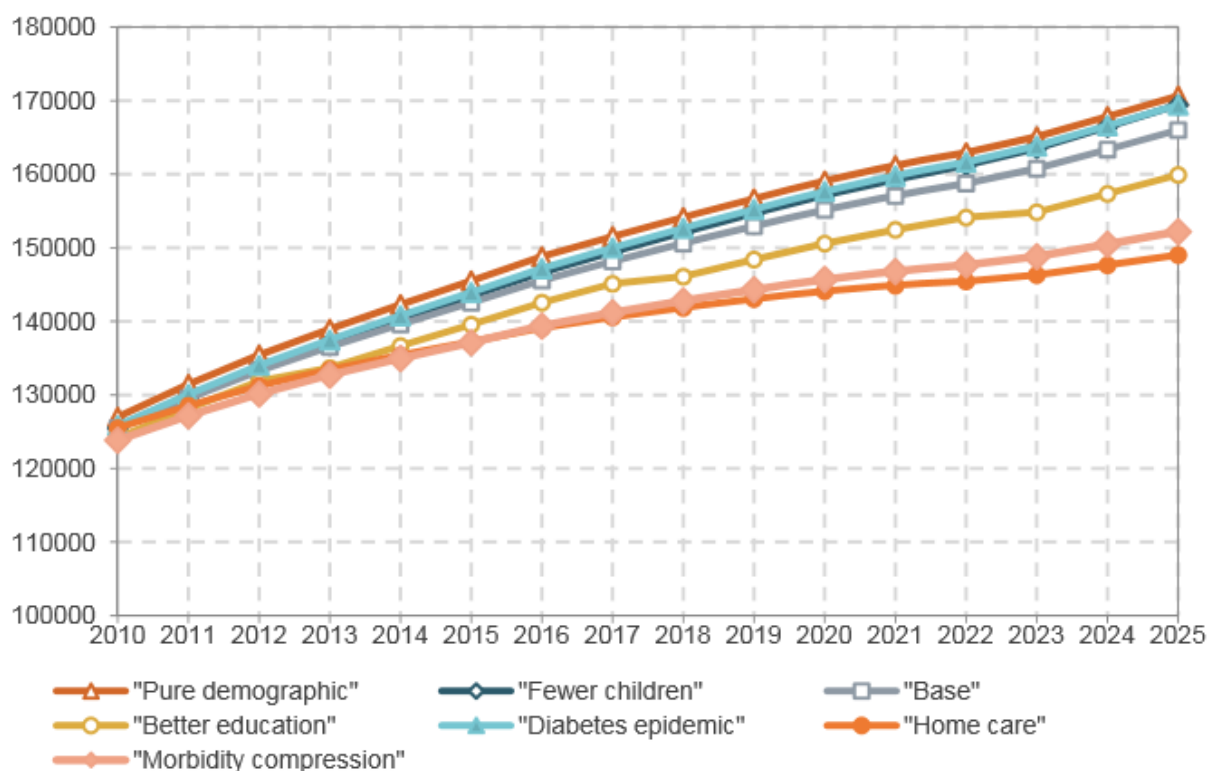


Figure 11 Projected trends in the number of older persons in residential care, Belgium 2010-2025, according to various scenarios

Source: Van den Bosch et al. (2011)

## Chapter 2

### The Flemish Social Protection

#### 1 Introduction

The first step towards a Flemish compulsory insurance system was set in 2001 with the Flemish care insurance. The aim of the Flemish care insurance was to help people living in Flanders to afford non-medical healthcare costs (Concept note FSP, 2016). Since 2016, with the Sixth State Reform, the Flemish responsibilities with regard to health and care policy have been radically changed (Bouvy et al., 2016). Long-term residential care became a responsibility of the regions, while the 'cure' remained largely under Federal responsibility (Concept note FSP, 2016). Therefore, many of the new competences with regard to long-term care were combined with some already existing Flemish competences, such as family and supplementary home care (social care, logistic help and surveillance help) and were combined in the Flemish Social Protection.

The Decree of the Flemish Social Protection legally anchors the principles and objectives of the Flemish Social Protection and outlines the guidelines within which the system will further be shaped. In the next paragraphs we describe these principles and objectives.

#### 2 Principles of the Flemish Social Protection

The following principles have served as the framework for the creation and development of the Flemish Social Protection (stated in art 6 §1 of the FSP Decree):

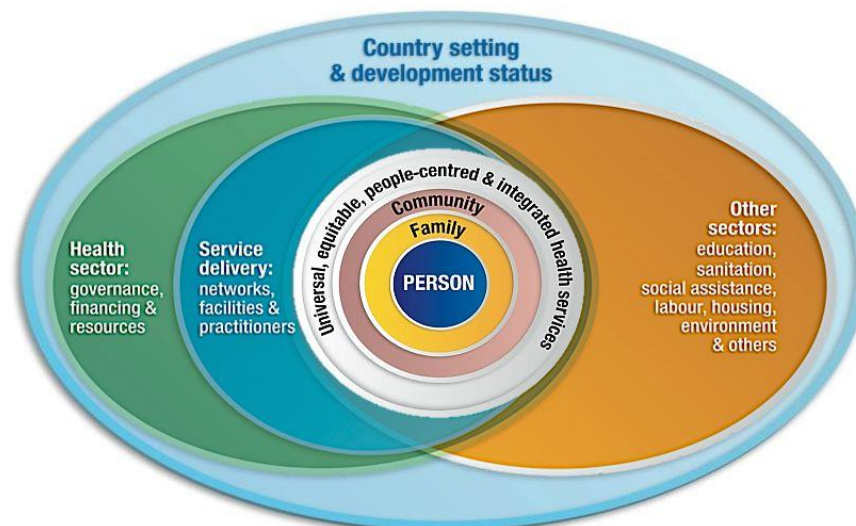
- Integrated care and support
- Increasing the self-reliance of people with a care need
- A good quality of life
- Focus on the person with a care need and his immediate environment
- Demand-driven care, directing one's own care with a view to maintaining and strengthening autonomy and quality of life
- Enforceable rights to benefits for care
- Financial accessibility of quality care
- Simplification of rights and procedures
- Avoiding double grading thanks to a unique assessment instrument
- Automatic granting of rights
- One contact point for all questions

With regard to the basic principles, we find the following citation in the decree (Art. 6. § 1.): “Flemish Social Protection contributes to integrated care and support and to an increase in self-reliance, taking into account the needs, questions and objectives of the person with care needs and their immediate environment, with the pursuit of quality of life as a starting point.”

The above principles are closely intertwined with the WHO-circle model for integrated services delivery (Figure 12), which focuses on person-centered and integrated care. This model has an important place in the conceptual framework of the Flemish Social Protection and was developed by the World Health Organization. This model formed the basis for the development of a new care policy around person-

following financing of care – both in the sector for people with disabilities and in the Flemish Social Protection.

## A model for integrated people-centred health services delivery



© World Health Organization 2015

Figure 12 WHO-circle model for integrated services delivery

Source: WHO (2015)

The WHO circle model starts from a dynamic support system that consists of five concentric circles. According to the principle of complementarity, each of these five concentric circles represents a potential level of support that can contribute to the health, well-being and quality of life of the person in need of care.

Central to this model is the person who has a care or support need. Social relationships can be both informal and formal. In this model, informal social relationships are closest to the individual, which are the family and friends. They form the second concentric circle. After family and friends, this model places informal contacts in the community (like neighbors and volunteers) as a third concentric circle around the person with a care and support need. The next circle is the universally accessible, person-centered and integrated care support offer (WHO, 2015).

All these concentric circles together form the social network of the person in need of care. Thus, the concept of “social network” refers to the web of social relationships that surrounds an individual. It is important to point out here that the circle model should not be understood in the sense that all possibilities of the inner circles must first be exhausted before support can be offered from the next circle. The starting point is the complementarity of the different circles. By opting for the principle of complementarity, an interplay between informal and formal care is made possible.

This model also supports the idea of socializing care. Socialization of care is based on the conviction that good care is part of people's daily social lives. Care provided in and by society is seen as better care that leads to a better quality of life. According to this model, this care is therefore an essential and central element that should be encouraged.



The Flemish Strategic Advisory Council on Welfare, Health and Family defines the concept of socialization of care in its vision statement of 2012 as follows: “A shift within care whereby the aim is to help people with disabilities, the chronically ill, vulnerable older persons, young people with behavioral and emotional problems, to allow people who live in poverty, ..., with all their possibilities and vulnerabilities, to occupy their own meaningful place in society, to support them where necessary and to ensure that care is integrated into society as much as possible. Concepts that play a role in this include de-institutionalization, community care, empowerment, strength- and context-oriented working, demand-side management and respite care”. (Policy letter Welfare, Public Health and Family, 2013; SAR WGG, 2012; Everaert et al., 2015; Vandeurzen, 2018). With this interpretation of socialization, Flanders wants to focus on quality care and assistance that enables every care user to participate in society, despite his or her care demand. An inclusive society is put forward as the goal, also for people in socially vulnerable situations (Vandeurzen, 2018).

The WHO-circle model for integrated services delivery indicates that the environment or context in which the care system functions also has an impact on the care and support that is provided. The organization of care is shaped by the policy pursued and the available resources (Concept note FSP, 2016). Policy aimed at integrated care and support also focuses on structural determinants of well-being and health (SAR WGG, 2012).

## **2.1 Objectives of the Flemish Social Protection**

Taking into account the WHO-circle model and the vision statement from the Flemish Strategic Advisory Council on Welfare, Health and Family, the following objectives were drawn for the Flemish Social Protection:

- First objective: To strengthen the person with care needs by allowing him/her to retain or regain as much autonomy and control over his own care as possible and to promote integration or reintegration into society;

The Flemish Social Protection focuses on directing one's own care with a view on preserving and strengthening self-management, autonomy and quality of life. This objective is linked to self-direction, which means making one's own decisions about life and self-reliance, as being able to perform self-care or having autonomy to perform household activities and maintaining a social network.

- Second objective: To support informal care and the further network of the client;

According to the FSP Decree, the intention is to further support informal care because this is an essential element of demand-driven care. A similar intention to support informal care can be found in the Decree on residential care (Art. 3.1°, 3°). The question then is how the support and stimulation of informal care can be implemented in practice. In the sector of people with disabilities, a first option was developed to pay informal carers from a personal financing budget. At FSP, this is also possible with the cash portion (the healthcare budgets), but this portion is rather limited and it is not currently the intention to increase it. In that case, other options should be considered.

- Third objective: To achieve demand-driven care by making maximum use of person-following financing;

This objective refers to the concept of demand-driven care, which has the patient's own management as a starting point (Verkooijen, L. 2009). The degree of demand-side management depends on how much

control the care user has over the interpretation and organization of his own care and support (Caldwell, 2007). In the FSP, the goal is to achieve demand-driven care by focusing as much as possible on person-following financing. The current contours of the decree fill in person-following financing by means of a healthcare ticket and/or a combination of healthcare budgets.

- Fourth objective: To maintain financial access and quality care

In the FSP, high-quality care is guaranteed and encouraged, among other things, by considering the quality of care in the organization-related financing when allocating the lump sum (Art. 136). It is the intention in this way to provide an 'incentive' to guarantee high-quality care and, where possible, to improve the quality of that care further.

Transparency with regard to the quality of care is of course also essential in the pursuit of coherent demand-driven care. In order to have true freedom of choice, it is necessary that the care user, as far as possible, has insight into the differences in quality between different care settings.

- Fifth objective: To achieve efficiency gains and transparency for citizens through the simplification, digitization and integration of different benefits for a more streamlined access to benefits and care rights;

It is the intention and the challenge of the FSP to connect different care settings in a uniform manner by developing a common framework. The different sectors in the FSP are working together to build this common framework, so that transparency and simplification can be guaranteed. This objective is also linked to the previous objective regarding the importance of demand-driven care.

- Sixth and seventh objectives: To use an objective, uniform and accessible assessment of the care need and to use this instrument as a unique scaling instrument for people with a care need;

The sixth and the seventh objectives are closely related and the FSP plans to implement the BelRAI tools in different sectors to implement the use of an objective and uniform assessment instrument. BelRAI is a collective term for the Belgian version of the interRAI instruments that were developed by the international research consortium interRAI. It is a comprehensive assessment toolbox that sketches a multi-dimensional picture of the care needs on the basis of an interdisciplinary interpretation. In addition, data is collected in a standardized and structured manner about the evolving care needs and preferences of the care recipient. Most interRAI instruments are scaled by a multidisciplinary team, on the basis of a computerized system. Based on the completed items, the software automatically calculates results with which the care and support team, in consultation with the client, can start drawing up or adjusting an individualized care plan.

- Eighth objective: To give access to a one-stop contact point for all questions about all rights concerning the health insurance fund with regard to allowances in the context of Flemish Social Protection;

This objective can only be achieved by the centralization of all data of the FSP into a digital platform. The Flemish government wishes to integrate the BelRAI instruments and the other existing scaling instruments into the Digital Care and Support Platform (DZOP). In the future, this DZOP will be a digital platform on which all relevant care data will be collected from a care user, as well as all results associated with an individual BelRAI assessment. DZOP aims to facilitate self-management, care coordination and case management in order to provide integrated and targeted care and support (Steyaert et al. 2020). Various data will therefore be collected in the DZOP. The coordination around this is still ongoing.

- Ninth objective: To achieve continuity of care and, where necessary, adaptive care.

The FSP is preparing to achieve this objective by implementing a system of organization-related financing, which is complementary to the person-following financing of care. This type of financing will make possible to monitor quality of care and to support cooperation between organizations, improving continuity of care. The implementation of the unique assessment instrument BelRAI will also make it possible to facilitate communication between organizations and sectors.

## **2.2 Organizations in the Flemish Social Protection**

Apart from the competences regarding residential long-term care and social care and assistance at home, especially the division of competences with regard to mental health policy has been radically changed with the Sixth State Reform. The Flemish Community has become competent for the policy regarding the provision of mental healthcare in institutions outside hospitals. For the hospitals themselves, jurisdiction is still Federal. The Flemish Community is now fully competent for psychiatric care homes and sheltered living initiatives. The mental health consultation platforms were also transferred in 2019.

In addition, the Flemish government became responsible for setting the licensing standards for psychiatric departments in general hospitals (also known as PAAZ) and for psychiatric hospitals, as well as for accreditation standards within the sectors of psychiatric care homes, sheltered housing initiatives and rehabilitation. With the policy on long-term care rehabilitation, stated in Article 5, §1, I, a large number of rehabilitation agreements were transferred to the competence of the Flemish government. In the mental healthcare sector, the following care organizations fall under the FSP:

- Centers for mental healthcare
- Centers for ambulatory rehabilitation
- Centers for addiction
- Psychiatric care homes
- Initiatives for sheltered housing
- Conventions 7.72 – Psychosocial rehabilitation centers for adults, 7.74.5 – Centers for rehabilitation of the early interactive disorders in the relationship between parents and children, 7.74.6 – Reference centers for Autism and 7.74.0 – Centers for specific child psychiatric disorders

In addition, the following organizations for physical rehabilitation are included in the FSP:

- Rehabilitation center for neurological and locomotor disorders
- Some rehabilitation conventions in hospitals
- Centers for visual rehabilitation
- Centers for rehabilitation of children and youth – respiratory and neurological disorders
- Institutions for respite care

### **3 Conclusion**

In an ideal world the expenditures of all the care organizations described in the previous chapter should have been integrated in one coherent projection model. However, as hinted at already, the data are not available to realize this ideal. More specifically, there are no sufficiently rich individual data to analyze the use of mental healthcare and rehabilitation care. The remainder of this report will therefore consist of two parts:

1. For residential care and home care (including nursing care, which is still at the federal level), we can make use of the individual data in the Permanent Sample (EPS) of IMA, that were also used in the model of the Belgian Healthcare Knowledge Centre described in the previous chapter. This makes it possible to estimate a model that is perfectly comparable to the models for other countries that have been described in chapter 1. As will become clear, the set of available explanatory variables matches what was available elsewhere. It is also possible to make projections of future expenditures and to run different scenarios in which we vary some relevant policy parameters. All this will be explained in detail in part II of this report.
2. Such an ambitious exercise is not possible for the mental and rehabilitation care sectors. In the present situation, there is more overlap and less transparency than is described in the objectives of the FSP. Moreover, there are no individual data that could be used to estimate a full model. In part III of this report we describe the sector with special attention for the data challenges. We close that part by making some recommendations to improve the data situation in the future.

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**Steunpunt Welzijn, Volksgezondheid en Gezin**

**Towards a projection model for the Flemish Social Protection**

**Part II**  
**A projection model for**  
**residential care for the older persons and for home care**

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**Titel rapport:** Towards a projection model for the Flemish Social Protection.  
 Part II: A projection model for residential care for the older persons and for home care

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Dit rapport kwam tot stand met de steun van de Vlaamse Overheid. In deze tekst komen onderzoeksresultaten van de auteur(s) naar voor en niet die van de Vlaamse Overheid. De Vlaamse Overheid kan niet aansprakelijk gesteld worden voor het gebruik dat kan worden gemaakt van de meegedeelde gegevens.

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# Chapter 1

## Introduction

The aim of this part of the report is to develop projection models to forecast the use of care by Flemish people living at home or in residential care homes. For these components of care, we have sufficiently rich information at the individual level to estimate a full econometric model, that can then be used to simulate future expenditures and policy scenarios.

The structure of the chapter follows the main steps of such an exercise. We first describe the available data bases: the Permanent Sample of the Intermutualistic Agency (IMA-AIM) and the VESTA-platform. We give an overview of the variables that will be used to describe care at home and residential care (the dependent variables) and of the potential explanatory variables. The latter correspond to a large extent to the variables used in similar models in other countries, as described in the first part of this report. We go into some detail to explain the construction of these variables in order to avoid possible misunderstandings of the results that will follow later.

In chapter 3 we justify the methodological choices we have made for the econometric analysis. Chapter 4 then presents our estimation results. These are based on the individual data for the period 2009-2017. We will explain how we have chosen between different specifications on the basis of their user friendliness and, more importantly, on the basis of their out-of-sample predictive performance. More specifically, we check how well the model estimated for 2009-2017 succeeds in predicting the real data for 2018-2019.

In chapter 5 we will then simulate future volumes of care and costs for the period of 2019 until 2035. Chapters 6 and 7 illustrate how different scenarios can be constructed and simulated to show the impact of relevant policy decisions on care use and costs.

Psychiatric care homes are a special case that does not really fit in this part of the report. They do not fit very well in part III of the report either, because that part is mainly focused on ambulatory care. Moreover, the available data are not well suited to construct a projection model for the psychiatric care homes. We illustrate these issues in chapter 8.



## Chapter 2

### Description of the databases and variables

We first describe the available databases with individual data that will be used in the estimations: the Permanent Sample and VESTA. Both these databases are samples and the resulting evolution of care should be compared with the real-world population data, as represented by the aggregate data from RIZIV and from the Flemish Agency for Care and Health (VAGZ). We compare the individual data for the dependent variables in our sample with these official records. Finally, we discuss the available explanatory variables and show their evolution in the past.

#### 1 Databases: samples of individual observations

##### 1.1 EPS

The 'Permanent Sample' (EPS) database was created by the IMA-AIM (Intermutualistic Agency) in cooperation with the National Institute for Health and Disability Insurance (RIZIV in Dutch), as well as other partners, in order to monitor health care expenditure and consumption. In the EPS, data about the specific codes of treatments, health services and drug delivery are recorded, as well as the cost of reimbursed care procedures and medications. The data refer to treatments that were reimbursed in the federal health insurance system, some of which have now been transferred to Flanders. In addition, some socio-economic variables such as age, gender, place of residence and insurance status are present in the database.

The EPS is a random sample drawn from the population of members of the Belgian sickness funds, stratified according to age and gender. The basic sample is 1/40 of the population with an additional oversampling of another 1/40 for the persons aged 65 and older. Each year the sample is replenished to keep the 1/40 ratio. For this study we used data for the period of 2009 until 2017 and restricted the sample to people living in Flanders who are 18 years or older. Residents of Brussels were not included in this study, as there is no identification variable in the EPS for persons living in Brussels who were registered in the Flemish Social Protection system.

##### 1.2 Construction of the weights of the EPS

Sampling weights are used in order to make the EPS representative of the total population, so that results can be extrapolated to population totals. In our study, we extrapolate to population totals on the basis of the official demographic data from Statbel. This implies that we have to take into account that the EPS data and the demographic data (Statbel) are not directly comparable:

- - The Statbel population data provide a picture of the total population on January 1st of a particular year (t).
- - The EPS data combines two images (those of June 30<sup>th</sup> and of December 31<sup>st</sup>) from a given year (t) and then adds all the people who died in that year. In our data, we only have the picture of December 31<sup>st</sup>.

The 'best comparable' situations are therefore the Statbel picture of January/1/t and the EPS picture of December/31/t-1. The observations in the EPS for persons who deceased in the same year, must be removed for this weighting exercise as in reality they are no longer in the snapshot of December 31<sup>st</sup>. Therefore, we calculate the new weights by dividing the totals of Statbel of a given year (January/1/t) by the totals in the EPS of the previous year (December/31/t-1) without the deceased. Table 1 shows the weights calculated for the EPS in this way. These weights are near the original 20 and 40.

Table 1 Weights of the EPS

Gender /age	2009	2010	2011	2012	2013	2014	2015	2016	2017
Female									
18-39	40.54	40.48	40.39	40.23	39.99	40.15	40.17	40.18	40.27
40-54	40.78	40.70	40.76	40.78	40.85	40.69	40.66	40.83	40.72
55-64	40.43	40.63	40.66	40.64	40.74	41.08	40.86	40.65	40.80
65-74	20.32	20.40	20.45	20.44	20.42	20.45	20.51	20.64	20.45
75-84	20.36	20.27	20.25	20.16	20.10	19.98	20.10	20.02	20.10
85plus	20.02	20.26	20.31	20.58	20.65	20.65	20.55	20.59	20.44
Male									
18-39	40.51	40.51	40.60	40.67	40.69	40.72	40.73	40.72	40.89
40-54	40.86	40.88	40.89	40.88	40.87	40.86	40.94	41.09	40.98
55-64	40.43	40.64	40.53	40.69	40.69	40.64	40.78	40.58	40.86
65-74	20.29	20.16	20.20	20.25	20.37	20.21	20.19	20.21	20.21
75-84	20.20	20.40	20.21	20.15	20.28	20.37	20.41	20.44	20.28
85plus	19.76	19.73	19.44	19.82	19.69	19.70	19.61	19.55	19.81

### 1.3 VESTA

The VESTA database was created to record data from an electronic data sharing platform between agencies for social family care, additional home care services and logistic assistance services and the Flemish Agency for Care and Health (VAZG). This platform enabled a more efficient and quick payment of subsidies for the home care services.

The VESTA database consists of data about the services delivered at home (hours and types of services), information about the personnel and the organizations delivering the services, as well as information about the users (age, gender, place of residence, household type, etc.). For this study observations from the VESTA database were matched to the corresponding observations in the EPS database, so that we could determine whether people from the EPS were using social care or home help services and to what extent.

## **2 Official sources of aggregated data**

Care and expenditure data are of course used by the official agencies to regulate and finance the services. It is these aggregate data that are relevant from the policy point of view. We will compare the results from the individual samples with the official aggregate data, as communicated to us by the VAZG and the RIZIV.

### **2.1 VAZG**

The Agency for Care and Health (in Dutch: het Vlaams Agentschap Zorg en Gezondheid - VAZG) is an agency of the Flemish Government responsible for the recognition, licensing and subsidizing of various providers and service agencies for home care (social care, logistic help and surveillance help), residential care, as well as some types of rehabilitation services [1,2]. In recent years, the Flemish Agency is the responsible for the Flemish Social Protection program [3]. For this study, the VAZG provided aggregated data about the total days in residential care based on invoicing, as well as data about hours and costs of social care and hours of logistic and surveillance help.

### **2.2 RIZIV**

The National Institute for Health and Disability Insurance (NIHDI – RIZIV in Dutch) is a federal public body of social security in Belgium, which functions under the authority of the Belgian federal minister of Social Affairs and Public Health. This institute is responsible for administering the national compulsory schemes for health insurance and disability benefits, and manages a compensation fund for medical accidents [4]. The effective reimbursement of health service costs to users is performed by the different health insurance organizations that exist in Belgium (called mutualities, or sickness funds). The RIZIV also controls the correct application of the reimbursement rules. For this study, the Actuarial Department of the RIZIV provided data about the reimbursed days in each residential care category and data about the total number of nursing tasks at home and total reimbursed nursing costs.

## **3 Dependent variables**

The dependent variables used in the models consist of the use of care in certain care categories or types of care. The care was provided either at home or in short-term or long-term residential care. In residential care, we distinguish days in long term care categories/levels O, A, B, C or Cd and the category short stay for short-term residential care. For home care, we use delivered tasks of nursing care at home, hours of social care, hours of logistic help and hours of surveillance help. The days in residential care are calculated for people 55 or older and the home care services for people 18 or older.

At the national level, care dependency in long term care (residential or nursing care at home) is assessed by an adapted version of the Katz scale called Belgian Evaluation Scale for Activities of Daily Living (BESADL) [5, 6]. The score on this scale determines the care level and the care costs that will be covered by the public health insurance scheme, organized by the RIZIV. In Flanders, social care needs are assessed using the BEL scale, which includes ADL and IADL limitations, social aspects and mental health. This assessment determines the amount of care to which the user is entitled. This financing is organized by the VAZG and the level of financing is also based on the household income.

In the following subsections we describe the dependent variables. For residential care and home nursing we start from the individual EPS data, for the home care categories we use VESTA data. For each of these variables we compare the weighted individual data with the aggregate data from VAZG and RIZIV. Data for some years are not available, which is the reason for the empty cells in the tables. As the data from the EPS is available for the period 2009-2017, all care categories in residential care and home care have missing data for 2018 and 2019. For the residential categories, data for all years were available from the VAZG database, except for short stay, for which data was available for 2014-2019. Data for residential categories from the RIZIV was available for the period 2011 until 2018. Nursing care data was available in the RIZIV database for all years (2009-2019). Data from the VAZG for social care was available for 2010 until 2019 and data for logistic help and surveillance help for the period 2012-2019, as these two services did not exist in the VESTA database before 2012.

### 3.1 Days in residential care – category O

The residential care category O as measured by the Katz scale, represents the lowest level of care in residential care. This category identifies people with no ADL dependency and no evident problems with orientation in time and space. The days in residential care category O are calculated from the EPS using the following codes: 763195, 763291, 760351, 760476. Table 2 and figure 1 show the total number of days in this care category for people 55 or older in the EPS (extrapolated to the population totals) and a comparison between the EPS data and the data from official sources (VAZG and RIZIV). In the period of 2009-2017 there was a decrease in the total days in category O. This decrease in the official data is not well captured by the extrapolated EPS data for the years 2013-2015.

Table 2 Days in residential care - category O

Year	Days care category O - EPS	Days care category O - VAZG	Days care category O - RIZIV	% days O EPS/VAZG	% days O EPS/RIZIV
2009	3 556 244	3 483 207		102.10%	
2010	3 324 219	3 362 439		98.86%	
2011	3 115 663	3 184 638	3 314 777	97.83%	93.99%
2012	2 990 806	3 016 077	3 121 698	99.16%	95.81%
2013	2 799 071	2 662 213	2 825 653	105.14%	99.06%
2014	2 672 141	2 504 009	2 639 795	106.71%	101.23%
2015	2 523 083	2 317 703	2 346 335	108.86%	107.53%
2016	2 242 232	2 184 010	2 216 035	102.67%	101.18%
2017	2 153 702	2 094 475	2 107 130	102.83%	102.21%
2018		1 993 878	1 986 096		
2019		1 943 854			



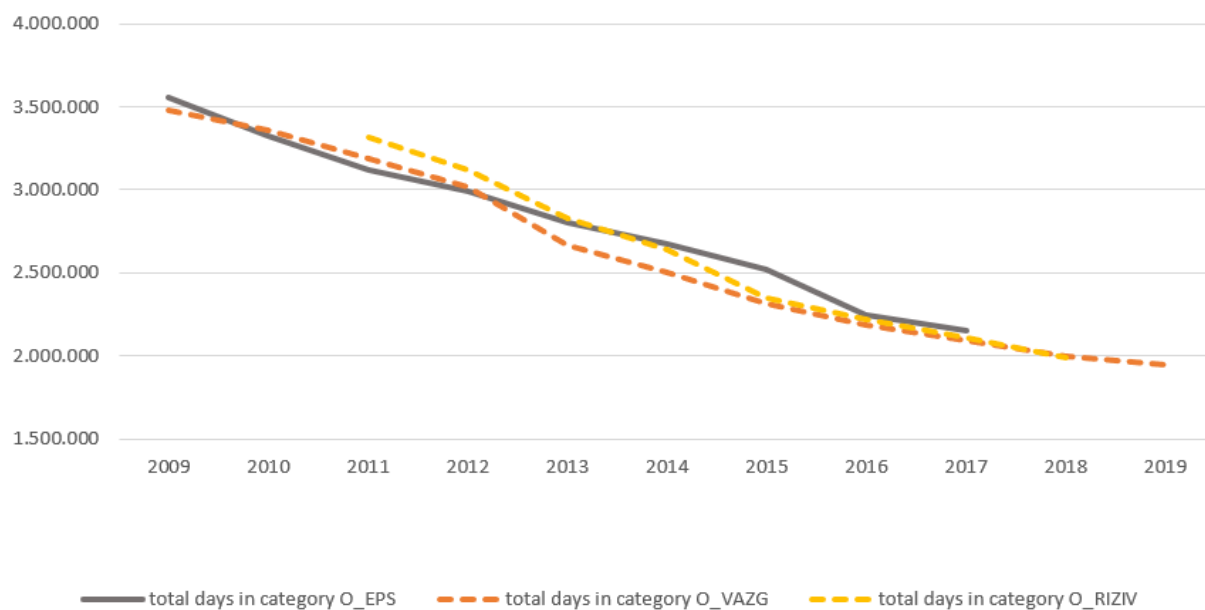


Figure 1 Evolution total days in care category O

### 3.2 Days in residential care – category A

In this residential care category, people have partial or full assistance for bathing and dressing or they have problems with orientation in time and space. The days in residential care category A are calculated from the EPS using the following codes: 763210, 763313, 760373, 760675. Table 3 and figure 2 show the total extrapolated number of days in this care category for people 55 or older and a comparison with the official totals (VAZG and RIZIV). The evolution in this category is quite erratic over time, not only in the EPS, but also in the official aggregates.

Table 3 Days in residential care - category A

Year	Days care category A - EPS	Days care category A - VAZG	Days care category A - RIZIV	% days A EPS/VAZG	% days A EPS/RIZIV
2009	3 808 002	3 573 328		106.57%	
2010	3 662 982	3 549 389		103.20%	
2011	3 658 145	3 460 939	3 557 311	105.70%	102.83%
2012	3 614 023	3 504 412	3 521 744	103.13%	102.62%
2013	3 147 293	3 164 790	3 318 280	99.45%	94.85%
2014	3 233 262	3 179 647	3 339 255	101.69%	96.83%
2015	3 115 938	3 224 538	3 218 077	96.63%	96.83%
2016	3 283 253	3 304 240	3 295 314	99.36%	99.63%
2017	3 197 078	3 383 987	3 381 061	94.48%	94.56%
2018		3 394 435	3 378 962		
2019		3 319 958			

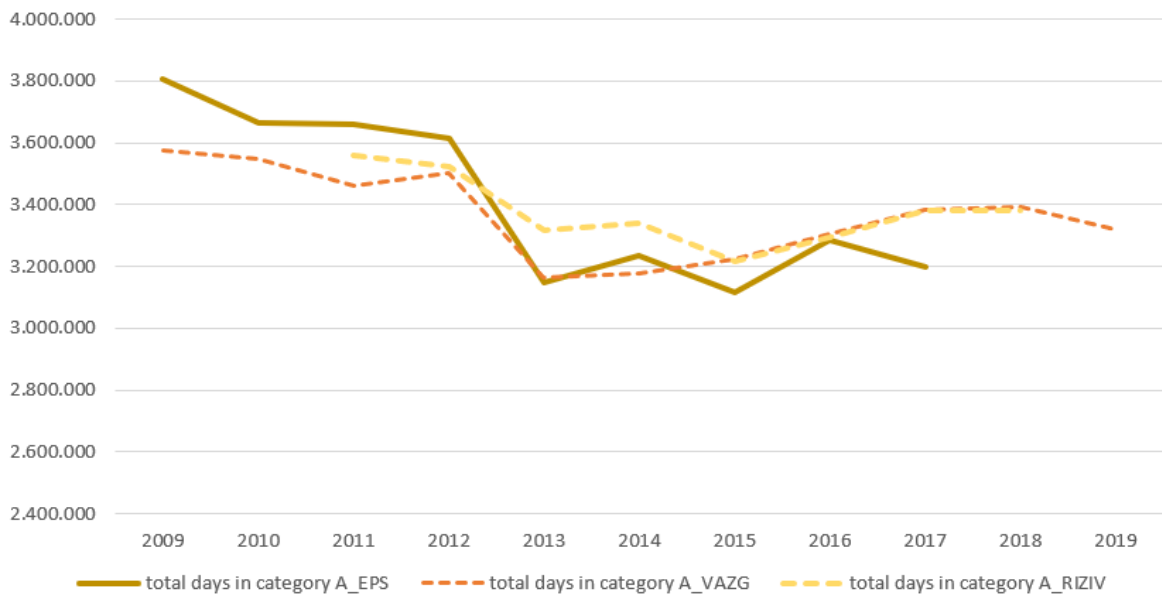


Figure 2 Evolution total days in care category A

### 3.3 Days in residential care – category B

People in this residential care category are either fully dependent or need partial help for bathing, dressing and transfer or toileting (i.e. help is needed in at least 3 ADL domains), or they have problems with orientation in time and space and need help for bathing and/or dressing. The days in category B are calculated from the EPS using the following codes: 763033, 763114, 763232, 763335, 760233, 760292, 760395, 760690. Table 4 and figure 3 show the total number of days in the EPS (extrapolated to the population totals) for people 55 or older. There is a clear increase in this total number of days during the period 2009-2017.

Table 4 Days in residential care - category B

Year	Days care category B - EPS	Days care category B - VAZG	Days care category B - RIZIV	% days B EPS/VAZG	% days B EPS/RIZIV
2009	6 225 438	5 846 138		106.49%	
2010	6 459 996	6 214 344		103.95%	
2011	6 853 240	6 553 004	6 619 804	104.58%	103.53%
2012	7 287 571	6 910 832	6 866 438	105.45%	106.13%
2013	7 511 621	7 229 482	7 271 028	103.90%	103.31%
2014	7 531 786	7 515 234	7 759 082	100.22%	97.07%
2015	7 884 274	7 895 016	7 778 224	99.86%	101.36%
2016	8 176 197	8 154 581	8 094 608	100.27%	101.01%
2017	8 301 405	8 560 817	8 421 729	96.97%	98.57%
2018		8 905 227	8 705 659		
2019		9 314 526			

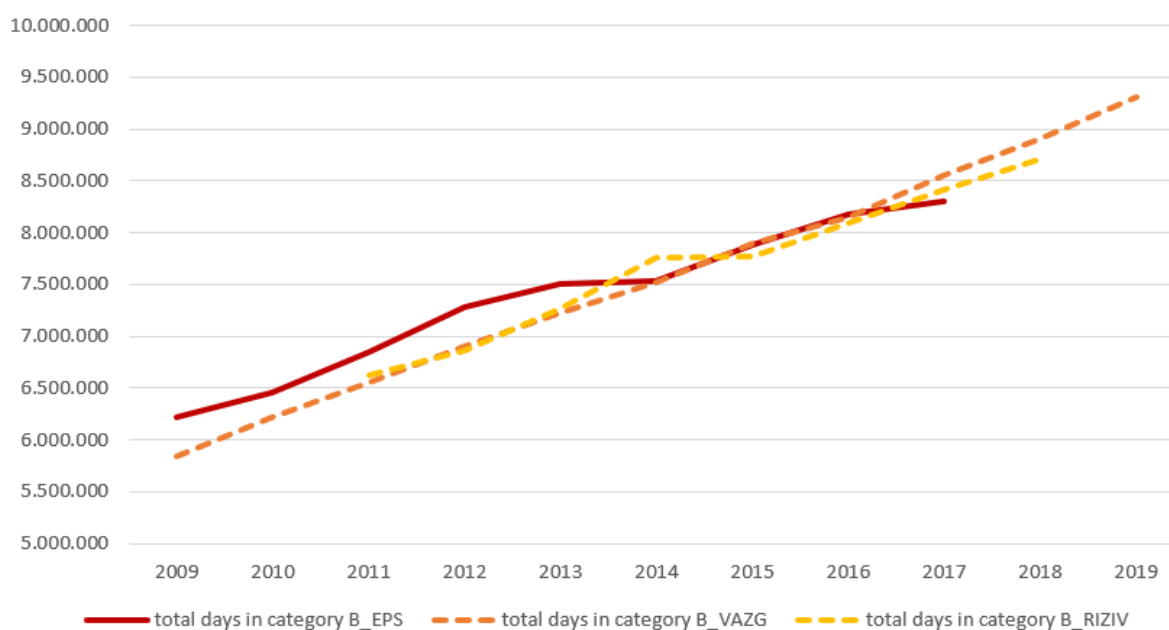


Figure 3 Evolution total days in care category B

### 3.4 Days in residential care – category C

This residential care category consists of people who need full assistance (are totally dependent) for bathing, dressing, transfer and toileting; and need partial or full assistance for eating and/or continence management. In this category, users do not have problems with orientation in time and space. The days in residential care category C are calculated from the EPS using the following codes: 763055, 763136, 763254, 763350, 760255, 760314, 760410, 760712, 763092, 763173. Table 5 and figure 4 show the total number of days in this care category for people 55 or older and a comparison with the official sources (VAZG and RIZIV). Again, there is a clear increase but it is less steep than for category B.

Table 5 Days in residential care - category C

Year	Days care category C - EPS	Days care category C - VAZG	Days care category C - RIZIV	% days C EPS/VAZG	% days C EPS/RIZIV
2009	3 019 850	2 905 352		103.94%	
2010	3 170 283	2 972 669		106.65%	
2011	3 195 573	3 105 198	3 138 770	102.91%	101.81%
2012	3 270 016	3 145 706	3 203 171	103.95%	102.09%
2013	3 303 302	3 206 504	3 269 344	103.02%	101.04%
2015	3 190 765	3 243 855	3 369 819	98.36%	94.69%
2015	3 344 248	3 319 209	3 305 944	100.75%	101.16%
2016	3 505 944	3 354 821	3 342 165	104.50%	104.90%
2017	3 530 622	3 362 300	3 366 732	105.01%	104.87%
2018		3 353 387	3 346 514		
2019		3 376 876			

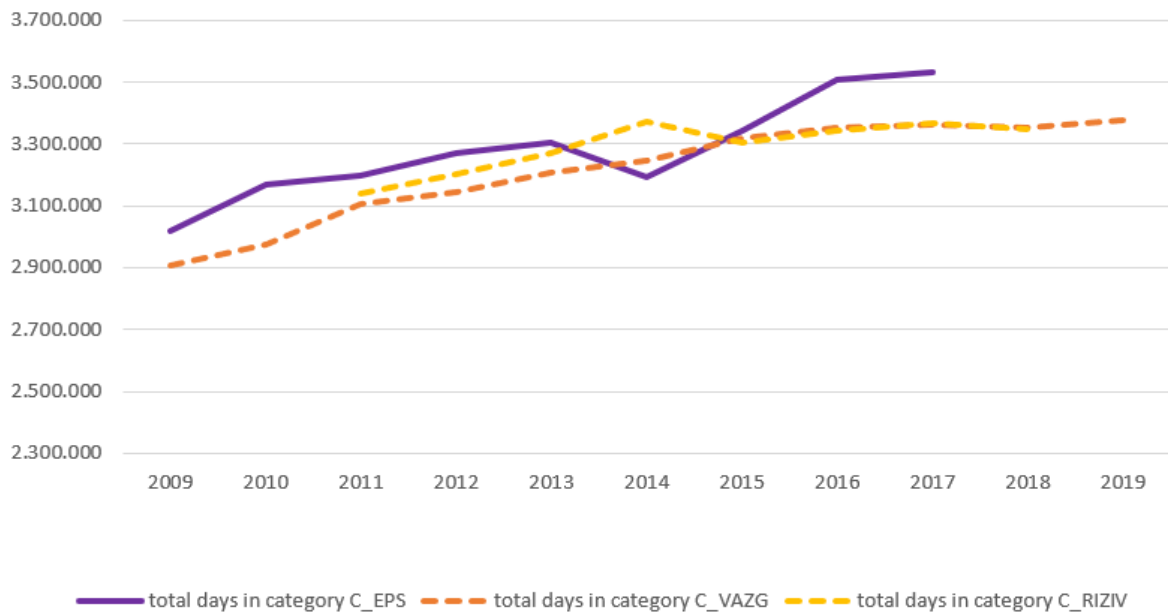


Figure 4 Evolution total days in care category C

### 3.5 Days in residential care – category Cd (and D)

In this residential category, both care levels Cd and D are included. Together, they form the largest category. People with level of care D are people with an official diagnosis of dementia, stated by a geriatrician, neurologist or a psychiatrist. Residential category Cd consists of people who need assistance for bathing, dressing, transfer and toileting; and possibly for eating and/or continence management. Therefore, the user needs help in at least 4 ADL domains. In addition, they have problems with orientation in time and space or they have an official diagnose of dementia, stated by a geriatrician, neurologist or a psychiatrist. Both categories Cd and D were combined because there were very few people in the EPS in category D and because of the common criterion of a diagnosis of dementia or the confirmed presence of cognitive problems. The days in residential care category Cd and D are calculated from the EPS using the following codes: 760270, 760336, 760432, 760734, 763070, 763151, 763276, 763372, 763696, 763711, 760454, 760756. Table 6 and figure 5 show the total number of days in this care category for people 55 or older in the EPS (extrapolated to the population totals) and a comparison with the official sources (VAZG and RIZIV). Similarly to category B, there was an increase in the total number of days in this category during the period 2009-2017.

Table 6 Days in residential care - category Cd

Year	Days care category Cd - EPS	Days care category Cd - VAZG	Days care category Cd - RIZIV	% days Cd EPS/VAZG	% days Cd EPS/RIZIV
2009	7 488 817	7 393 314		101.29%	
2010	7 937 849	7 601 894		104.42%	
2011	8 128 084	7 918 002	7 947 790	102.65%	102.27%
2012	8 133 428	8 088 702	8 081 965	100.55%	100.64%
2013	8 870 904	8 802 551	8 662 147	100.78%	102.41%
2014	8 934 811	9 257 972	9 379 720	96.51%	95.26%
2015	9 383 776	9 578 877	9 462 706	97.96%	99.17%
2016	9 694 074	9 915 921	9 796 680	97.76%	98.95%
2017	9 854 070	10 063 342	9 948 953	97.92%	99.05%
2018		10 226 698	10 066 246		
2019		10 357 844			

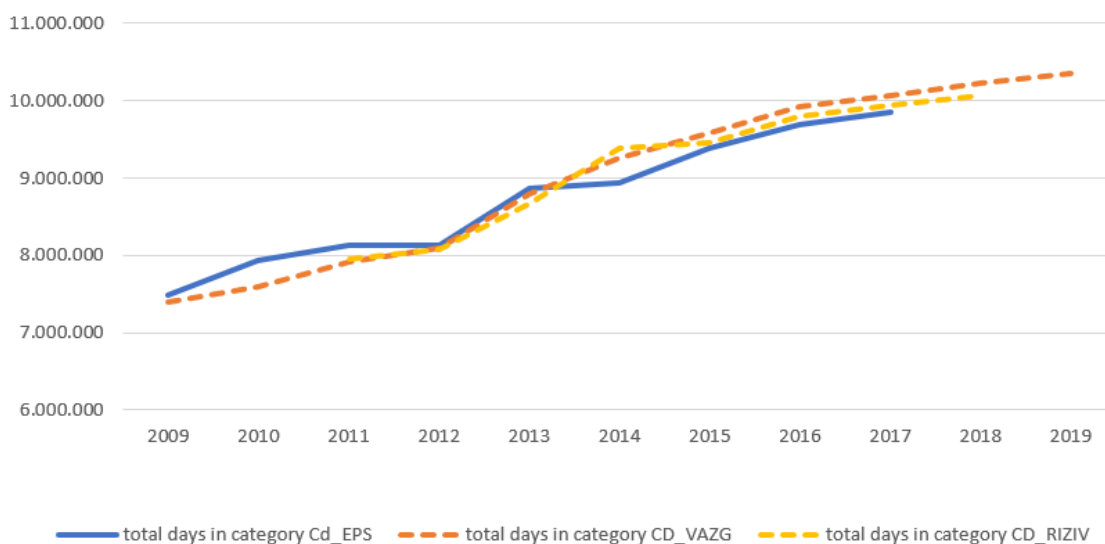


Figure 5 Evolution total days in care category Cd

### 3.6 Days in residential care – category Short stay

This category comprises people who stay for short periods in residential care. There are different care levels in short stay, but we combined all these levels in one category, as there were too few people in the EPS in each of the individual care levels for a meaningful empirical analysis. The days in this category were calculated from the EPS using the following codes: 763475, 763571, 763733, 763755, 760874, 760992, 760852, 760970, 763453, 763556, 760830, 760955, 763431, 763534, 760815, 760933, 763416, 763512, 760793, 760911, 763394, 763490, 760771, 760896. Table 7 and figure 6 show the total number of days in this care category for people 55 or older and a comparison with the official sources (VAZG and RIZIV).

Table 7 Days in residential care - category Short stay

Year	Days care category Short stay - EPS	Days care category Short stay - VAZG	Days care category Short stay - RIZIV	% days Short stay EPS/VAZG	% days Short stay EPS/RIZIV
2009	304 590				
2010	324 272				
2011	396 620		394 221		100.61%
2012	485 157		462 135		104.98%
2013	572 533		521 815		109.72%
2014	593 244		579 510		102.37%
2015	638 837	639 691	614 549	99.87%	103.95%
2016	614 590	676 947	663 027	90.79%	92.69%
2017	691 522	691 644	683 865	99.98%	101.12%
2018		796 423	703 577		
2019		803 264			

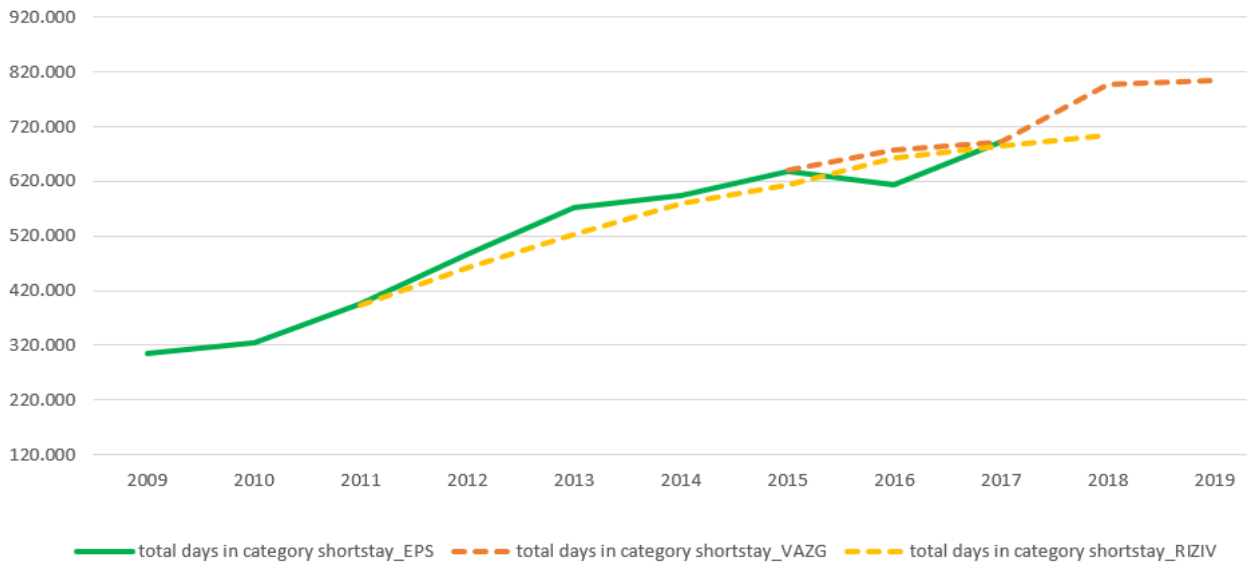


Figure 6 Evolution total days in care category Short stay

### 3.7 Nursing tasks at home

The individual data on home nursing are also taken from the EPS. We include all nursing tasks related to ADL dependency. People need at least partial assistance for bathing and dressing and transfer or toileting. To calculate the total nursing home tasks delivered at home the following codes were used: 419274, 425110, 425272, 425294, 425316, 425515, 425670, 425692, 425714, 425913, 426075, 426090, 426112, 426311, 427011, 427033, 427055, 427070, 427092, 427114, 427136, 427151, 427173, 427195, 427755, 429096, 429111, 429133. These codes consist of hygiene care or nursing care based on the codes A, B or C of the Katz scale for home care. In our models, we have followed the approach taken by the RIZIV and aggregated all these tasks as a whole. As each of them is identified by an invoice, this boils down to summing up all the invoices for all these codes. Table 8 and figure 7 show a comparison between the total nursing tasks in the EPS and the total nursing tasks in the official source (RIZIV) for people who are 18 or older. During the period of 2009-2017 there was a strong increase in the delivery of this category of care. Note that this care component is still regulated and financed at the federal level and is therefore not a part of the Flemish Social Protection.



Table 8 Nursing tasks

Year	Nursing tasks - EPS	Nursing tasks - RIZIV	% Nursing tasks EPS/RIZIV
2009	27 523 451	26 528 796	103.75%
2010	28 566 385	27 746 958	102.95%
2011	29 655 357	28 828 740	102.87%
2012	30 515 342	30 115 980	101.33%
2013	30 840 625	30 606 640	100.76%
2014	32 287 212	31 935 660	101.10%
2015	32 784 715	32 897 191	99.66%
2016	33 857 582	33 622 007	100.70%
2017	34 860 347	34 709 207	100.44%
2018		35 355 949	
2019		36 274 145	

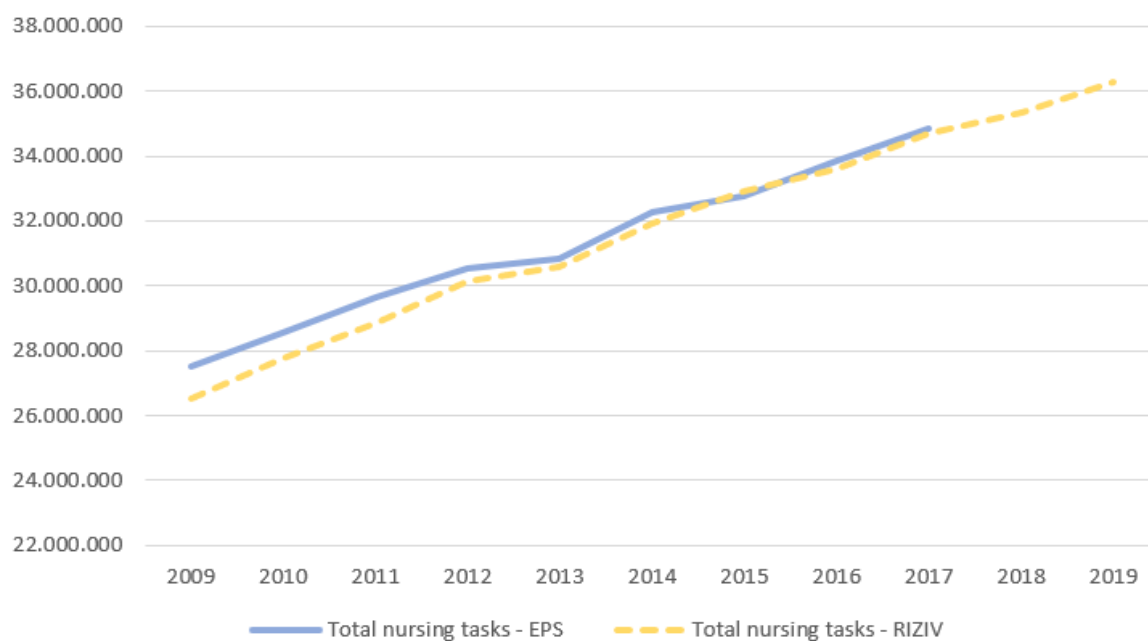


Figure 7 Evolution total tasks nursing at home

### 3.8 Hours of social care at home

To calculate the total hours of social care delivered at home, we used the code 4000 from the VESTA database. These data have been matched to the EPS data, so that we can analyze them on the basis of the individual information that is available in the latter. Table 9 and figure 8 show a comparison between the total number of hours of social care for the people who are 18 or older in the EPS and the totals in the official source (VAZG). The extrapolated VESTA data matched with the EPS are in many years an underestimate of the aggregate VAZG data.

Table 9 Hours of social care

Year	Hours of social care - VESTA matched with EPS	Hours of social care - VAZG	% Hours of social care - VESTA matched with EPS/VAZG
2009	15 489 931		
2010	15 360 133	15 234 260	100.83%
2011	15 120 048	15 487 195	97.63%
2012	15 582 756	15 483 488	100.64%
2013	15 830 411	15 880 480	99.68%
2014	16 153 508	16 134 957	100.11%
2015	15 921 251	16 406 979	97.04%
2016	15 545 630	16 201 427	95.95%
2017	15 623 873	15 837 018	98.65%
2018		16 046 011	
2019		16 252 556	

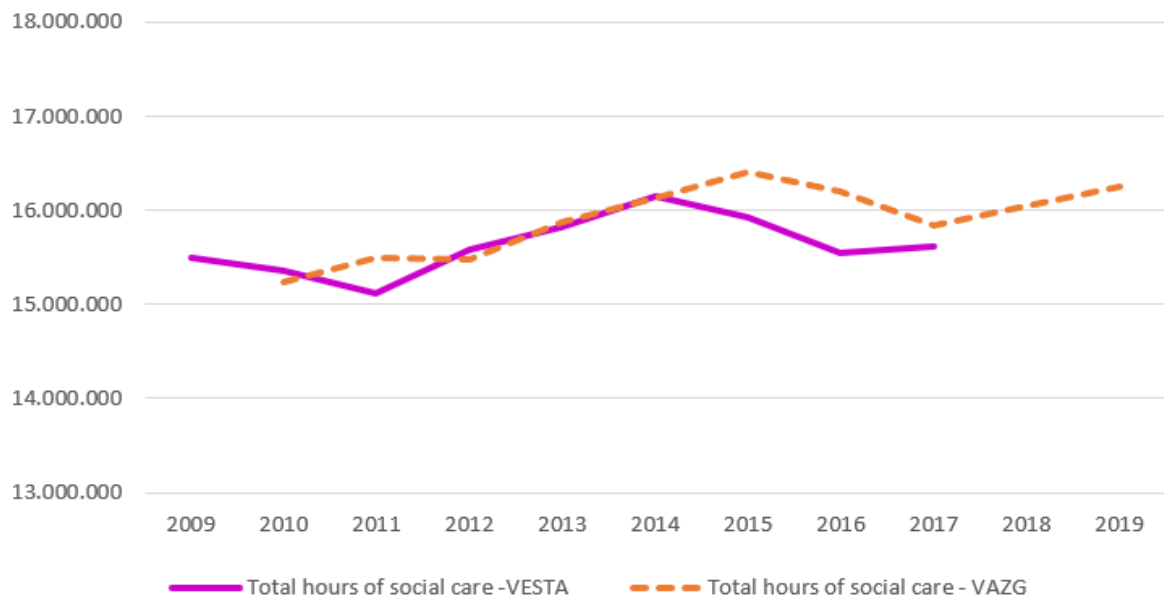


Figure 8 Evolution total hours social care at home

### 3.9 Hours of logistic help at home

The same matching procedure is used to calculate the number of hours of logistic help at home, based on the codes 4009 and 4010 from the VESTA database. Table 10 and figure 9 show a comparison between the total number of hours of logistic help for the people who are 18 or older in the EPS and the totals in the official source (VAZG). Again, the extrapolated VESTA data, matched with the EPS, are rather an underestimate of the aggregated VAZG data.

Table 10 Hours of logistic help

Year	Hours of logistic help - VESTA matched with EPS	Hours of logistic help - VAZG	% Hours of logistic help - VESTA matched with EPS
2012	4 585 210	4 737 000	96.80%
2013	4 617 395	4 785 190	96.49%
2014	4 573 197	4 641 762	98.52%
2015	4 448 194	4 601 880	96.66%
2016	4 535 077	4 646 929	97.59%
2017	4 625 883	4 514 221	102.47%
2018		4 456 867	
2019		4 446 528	

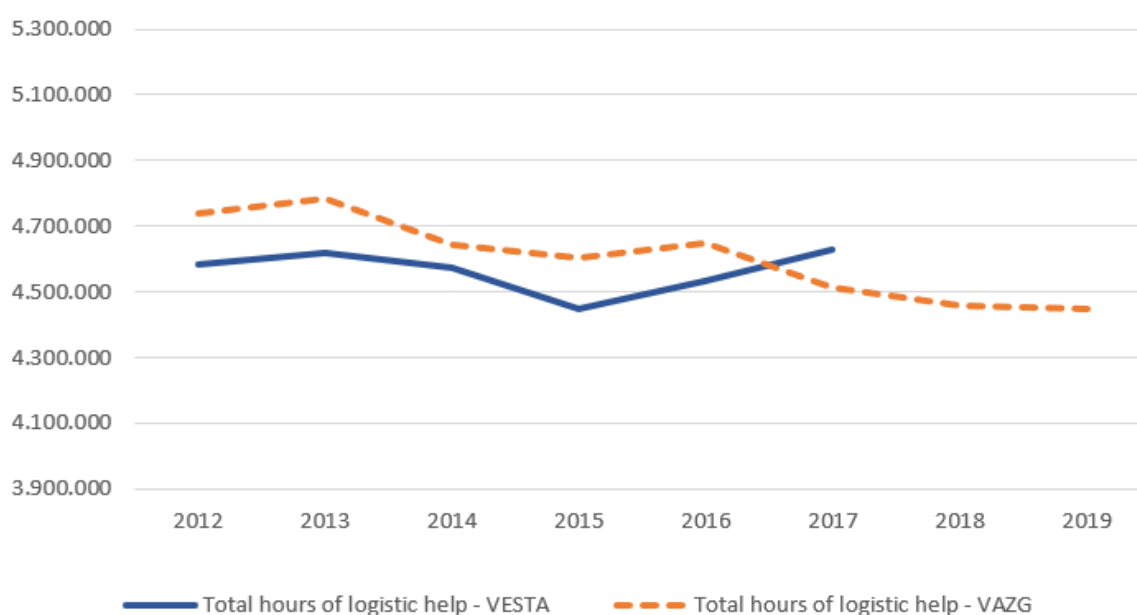


Figure 9 Evolution total hours logistic help at home

### 3.10 Hours of surveillance help at home

To calculate the total hours of surveillance at home, we used the code 4011 from the VESTA database. Table 11 and figure 10 show a comparison between the total number of hours of surveillance help for people who are 18 or older in the EPS and the totals in the official source (VAZG). This is a rather small category and the correspondence between the extrapolated VESTA data and the totals from the VAZG is not satisfactory. In some years the underestimate is huge: it is e.g. 30% in 2015. Moreover, the number of hours of surveillance help in the VESTA-EPS fluctuates a lot over the period 2012-2017, while in the official VAZG source they are more stable. We concluded that the available individual data are not suitable to make future predictions for surveillance help and we will not show any forecast models or simulations results for this care category.

Table 11 Hours of surveillance help

Year	Hours of surveillance help - VESTA matched with EPS	Hours of surveillance help - VAZG	% Hours of surveillance help - VESTA matched with EPS
2012	160 550	164 552	97.57%
2013	151 024	182 959	82.55%
2014	175 273	188 435	93.02%
2015	136 060	193 030	70.49%
2016	145 623	193 874	75.11%
2017	176 845	190 900	92.64%
2018		190 900	
2019		199 053	

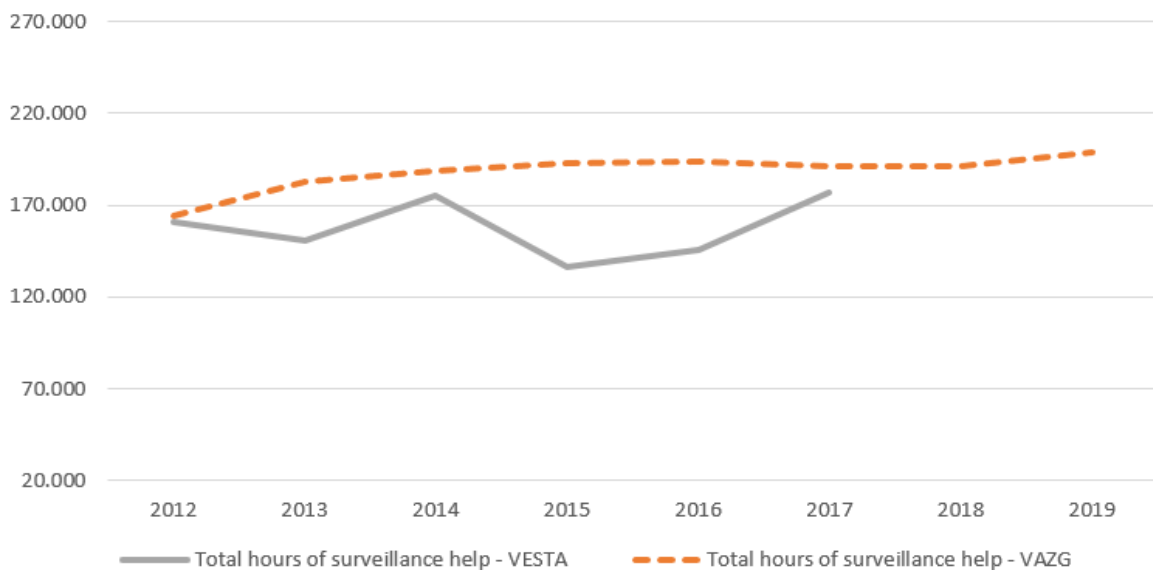


Figure 10 Evolution total hours of surveillance at home

## 4 Explanatory variables

We now give an overview of the available explanatory variables in the EPS database, that will be used as independent variables in the regression models. We explain how they were calculated and how they evolved over the period of 2009-2017. These variables largely correspond to the drivers of the use and costs of care that have been introduced in the overview of projection models in the first part of this report. The fact that we will use the term "explanatory variables" does not imply that it is possible to give a causal interpretation to the associations that we found in the models. The interpretation must be cautious.

### 4.1 Low income

The variable 'low income' is a combination of socio-economic indicators present in the EPS. It is the best available approximation for economic status, since in the EPS there is no explicit variable about income or the level of income. It identifies whether the person has a 'preferential' status in health care, has level of income equal to or lower than the minimum wage or is supported by welfare services. The indicator 'low income' works as a dummy variable with the value 0 (when the income cannot be considered low) or 1 (when income can be considered low).

#### Variable 'lowincome'

Definition: Low income

Description: Proxy variable which indicates whether the person has a low income or not.

Values: 0 (no low income), 1 (low income)

Calculation: Calculated with the following variables from the EPS:

'Preferential': variable PP0030 with '1' as third digit (Code Person 1: CGI=xx1)

PP1008= 1, 2, 4, 5 (people with a low salary or benefit equivalent to a minimum wage or the family income is lower than in article 134, lid 3 of the law K.B. 03 July 1996 or people with a year income lower than in the article 134, lid 5 of the law K.B. 03 July 1996) – These values for PP1008 are only attributed to a small portion of individuals (in case they have a code CG1/CG2 equal to 100/100 or 101/101 100/100 101/101). Otherwise, a value=0 is attributed.

PP3002=3 – MAF family – this code is only attributed if the MAF (maximum invoicing) ceiling is achieved.

PP3010=1 – Right to a basis income, income guarantee for older people.

PP3013=1 – Right to receive help from the Public Centra for Welfare (OCMW)

If preferential=1 or PP1008 is (1,2,4,5) or PP3002=3 or PP3010=1 or PP3013=1 then 'low income'=1

Table 12 Evolution of low income

Year	Low income (55+)	Low income (18+)	Low income in population Statbel (55+)	Low income in population Statbel (18+)
2009	28.87%	16.61%	567 235	844 337
2010	27.84%	16.68%	556 576	856 369
2011	26.96%	16.64%	548 414	860 192
2012	26.49%	16.63%	548 272	864 851
2013	26.09%	16.76%	548 848	875 683
2014	25.15%	16.84%	538 096	883 938
2015	24.60%	17.00%	535 878	897 873
2016	24.43%	17.39%	541 119	923 990
2017	23.89%	17.21%	538 268	919 387

Table 12 shows the evolution of the proportion of low-income people in the EPS and the extrapolation for the total numbers on the basis of the Statbel population data for the period of 2009 until 2017. The same proportions are represented in figure 11, where we also show the result of a simple extrapolation beyond 2017 and until 2035. The evolutions are in line with what is known from other sources. The proportion of people with low income is larger in the category 55+ than in the category 18+, but it is declining in the former and slightly increasing in the latter [7, 8]. In our simple extrapolation the former becomes even smaller than the latter around 2030, but this is of course a "prediction" that has to be taken with a grain of salt. It is highly likely that there will be changes in the socio-economic or policy environment that have an impact on these long-run trends.

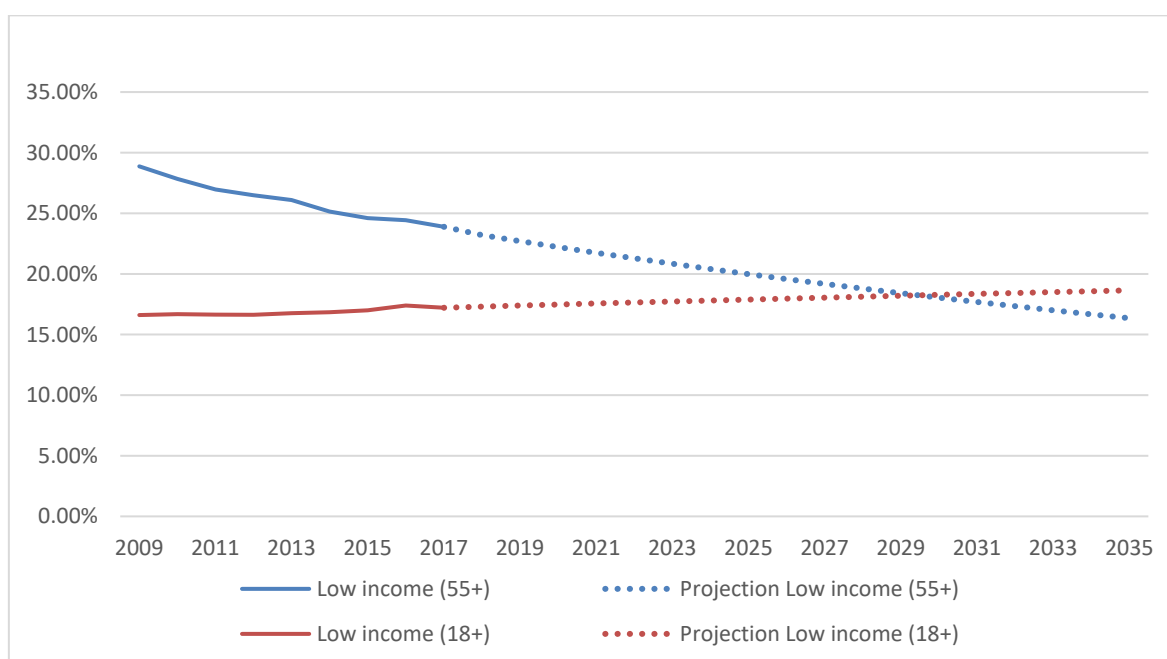


Figure 11 Evolution variable low income

## 4.2 Handicap

The variable handicap is a proxy for the disability status and was created from several indicators from the EPS. A disability status can be considered an official recognition that the person has some type of disability, and that the client is entitled to financial support for the purchase of materials or aids, to pay for private support, rehabilitation and other services. If the person is not able to work due to the disability, the person receives a monthly living allowance. In the EPS, only the Federal definition of disability can be found. This definition is partially based on the type of replacement income that the person is entitled to. If the person receives a disability allowance, he or she is considered to have a disability. The created dummy variable has values 0 (no handicap status) and 1 (handicap status).

The definition of disability in the EPS differs from the definition of 'handicap' as used by the Flemish government, which is responsible for the payment of an allowance to all people with a disability, as well as the provision of help for the purchase of materials. The Flemish definition of disability is broader and it depends on the scores of a clinical instrument, which measures the functional and psychological status, as well as disabilities, and on the advice from a multidisciplinary team from the VAPH (the Flemish Agency for People with a Disability). In principle, we would have preferred to use in our analysis this broader definition and for that purpose the EPS-VESTA database was also matched with the VAPH database. However, we could only identify a few people present in both databases: 147 people in 2015, 391 people in 2016 and 1017 in 2017. Moreover, as the VAPH database was only available for these three years, containing the new budgets for people with handicap in the context of the Flemish Social Protection, we could not do any matching for the years before. As the matching between the databases was not effective and a lot of uncertainty remained, we used only the data from the EPS, and, hence, the Federal definition of handicap as disability.

### Variable 'handicap'

Definition: Handicap.

Description: Proxy which identifies whether the person has a disability status or not.

Values: 0 (no disability status), 1 (disability status)

Calculation: Calculated based on the following variables in the EPS. If one of the variables has one of the values indicated below, the status 'disability' is attributed to the individual:

PP0030 (2nd digit= 2): disabled

PP0035 (2nd digit= 2): disabled

PP1003=5: disabled persons of the general scheme

PP1003=6: disabled persons under the self-employed persons scheme (until the end of 2007)

PP1009<>0 (differs from 0): Origin recognition as disabled

PP2005=1: Allowance for the integration of disabled people (cat III, IV or V)

PP3011=1: Entitled to disability allowance.



Table 13 Evolution of handicap

Year	Handicap (55+)	Handicap (18+)	Handicap in population Statbel (55+)	Handicap in population Statbel (18+)
2009	19.53%	17.60%	383 631	894 855
2010	19.66%	17.85%	393 055	916 366
2011	19.63%	17.93%	399 241	927159
2012	19.45%	18.01%	402 550	936 328
2013	19.41%	18.10%	408 370	945 461
2014	19.39%	18.24%	414 856	957 866
2015	19.53%	18.60%	425 331	982 759
2016	19.50%	18.71%	431 844	993 999
2017	19.25%	18.78%	433 800	1 003 440

Table 13 and figure 12 show the evolution of the percentages and absolute numbers of people with a handicap for the EPS samples of people 18 or older and of people 55 or older. The evolution is similar to the one of "low income". The proportion of people with a handicap is larger for the 55+ than for the 18+ in the beginning of the period, but it is increasing for the latter and not for the former.

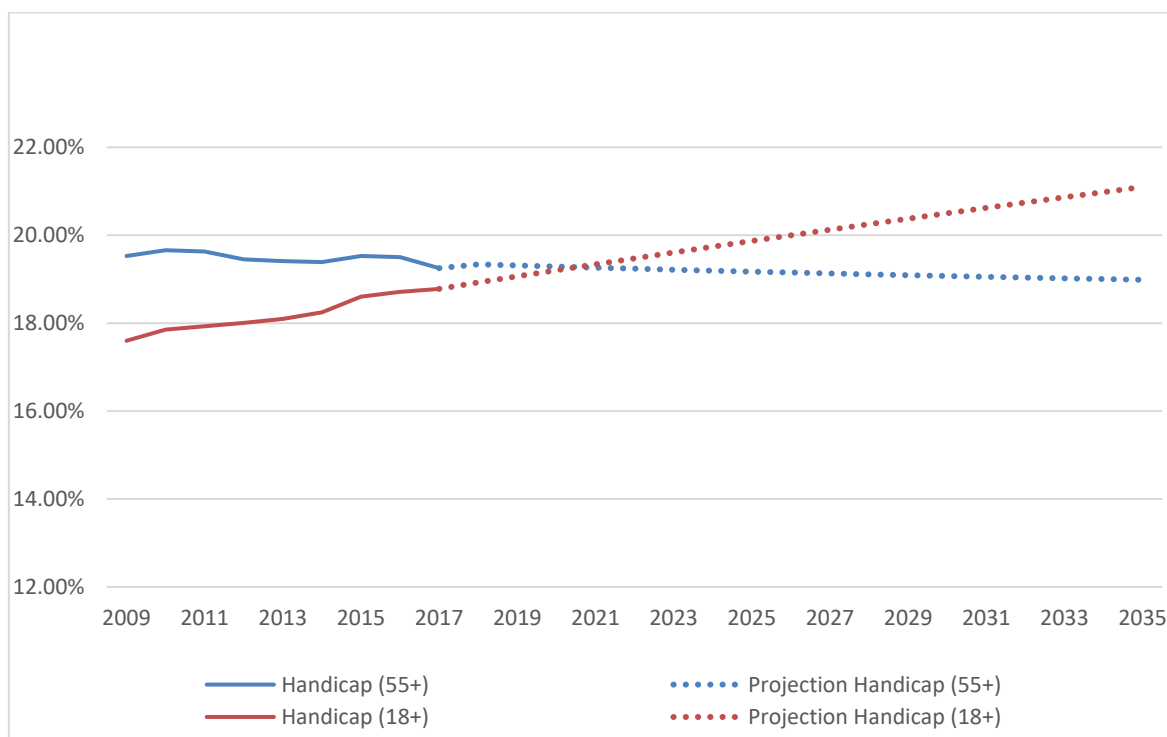


Figure 12 Evolution variable handicap

### 4.3 Availability of informal care

The availability of informal care is a crucial factor to explain the use of formal care, both residential and non-residential. The decrease in the availability of informal care in the future, due to changes in the demographic composition and in the labor market behavior, is generally considered to be one of the main challenges for the future organization and financing of care. It is certainly essential to have this variable in the model, although a full analysis of the future supply of informal care would require the estimation of a behavioral model, for which we obviously do not have sufficient information.

The EPS database contains a constructed proxy variable indicating whether household members can potentially give informal care to the person. Twelve variables in total are used to calculate this proxy (from IC\_AVAIL\_SA11 until IC\_AVAIL\_SA16 and from IC\_AVAIL\_SA21 until IC\_AVAIL\_SA26). The potential for giving care is calculated with the variables age, work situation and health status of household members other than the person. People who are household members and are older than 25, unemployed or retired, and neither chronically ill nor disabled are considered to be potentially available for informal care. The created variable has values 0 (no informal caregiver available) and 1 (at least one informal caregiver available).

#### Variable 'Informal caregiver'

Definition: Informal care.

Description: Proxy which indicate the availability of at least one informal carer.

Values: 0 (no informal caregiver available), 1 (1 or more informal caregivers available)

Calculation: Calculated from 12 variables in the EPS: IC\_AVAIL\_SA11 until IC\_AVAIL\_SA16 and IC\_AVAIL\_SA21 until IC\_AVAIL\_SA26, which indicate the availability of an informal caregiver. It indicates whether family members (living together) with the older person, may be potential informal carers. The variable considers the age, the working status and the health situation of the family members or co-habitants to calculate the potential to give care.

Family members over the age of 25, who are unemployed or retired and who are not chronically ill or do not have a disability, are considered as potential caregivers.

To calculate this variable, a sum is made of the values from the 12 variables. Each variable can have the values '0' (not potentially available) or '1' (potentially available). If the sum is greater than 0, it is assumed that the person may have at least one available caregiver.

Table 14 Evolution of the availability of informal care

Year	Informal care (55+)	Informal care (18+)	Informal care in population Statbel (55+)	Informal care in population Statbel (18+)
2009	58.22%	37.69%	1 143 938	1 916 308
2010	57.84%	37.87%	1 156 432	1 943 693
2011	57.11%	37.02%	1 161 646	1 914 151
2012	56.36%	36.24%	1 166 301	1 884 122
2013	55.95%	36.55%	1 176 960	1 909 591
2014	55.49%	36.08%	1 187 380	1 894 222
2015	55.13%	35.94%	1 200 706	1 898 388
2016	54.34%	35.21%	1 203 325	1 870 613
2017	53.38%	34.16%	1 202 834	1 825 577

Table 14 and figure 13 show again the evolution (and projection) of the variable informal care over time. The decrease in the potential availability of informal care is striking, both for people 18 or older and for people 55 or older.

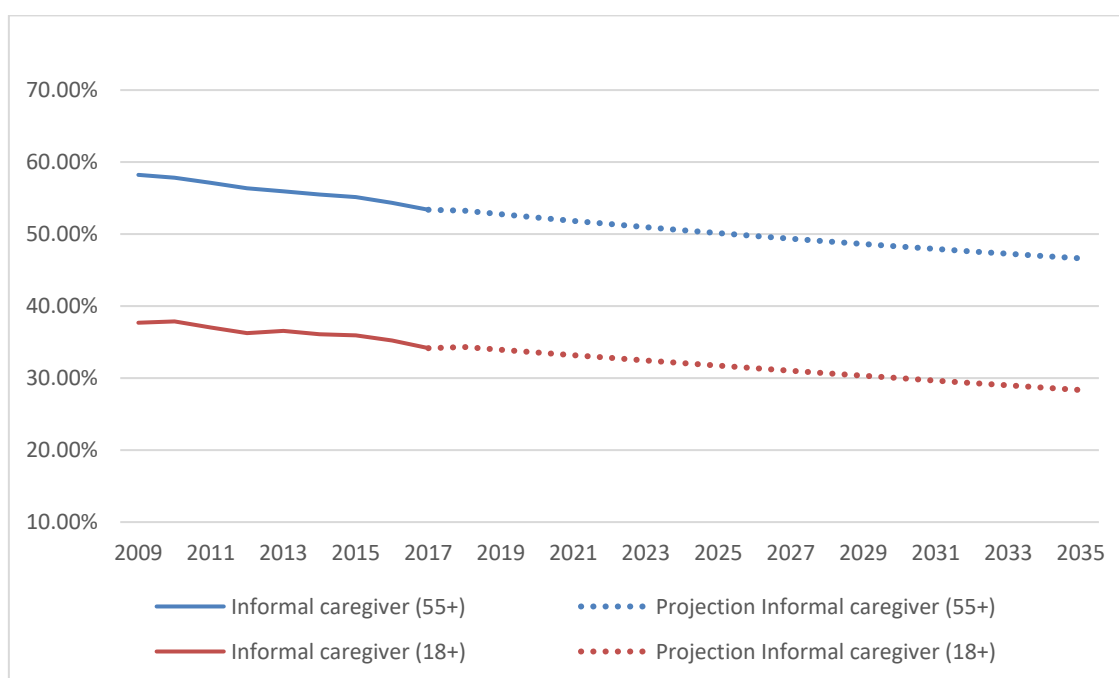


Figure 13 Evolution variable informal care

#### 4.4 Morbidity variables – diagnoses derived from the use of drugs

In the EPS database, data recorded about medication serves to flag clients with chronic use of certain medication classes (that are more or less specific for medical diagnoses).. The IMA uses a list of drugs to calculate these flags and adds them to the EPS database. We now give a brief overview of these flags. For some of them the evolution over time remains fairly stable (cardiovascular problems and Parkinson), for others there is a clear increase (COPD and diabetes). We discuss in more detail the calculation of the indicator for Alzheimer's disease, because it is essential to explain the care developments, e.g. for the residential category Cd (and D), and because the identification on the basis of the use of drugs is tricky.

##### Cardiovascular problems

###### **Variable 'cardiovascular'**

Definition: Cardiovascular problems.

Description: Flag that identifies the use of medication for cardiovascular disease based on the physician's prescription and drug collection from the pharmacy.

Values: 0 (no cardiovascular disease), 1 (cardiovascular disease)

Calculation: Calculated based on the following variables in the EPS:

ATC code(s):

C01 - Heart medication

C02 - Antihypertensives

C03 - Diuretics

C07 - Beta blockers

C08 - Calcium channel blockers

C09 – Renin-angiotensin system drugs

Table 15 Evolution of cardiovascular problems

Year	Cardiovascular problems (55+)	Cardiovascular problems (18+)	Cardiovascular problems in population Statbel (55+)	Cardiovascular problems in population Statbel (18+)
2009	56.90%	27.20%	1 117 848	1 382 895
2010	57.65%	27.65%	1 152 562	1 419 274
2011	58.12%	28.08%	1 182 107	1 452 071
2012	58.42%	28.51%	1 208 928	1 482 573
2013	58.43%	28.73%	1 229 064	1 500 725
2014	58.27%	28.86%	1 246 820	1 515 062
2015	58.22%	29.04%	1 268 001	1 533 871
2016	58.19%	29.18%	1 288 691	1 550 015
2017	57.82%	29.13%	1 302 958	1 556 729

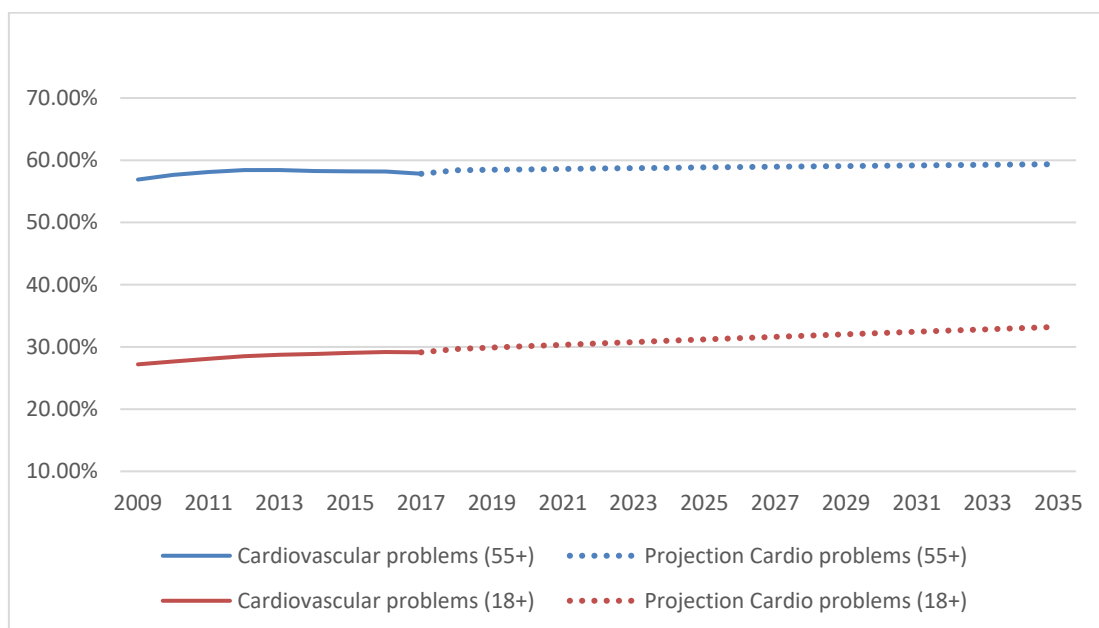


Figure 14 Evolution variable cardiovascular problems

Chronic obstructive pulmonary disease (COPD)

<b>Variable 'COPD'</b>
<p><b>Definition:</b> Chronic obstructive pulmonary disease (COPD), variant A of B.</p> <p><b>Description:</b> Flag that identifies the use of medication for COPD based on the physician's prescription and drug collection from the pharmacy.</p> <p><b>Values:</b> 0 (no COPD), 1 (COPD)</p> <p><b>Calculation:</b> Calculated based on the following variables in the EPS:</p> <p><i>ATC-code(s) (variant A):</i></p> <p>R03BB - Anticholinergics  R03DA04 - Xanthines  R03A - Adrenergics  R03BA - Guccorticoids</p> <p><i>ATC-code(s) (variant B):</i></p> <p>R03</p>

Table 16 Evolution of COPD

Year	COPD (55+)	COPD (18+)	COPD in population Statbel (55+)	COPD in population Statbel (18+)
2009	7.10%	3.06%	139 573	155 483
2010	7.27%	3.10%	145 317	159 209
2011	7.45%	3.22%	151 537	166 363
2012	7.48%	3.28%	154 836	170 547
2013	7.63%	3.35%	160 609	175 072
2014	7.71%	3.45%	164 971	181 033
2015	7.85%	3.54%	170 888	186 758
2016	8.14%	3.65%	180 189	193 965
2017	8.42%	3.78%	189 689	202 052

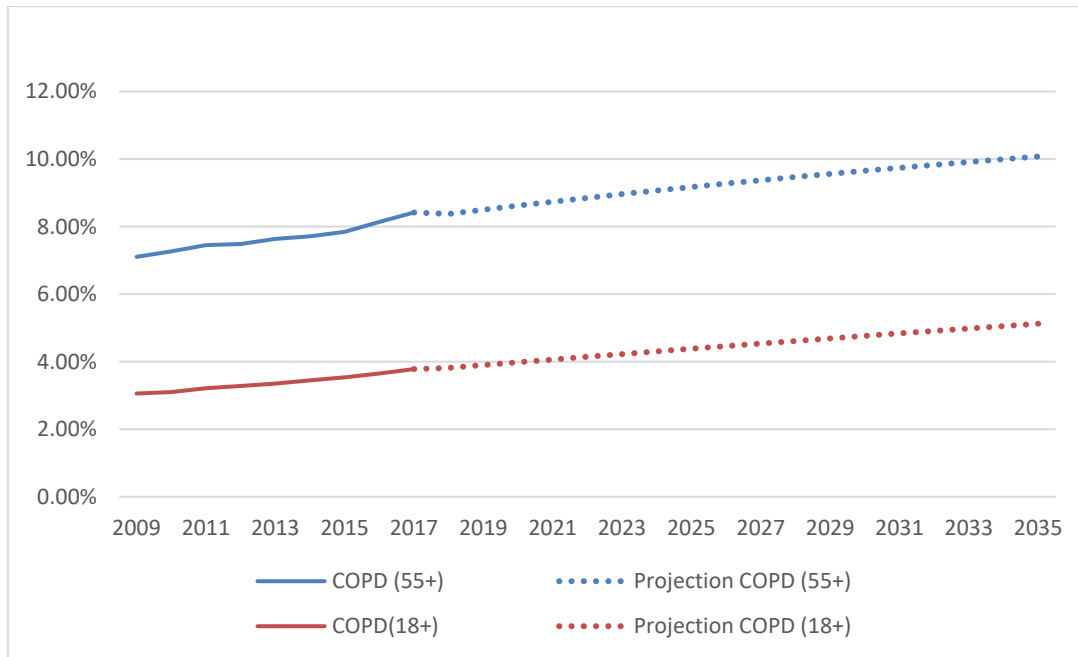


Figure 15 Evolution variable COPD

Diabetes**Variable 'diabetes'**

Definition: Diabetes.

Description: Flag that identifies the use of medication for diabetes based on the physician's prescription and drug collection from the pharmacy.

Values: 0 (no diabetes), 1 (diabetes)

Calculation: Calculated based on the following variables in the EPS:

ATC-code(s):

A10A - insulin

A10B – blood glucose lowering drugs

Table 17 Evolution of diabetes

Year	Diabetes (55+)	Diabetes (18+)	Diabetes in population Statbel (55+)	Diabetes in population Statbel (18+)
2009	11.61%	5.34%	228 168	271 507
2010	11.99%	5.58%	239 754	286 537
2011	12.27%	5.73%	249 463	296 446
2012	12.39%	5.84%	256 493	303 897
2013	12.56%	5.99%	264 127	313 088
2014	12.57%	6.09%	268 724	319 532
2015	12.63%	6.18%	275 002	326 289
2016	12.62%	6.23%	279 542	330 981
2017	12.62%	6.30%	284 375	336 822

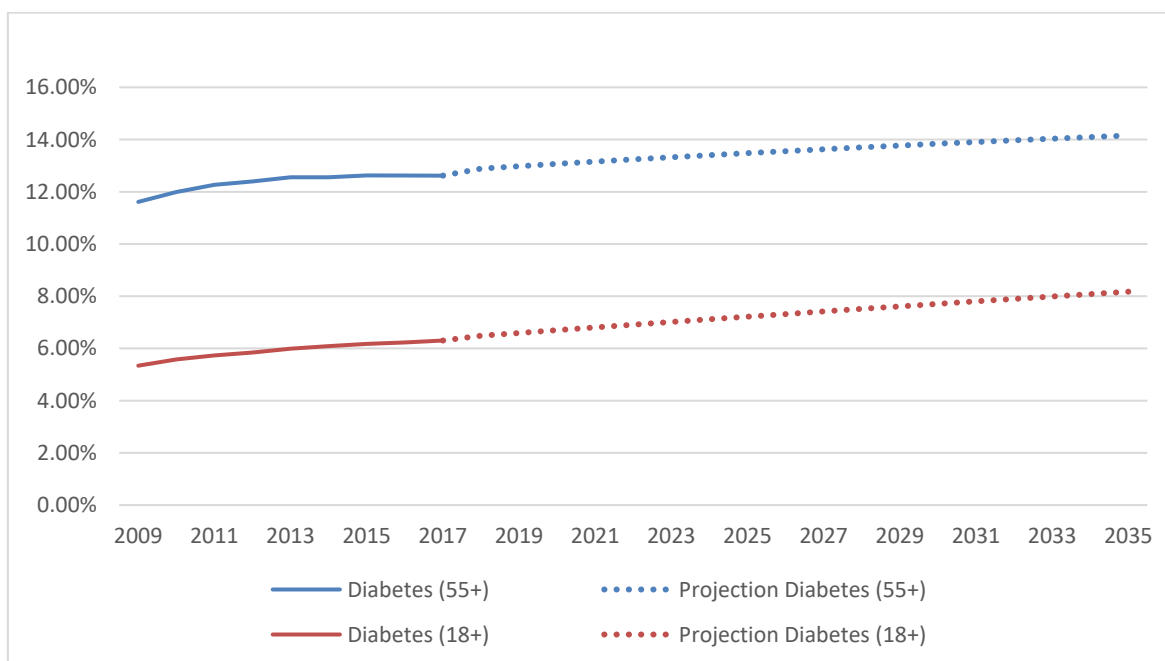


Figure 16 Evolution variable Diabetes



Parkinson's disease

<b>Variable 'Parkinson'</b>
<u>Definition:</u> Parkinson.
<u>Description:</u> Flag that identifies the use of medication for Parkinson's disease based on the physician's prescription and drug collection from the pharmacy. The developers of this flag have reported that not all people having medication reimbursed for Parkinson's disease actually have Parkinson's.
<u>Values:</u> 0 (no Parkinson's disease), 1 (Parkinson's disease)
<u>Calculation:</u> Calculated based on the following variables in the EPS:
<i>ATC-code(s) :</i>
N04AB - Anticholinergic agents
N04AC - Anticholinergic agents
N04B - Dopaminergic agents

Table 18 Evolution of Parkinson's disease

Year	Parkinson's disease (55+)	Parkinson's disease (18+)	Parkinson's disease in population Statbel (55+)	Parkinson's disease in population Statbel (18+)
2009	1.04%	0.42%	20 524	21 471
2010	1.08%	0.45%	21 508	22 929
2011	1.12%	0.46%	22 699	24 038
2012	1.09%	0.45%	22 472	23 380
2013	1.10%	0.46%	23 123	23 772
2014	1.14%	0.48%	24 376	25 237
2015	1.11%	0.47%	24 094	25 052
2016	1.10%	0.48%	24 295	25 310
2017	1.09%	0.48%	24 668	25 460

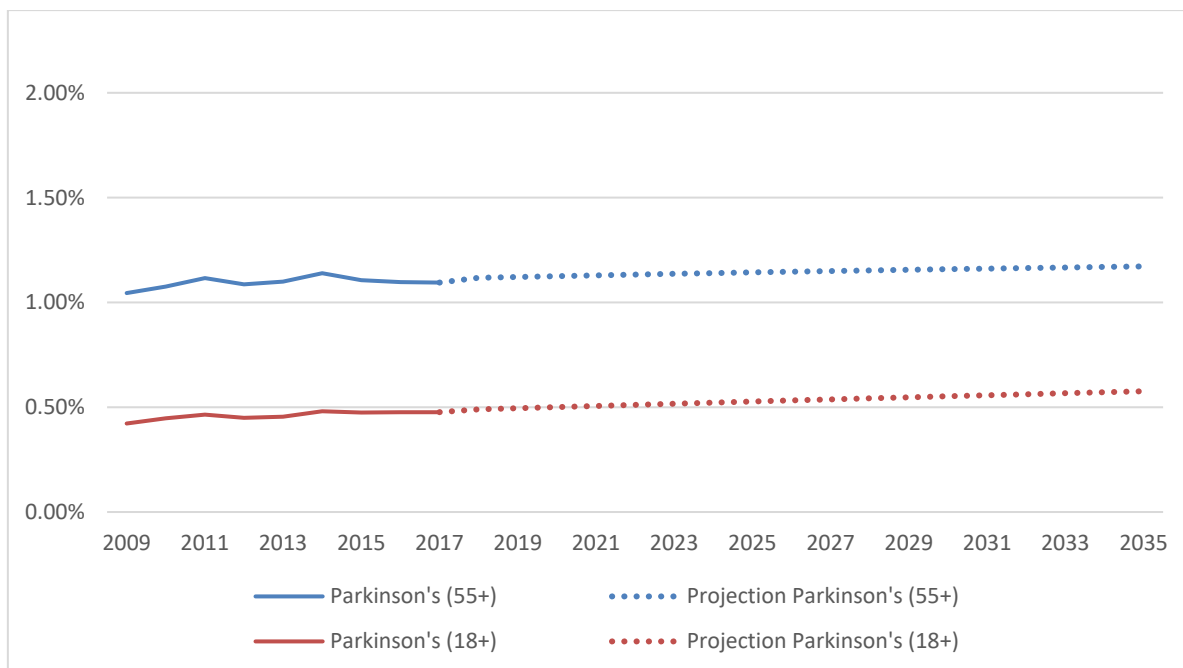


Figure 17 Evolution variable Parkinson's disease

### Alzheimer's disease

The variable Alzheimer's is a crucial one. We therefore look in more detail at the information in the EPS-data. The clearest picture is offered by figure 18. This figure shows a strange bumped pattern and overall a slight decline, mainly for the 55+. This is definitely not the evolution that we can find in other sources about the prevalence of Alzheimer's. Moreover, the EPS flag also underestimates the absolute prevalence level of dementia (Prince et al., 2014, Alzheimer Europe Report: European Dementia Monitor, 2017). This is explained by the fact that the EPS flag is based solely on medication use. Not every person with Alzheimer's is taking medication for dementia, and the practice concerning the prescription of the drugs has changed over time.

#### **Variable 'Alzheimer'**

Definition: Alzheimer.

Description: Flag that identifies the use of medication for Alzheimer's disease based on the physician's prescription and drug collection from the pharmacy.

Values: 0 (no Alzheimer's), 1 (Alzheimer's)

Calculation: Calculated based on the following variables in the EPS:

*ATC-code(s)* :

N06DX01 - Memantina

N06DA - Anicholinesterases

Extra randomisation based on the prevalences in the report: Prince, M., et al. (2014). Dementia UK: Update. Alzheimer's Society.

Table 19 Evolution of Alzheimer's disease

Year	Alzheimer's disease (55+)	Alzheimer's disease (18+)	Alzheimer's disease in population Statbel (55+)	Alzheimer's disease in population Statbel (18+)
2009	1.16	0.45	22 790	22 880
2010	1.26	0.50	25 192	25 663
2011	1.36	0.54	27 661	27 923
2012	1.32	0.53	27 317	27 559
2013	1.12	0.46	23 561	24 032
2014	1.00	0.41	21 397	21 526
2015	1.03	0.43	22 433	22 716
2016	0.96	0.40	21 260	21 249
2017	0.97	0.41	21 858	21 908

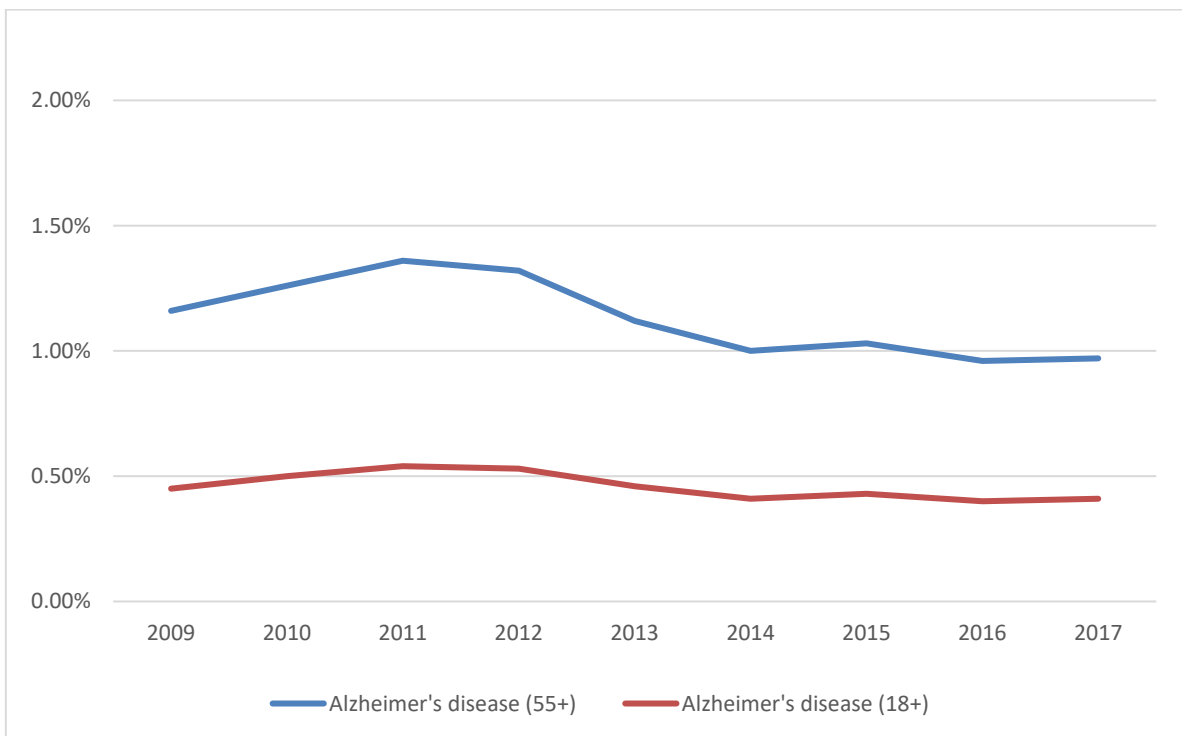


Figure 18 Evolution variable Alzheimer's disease in the EPS

To correct for this underestimation, we have randomly allocated 'Alzheimer's' to people in the sample, so that the prevalence of dementia increases and becomes comparable to the real-world prevalence. In fact, our variable for Alzheimer's is constructed as a combination of the Alzheimer variable from the EPS and a randomization of the Alzheimer variable based on data from the Alzheimer report (Prince et al., 2014). This variable was constructed as follows:

- First, the IMA flag was used: for each person in the EPS, a value of 1 was assigned in case the person had been reimbursed for medication for Alzheimer's. People who were not taking any drug for Alzheimer's, received a value '0'.

- Percentages were then calculated for both statuses (Alzheimer's=0 or 1) and all people with a value 0 were included in a separate database. To reproduce the prevalence data from the Alzheimer's report on the prevalence of Alzheimer, according to age and gender, we randomly assigned a value of 1 for the presence of the disease to people with no Alzheimer's disease according to the original EPS-variable (previous value=0). During this step, a new variable 'Alzheimer\_random1' was created including two values: '0' for 'no Alzheimer in new database' and '1' for 'Alzheimer randomized in new database', which contains the persons for whom the disease was randomly assigned. The randomization was performed with the command 'seed' in STATA. This command checks a condition (in this case age and gender) before doing the randomization and then performs the randomization for all people included in the condition. This randomization was performed to reach the prevalence data from the Alzheimer's report.

- After the creation of the new variable 'Alzheimer\_random1' in the first randomization, the proportion of people with Alzheimer was lower in the residential care setting than at home. This was due to the fact that the majority of the people in the EPS are at home and are not receiving any care. A second randomization was then applied, in order to attain more realistic results. According to Prince (2014), about 35% of the people with Alzheimer are in the residential setting. In order to reach this percentage, a second randomization was performed. In STATA, a second variable called 'Alzheimer\_random2' was created and the program removed values of '1' from the population in 'no care' and replaced them by '0'. So, for each value of 1 that was taken out of the 'no care' population, a value of '1' was assigned into the population in residential care. This second randomization was performed until the total percentage of 35% for people with Alzheimer in residential care was reached.

Table 20 shows the percentages and the population totals for people with Alzheimer's disease after the randomization procedures. Figure 19 shows the development of the variable Alzheimer's over time. We now see the steady increase, that is expected on the basis of the other sources.

Table 20 Evolution of Alzheimer's disease (after randomization)

Year	Alzheimer's disease (55+)	Alzheimer's disease (18+)	Alzheimer's disease in population Statbel (55+)	Alzheimer's disease in population Statbel (18+)
2009	4.47%	1.76%	87 876	89 246
2010	4.55%	1.80%	90 933	92 163
2011	4.57%	1.82%	93 039	94 005
2012	4.66%	1.87%	96 428	97 004
2013	4.64%	1.86%	97 650	97 195
2014	4.65%	1.88%	99 483	98 962
2015	4.77%	1.98%	103 780	104 385
2016	4.78%	2.01%	105 909	106 514
2017	4.81%	2.04%	108 359	109 066

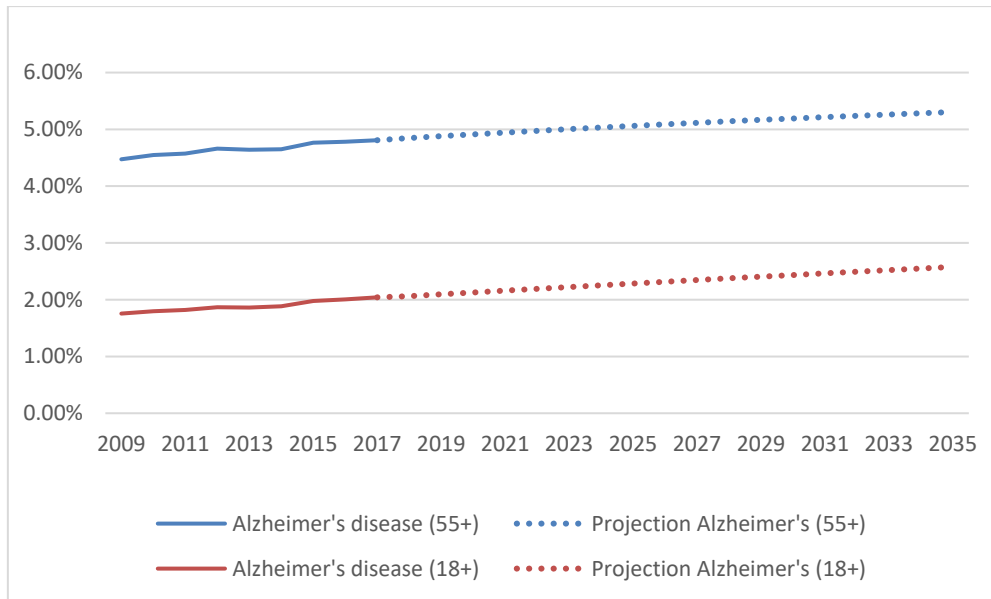


Figure 19 Evolution variable Alzheimer's disease (after randomization)

#### 4.5 Supply variables

Until now we only focused on variables related to the demand for care. It is likely, however, that the supply also matters. Suppose we were in a situation with a shortage of nursing home beds: in that case the need and/or the demand would not be translated in a larger use, because the use would be rationed.

To capture interregional differences in supply, we calculated the total numbers of hours of social care per inhabitant and the total number of nursing home beds per inhabitant for the different care regions in Flanders [9]. Care regions are geographic divisions created by the Flemish government to make it possible to offer a better performing health care and social delivery system, where care agents and organizations are more integrated. Other goals of the creation of the care regions were to offer conditions for coherency in social delivery (by the social services and organizations like the CAW, OCMW and mutualities) and the formation of solid networks between local hospitals. There are a total of 14 care regions: Aalst, Sint Niklaas, Gent, Oostende, Roeselare, Kortrijk, Brugge, Turnhout, Mechelen, Antwerpen, Leuven, Genk, Hasselt and Brussels. For the reasons explained before, Brussels was not included in the analysis.

##### Supply of social care

To proxy the supply of social care, we calculated the number of hours of social care per inhabitant in each of the care regions. While we will interpret this variable as capturing supply, it is evident that this interpretation should be handled cautiously. What is true is that this total number of hours can be introduced in our models as an exogenous variable at the level of the individual, as each individual certainly has no influence on this aggregate total. However, the total number of hours of social care does not only measure supply decisions, but may also be influenced by other features of the region, such as population density, rural versus urban environment or a specific socio-economic profile.

Figure 20 shows for some regions the development over time of this variable. The projections use the assumption that the proportion as a fraction of the population remains constant.

**Variable 'total hours of social care per inhabitant'**

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Definition: Variable indicating the number of social care hours per inhabitant in each care region.

Bron: Flemish Agency for Care and Health (2009 – 2017)

Calculation: Calculated with two variables:

The total number of total hours of social care per care region

The total number of people living in each region

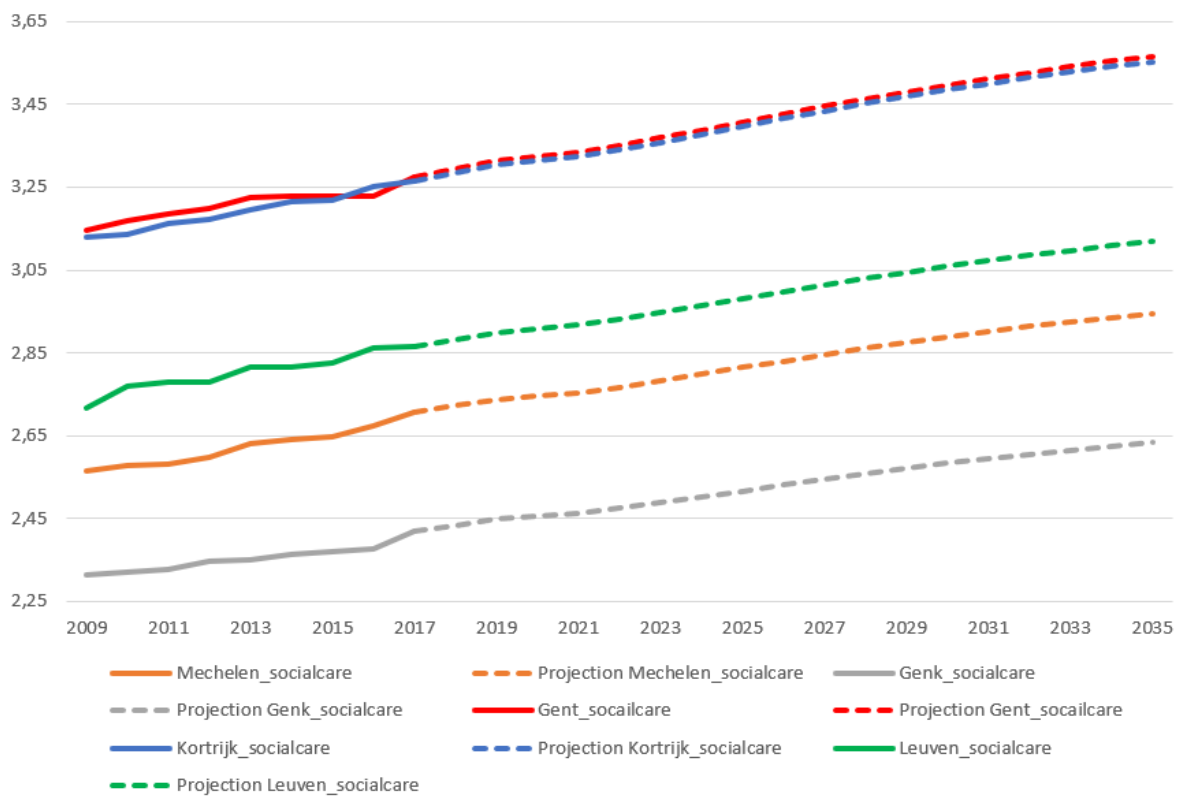


Figure 20 Evolution of the supply of social care for some selected care regions

Supply of nursing home beds per inhabitant in each care region

This supply of residential care is proxied by the number of nursing home beds (ROB, RVT, Short stay) per inhabitant in the different regions. The same *caveat* applies as was formulated for social care. Figure 21 illustrates for some selected regions.

Variable 'number of nursing home beds per inhabitant'
<b>Definition:</b> Variable indicating the number of nursing home beds per inhabitant in each care region.
<b>Source:</b> RIZIV (years 2009 – 2017)
<b>Description:</b> This supply variable measures the number of beds available to residents in every care region.
<b>Calculation:</b> Calculated based on 2 variables: The total number of nursing home beds per care region The total number of inhabitants per care region

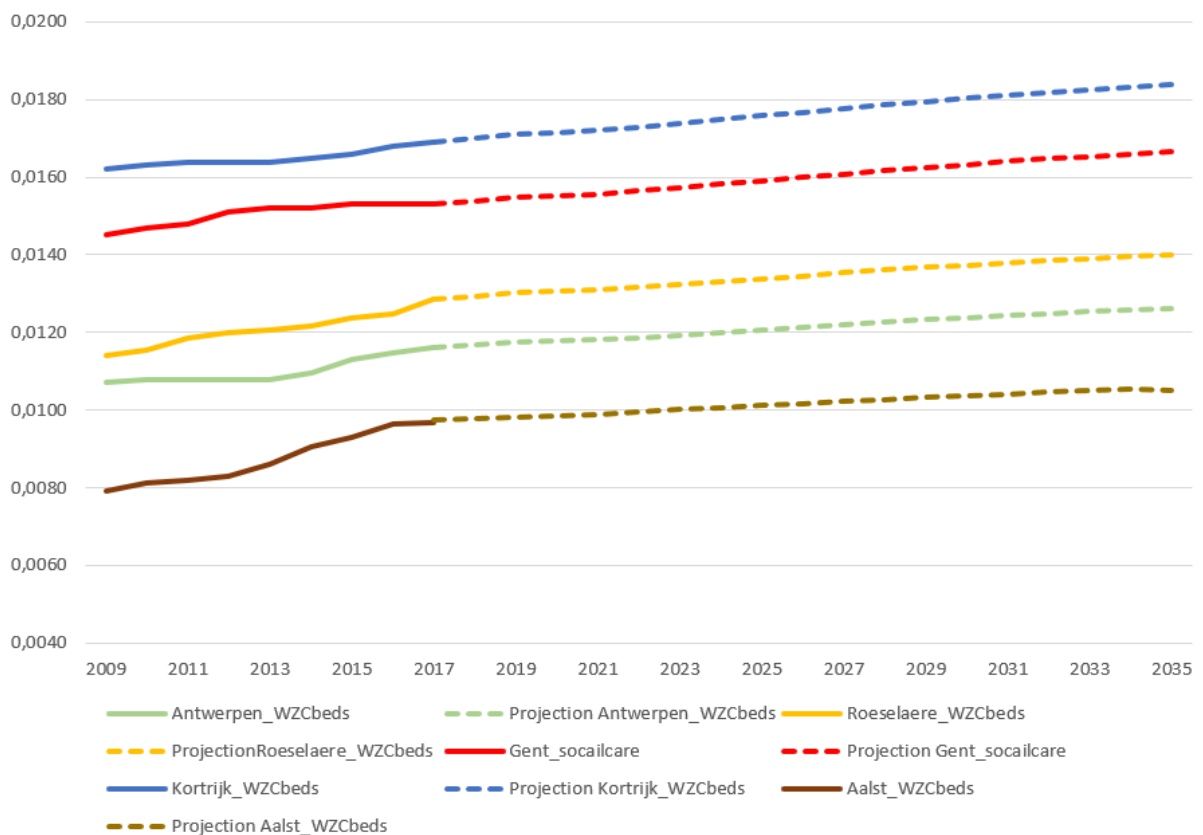


Figure 21 Evolution of the supply of residential care for some selected care regions





## Chapter 3

### Some methodological choices

Our basic aim is to project expenditures for home and residential care in the future, considering the evolution of the set of explanatory variables that was described in the previous section. The first step in this exercise is the estimation of the effects of these different explanatory variables in the past. The focus in this report will be on the projection of the volumes: the number of hours of social care and logistic help, the number of tasks in nursing care, the number of days in the various residential categories. We do not predict the future development of prices or unit costs and do not analyze their development in the past. In the simulations of the future, we keep the unit costs in the last period of observation constant. We will illustrate in our policy simulations how these prices can be seen as policy variables and how different hypotheses about future socio-economic developments can be implemented in the simulations.

In this section we discuss a set of methodological issues. After a comparison of different methods, we opted for one of the simplest approaches. We just pooled all the data for all the periods and we estimated a simple linear OLS model. This approach is explained in section 3.1, in which we also discuss how we tackled the problems of the trend and of the incomplete periods for people who died in the course of the year. The results for this OLS approach will be described in the next section. We also explored the potential of some alternative approaches. These are described in general terms in section 3.2. We do not show all the results for these alternative approaches, but they are available from the authors on request and some of them are shown in the Appendix. In fact, this section 3.2 can easily be skipped by readers who are mainly interested in the results.

#### 1 Estimation and selection of pooled model

In order to see better the methodological issues involved, let us briefly describe the structure of our dependent variables. In a given year, individuals can be in four different states: no care, home care for the whole year, moving from home to a nursing home during the year, or residential care for the whole year. The period can be incomplete if they die in the course of the year, or enter (when they reach the lower age boundary of the sample, or move into Belgium), or leave the sample at some point in that period (when they leave Belgium). If they are at home, they can use a number of hours of care (social care, logistic or surveillance help) or a number of services of nursing care, as explained in the previous section. If they are living in residential care, they can be in category O, A, B, C, Cd, or a short stay. We count these in numbers of days. Of course, in the course of the year they may move from one category to another.

The theoretically most attractive way to model this structure is to assume a hierarchical model. Indeed, it does not look very meaningful to include all the observations of people in all the social states to explain the allocations within one state. As an example: the observations of people living at home only add noise when one wants to explain the allocation of persons living in a nursing home over the different residential categories. Or: the variables that explain the substitution (or complementarity) between social care and nursing care become irrelevant, as soon as people are admitted into residential care. Moreover, the decision to move from one state to another, e.g., the decision to enter a nursing home,

is likely to be explained by other variables than the allocation within a state. Again, these effects can then better be estimated by focusing specifically on this decision. As an example, the availability of informal care – or the supply of social care – may have a strong influence on the decision to move to a nursing home, but will have less (or no) influence on the category in which people come as soon as they are admitted into residential care. We will discuss such a hierarchical model in section 3.2. While we have estimated it, we finally decided not to simulate with it, for the reasons that will be explained. These have mainly to do with the difficulties to make reliable projections of the allocation of the observations to the different social states, further complicated by the burdensome treatment of incomplete periods. As a result, despite its theoretical attractiveness, the estimated hierarchical model is not user-friendly at all, and, even more importantly, performs worse as a projection tool (our main aim).

The simpler alternative that we pursue is just to pool all the observations over all the time periods and over the four social states and then estimate the effects of the different variables by linear OLS. This method is very robust and well suited to make predictions, certainly when there are a large number of observations. For the reasons explained above, it is more difficult to give a theoretical interpretation to the estimated individual coefficients, but this is less important if the focus is on projections. Indeed, we are not strongly interested in the specific effects for different individuals, but only in the effects at the average level. At that level, our linear OLS model does perform reasonably well. Of course, this implies that one has to be cautious with the interpretation of the coefficients. We will illustrate this when discussing the results in the next section.

Even after opting for OLS, there is still a number of choices to be made. To choose between the different models, we used two criteria. First, in choosing between models that perform similarly on the other criteria, we opt for the simplest one. Second, and more importantly, our main choice criterion is derived from the final purpose of this whole exercise, which is to predict future expenditures. As has been described above, we have individual observations in the EPS for the period 2009-2017, and this is the period that has been used for the estimation. However, we have already aggregated administrative data for 2018-2019. Our preferred test of the quality of the models is to investigate how well they predict out-of-sample, i.e. how well the model estimated with the individual data for 2009-2017 predicts the observations for 2018-2019. We will discuss in more detail in the next section how this predictive performance has guided our model selection.

There are still two more crucial methodological choices to be made: the treatment of trends and of incomplete periods. These are discussed in the next two subsections.

### **1.1 Dummies or trends?**

Section 2 has already shown that the raw data for the dependent variables show some clear trends. An obvious example is the development of the number of days in residential categories O, B and Cd, but some trend can also be spotted in the other variables. Since we have data over a period of 10 years, this does not come as a surprise. Of course, the whole point of the estimation exercise is to see how far these evolutions over time can be explained by the evolution of the explanatory variables, e.g. the decreasing availability of informal care or the increasing prevalence of Alzheimer. Yet, as we will see in section 4, in many cases the estimated trend remains significant after controlling for all the variables that are included in the model. This estimated trend can then only reflect variables that are not taken up in the model and, most likely, structural changes. It is not straightforward to assume that these trends

will just continue in the future, but, given that this is the unexplained (or unobservable) part in the whole exercise, careful interpretation is needed.

We will therefore in each case start from a full set of year dummies and then try to interpret as well as possible what may be the causes underlying the pattern of dummies. In some cases, the estimates strongly suggest the existence of a trend, in other cases this is much less the case. In line with what was said before, we made the final choice of including a trend or not by investigating the pattern of time dummies and by looking at the simulation results for 2018-2019. This procedure will become clearer in the results sections below.

## 1.2 Treatment of incomplete periods

As mentioned before, in each of the different categories, we have observations with incomplete periods, as some people enter or leave the sample. The most common and important example is that of people dying in the course of the year. We will illustrate the methodological issue for that case.

Let us start from a simple hypothetical example. Assume that we have 4 observations of very sick people who (should) stay in a nursing home for the whole year. However, two of them die in the middle of the year. Our observations will then be as follows:

observations	number of days
1	360
2	360
3	180
4	180

If we estimate the average length of stay, we would then obtain that an individual of this type would stay 270 days in that category, while in reality he stays for the whole year if he does not die. At first sight, this is not a real problem since what interests us most are the averages and not the individual effects. The average is estimated perfectly. However, this *perfect estimate of the average holds only when the distribution of the deceased remains the same between the period of estimation and the prediction period*. Predictions with an estimated average length of stay of 270 will be wrong when that distribution changes. Consider as an example the following situation in the prediction period, with again four individuals but in which three of them die and at other moments in the year than in our estimation period:

observations	number of days
1	360
2	180
3	90
4	90

Our “biased” model would still predict an average of 270, while the true average is now 180.

What can we do about this? At first sight, it might seem that an adequate solution to estimate the individual effect would be to remove the deceased from the sample, keeping (in our primitive example) only observations 1 and 2. We then estimate a “true” individual effect, but in this case the simplicity of our example is somewhat misleading. Indeed, it is likely that the deceased are not a random sample of the population, so that just removing them would lead to biased estimates. Moreover, since our aim is to predict the total number of days in a given period, the days of the deceased have to be included in the projections in one way or another.

A better solution is to “annualize” the data. This means that we compute full year-equivalents and adjust the data for the deceased by multiplying them with the inverse of the proportion of time that they were alive. In the observation period the deceased individuals then would get the hypothetical value of 360 – and that would then also be the estimate. This approach leads to a better estimate of the number of days in the different care categories for someone who lives for a whole year, considering all individuals in the group. Yet, this also means that the projections will be in full-year equivalents and to predict the “real” data, the periods for the deceased then have to be converted into full year-equivalents. A simple approach is the following: if the time of death is spread uniformly over the whole year, we can assume that the deceased have lived on average for six months and in full-year equivalents we then add half the number of deceased to the number of people who lived for the whole year.

While this approach is attractive, it is also cumbersome and we have opted for a third alternative. This boils down to include in the estimations a dummy for the “deceased”. As we will see in the next section, the interpretation of the effect of that dummy may be a bit ambiguous. On the one hand, we expect this effect to be negative, as *ceteris paribus* the deceased live for a shorter period and this mechanical effect is captured by the dummy. On the other hand, dying is also an indicator of morbidity in that people who died during the year are likely to have been less healthy – and this state of health may influence the use of care. Let us give an obvious example. Take someone staying at home and using nursing care, who dies during the year. Because of this death, he or she will not use care for the whole year. On the other hand, it is well possible that the amount of nursing care used increases in the last months before his/her death. The estimated effect of the dummy will capture both effects. This can be seen as an illustration of the fact that our simple linear OLS model may yield results that are difficult to interpret at the level of the individual. It is not problematic, however, if we focus on predictions as then it is in a certain sense the global effect that is the most relevant.

We have explained the problem of incomplete periods for the case of the deceased, as this is by far the most important issue in our setting. Yet, the same problem occurs for all “incomplete” periods in our sample, e.g. people leaving Belgium. We do not have sufficient information about these people to tackle the issue in a satisfactory way. However, the number of such cases is more limited. Moreover, it is likely that this selection is “more random” than that of the deceased and that the proportion of people with such incomplete periods remains rather stable in the prediction period.

## 2 Two alternative approaches

We now discuss briefly two alternative approaches. We only explain what could be the rationale for implementing them. Some estimation results are shown in the appendix and the full set of results is available on request, but we will not use these models in the projections.

### 2.1 Fixed effects

Just pooling the data over all the years without considering the identity of the individuals means that we neglect completely the information that is given by the longitudinal nature of the data. Following individuals is possible by introducing so-called individual fixed effects. These make it possible to control for so-called unobserved heterogeneity, i.e. the many features of individuals that influence the state and category in which they end, but are not observed in the data.

In such a fixed effects approach, the effects of the different variables are identified on the basis of changes over time. The effects of individual characteristics that remain constant during the whole observation period cannot be identified. An obvious example is the difference between men and women. To give another example: for a person with Alzheimer during the whole period, the effect of Alzheimer will be taken up in the fixed effect (and is hence not identifiable). For individuals that get Alzheimer at some moment in the period 2009-2017, the estimated coefficient will capture the effect of that change.

It is not convenient to simulate with the estimates of the fixed effects model. If there is a change in the gender composition of the population, the effects of this change cannot be simulated because the gender effect is not identified. However, estimation of the fixed effects model is very useful as a kind of robustness check and to interpret better the results of the standard model. More specifically, since all the unobserved individual heterogeneity is controlled for through the fixed effects, the interpretation of the coefficients of the explanatory variables is much cleaner.

### 2.2 Hierarchical approach

As explained before, there are *a priori* good reasons to explain days and hours conditional on the individuals being in one of the four states. For example, the use of social and nursing care can better be estimated on the sample of people that are living at home, and the allocation over the different categories of people living in a nursing home can better be estimated on the sample of people living in such a home. This means that we get similar models as the one in the pooled model, but estimated on a restricted set of observations. The results of these estimations display the pattern that we could have expected.

If we estimate the model for days and hours separately for the different states, we need an additional module that can explain how the population must be divided over the different states, and what are the variables causing a move from one state to another. We then try to explain why an individual starts using care when she is at home, or why she is moving into residential care. A natural way to analyse these shifts is to estimate a multinomial model.

The most natural approach is to specify the multinomial model for the four possible states. To check the value of the model, the probabilities of ending in one of the four states, are evaluated for all the individuals, and individuals are then allocated to the state for which the highest probability is estimated.

We can then compare the resulting allocation with the real observations. This is a demanding test, however, too demanding in fact for our purposes. It turned out that the results were rather poor. It is therefore also useful to look at the aggregate predictions. These are better, although still far from satisfactory.

One specific issue is that the predictive power of the multinomial model is really bad for (the crucial) state in which persons move from home to residential care (state 3). This poor predictive power is not surprising given that we have only a limited number of observations in that state, and that, moreover, the sample characteristics of the individuals moving into residential care are very similar to the characteristics of those that are in residential care for the whole year (this is state 4). We therefore also estimated a model in which states 3 and 4 are brought together. Of course, bringing these two groups together is only an approximation, and it leads to additional problems in the simulations, as the individuals in state 3 have (by definition) only incomplete periods. Lumping together states 3 and 4 gives us the characteristics of the individuals for these two states combined, but not the information needed to distinguish between the two.

Using the same criterion to evaluate the usefulness of the models as was used for the pooled model, we have simulated outside the estimation sample, i.e. for the periods 2018-2019. Combining the results of the multinomial model with the separate estimates for days and hours, the simulation now proceeds in two steps:

(a) we use the multinomial model to make average predictions of the number of individuals in the different states. This also gives us an estimate of the average allocation into the different states of individuals with different characteristics, e.g. how the different age-gender groups or the number of Alzheimer patients are spread over the different states.

(b) we then use these simulated marginals in the separate models for days and hours to simulate the use of care.

It turned out that the predictive performance of the hierarchical model is definitely not better and, in some cases, even clearly worse than the performance of the simple pooled OLS model. The crux of the problem is the first step in which the multinomial model is used to allocate the individuals to the different states. This is not surprising given the relative poverty of the individual information in our data, e.g. we have only little information about health shocks or changes in the family situation of the individuals in the sample. In any case, in the light of these disappointing predictive performance, it seemed to us obviously preferable to focus on the much simpler pooled OLS model. The estimation results for that model are shown and discussed in the next section.

## Chapter 4

### Results from the pooled OLS models

We will now describe the estimation results for the ordinary least squares (OLS) models. We first discuss the results for the different residential care categories and then for the components of home care. In each case, a full OLS model with year dummies was constructed with 2017 as the reference year. As described before, the full model with year dummies helped to determine whether there was a trend in the dependent variable or not. In addition, we also estimated backward models, one with year dummies and one with trends, keeping only the significant variables from the full model. The backward model does not only have the advantage that it is simpler, it also avoids the problem that the projection can be dominated by the evolution of an explanatory variable with a coefficient that is very large in absolute terms, but at the same time insignificantly different from zero because it is estimated with a large standard error.

In all models the variables described in section 2 were used as explanatory variables. In fact, while the size of the effects of these variables differs between the different models, the direction of the effect is almost always the same. We will interpret these effects in detail for the first category (the number of days in category O). In the later sections we will not repeat all these interpretations but only point out some interesting additional findings.

Each of the following sections is constructed in the same way. A first table shows the estimation results for different models. A second table compares the model predictions for 2018-2019 with the real aggregate data. Finally, these latter results are illustrated with a figure. Again, since the setup of the tables is similar in all the sections, we will discuss it in detail only for the first category and in later sections we restrict the discussion to the interesting new insights.

The models for residential care are estimated on the subsample of the EPS with persons older than 55, because younger people are not staying in nursing homes. The models for home care on the other hand are estimated for the full sample of 18+.

#### **1 Estimations of the pooled OLS models for residential care and the results from the simulations**

We first consider the estimation results for the number of days in the different residential categories. The structure of all the sections is similar. However, in some cases we went further than a simple linear trend, in order to improve the predictive performance. These alternative approaches will be explained at the point where they are introduced.

##### **1.1 Estimations for days in care category O**

The estimation results for the number of days in category O are summarized in Table 21. Let us first look at the results for the full model with year dummies, given in the second column. As mentioned before, we will interpret these results in detail so that we do not have to repeat all the details in the following sections.

For age-gender we choose as the reference category "women between age 55 and 64". The coefficients of the other age-gender groups then have to be interpreted with respect to that reference. Hence, we see that men between 55 and 64 do not differ significantly from women of the same age. However, when we turn to the older age groups, the expected pattern appears with older persons spending more days in residential category O. As an example, if there are in the population 1,000 more women older than 85, the model estimates that there will be an increase of 8200.59 days of residential care category O. Remember that the safe interpretation of the model is at that level of the averages and that it is not very meaningful to state that any individual woman of 85+ can be expected to stay an additional 8.2 days in category O.

The other explanatory variables can be interpreted similarly. Having a handicap or having a low income both increase the expected number of days in category O. An important and rather large effect is that of the variable "availability of informal care". Despite the problems with the measurement of that variable, it has a highly significant negative effect. We mentioned in the previous section that in a full hierarchical model, the availability of informal care will mainly have an effect on the probability that a person moves into a nursing home. In the simple OLS approach that we finally selected, the resulting postponement of being admitted into residential care will show up as a negative effect on all the categories of residential care.

The interpretation of the dummy for the "deceased" was discussed in the previous section. Its estimated effect is negative here, suggesting that it is dominated by the "incomplete periods" effect. Next, we have a series of morbidity variables. Suffering from COPD, Alzheimer's or Parkinson's increases significantly the number of residential days in category O, for cardiovascular problems and diabetes the effect is not significant.

The supply variables also have the expected effects. If in the region where the individual lives, there is a larger density of hours of social care and a smaller density of residential beds, the number of days in category O decreases. Again, this effect works mainly through the probability of being taken up in a nursing home.

Let us finally look at the time dummies. The reference period is here the last year (2017). Each year dummy can then be interpreted as the difference between that year and 2017, after having controlled for all the variables in the model. This means that each of these dummies can be seen as a kind of residual effect that remains after the effects of age composition, income, availability of informal care, morbidity, etc. have been considered. In this case the pattern of the dummies is clear: the implied residual trend between 2009 and 2016 is clearly negative, as the effects of the time dummies decline steadily over time. There is no significant difference between 2016 and 2017, however, suggesting that the declining trend perhaps has stopped or at least weakened in the more recent years.

At the bottom of the table, the R-square gives an indication of the explanatory power of the model. The share of explained variance at the individual level turns out to be very low. This is not at all surprising, but it is an additional argument not to interpret our results at the level of the individual persons. On the other hand, a nice feature of OLS is that it perfectly predicts the mean value of the dependent variable in each period, if time dummies (i.e. year-specific constants) are introduced.

The third column then gives the results for the backward model, in which the non-significant variables are removed from the model. The estimates of the retained variables remain fairly constant.



Let us now consider the results for the dummies and the trends. As indicated in the previous section, we will choose between the different specifications on the basis of their predictive performance in 2018-2019. The relevant empirical material is put together in table 22 and illustrated in figures 22-23. For each of the models the columns in the table give respectively the predictions for 2018 and 2019, as derived from the OLS model, the actual number of days in category O as given in the VAZG data and the RIZIV data and the ratio between the model predictions and the real-world data. In this case, the difference between the RIZIV and the VAZG data is minimal and we will focus the discussion on the VAZG data.

Table 21 Estimation results of OLS models for days in care category O

<b>Days in Category O</b>	<b>Full pooled model with year dummies</b>	<b>Backward model with year dummies</b>	<b>Backward model with trend</b>	<b>Backward model with logarithmic trend</b>	<b>Backward model with logarithmic trend (from 2012) and year dummies 2009-2011</b>
Intercept	0.71119 ** (0.17821)	0.69670 ** (0.15954)	2.20494 ** (0.14909)	2.27421 ** (0.15050)	1.63332 ** (0.15020)
Man-5564	-0.11243 (0.10449)				
Man-6574	0.81474 ** (0.09849)	0.86139 ** (0.08272)	0.86153 ** (0.08272)	0.86009 ** (0.08272)	0.86094 ** (0.08272)
Woman-6574	0.69267 ** (0.09699)	0.74035 ** (0.08124)	0.74065 ** (0.08124)	0.74019 ** (0.08124)	0.74028 ** (0.08124)
Man-7584	1.61961 ** (0.11055)	1.66116 ** (0.09557)	1.66181 ** (0.09557)	1.66452 ** (0.09557)	1.66237 ** (0.09557)
Woman 7584	1.85518 ** (0.10347)	1.89669 ** (0.08686)	1.8972 ** (0.08686)	1.90115 ** (0.08686)	1.89842 ** (0.08686)
Man-85plus	5.32173 ** (0.15698)	5.36226 ** (0.14642)	5.36261 ** (0.14642)	5.35968 ** (0.14642)	5.36151 ** (0.14642)
Woman 85plus	8.20059 ** (0.13009)	8.24046 ** (0.11648)	8.24087 ** (0.11648)	8.24027 ** (0.11649)	8.24052 ** (0.11648)
Handicap	0.61442 ** (0.07258)	0.61097 ** (0.07252)	0.61054 ** (0.07252)	0.60991 ** (0.07252)	0.61037 ** (0.07252)
Low income	0.49281 ** (0.06604)	0.49364 ** (0.06587)	0.49299 ** (0.06587)	0.49393 ** (0.06587)	0.49332 ** (0.06587)
Informal care	-2.09212 ** (0.05657)	-2.09056 ** (0.05652)	-2.09099 ** (0.05652)	-2.0899 ** (0.05652)	-2.09041 ** (0.05652)
Deceased	-3.11335 ** (0.15244)	-3.1084 ** (0.15224)	-3.1082 ** (0.15224)	-3.10461 ** (0.15224)	-3.10798 ** (0.15224)
Cardiovascular-problems	-0.03745 (0.05784)				

COPD	0.33255 * (0.09503)	0.32833 * (0.09481)	0.3284 * (0.09481)	0.325 * (0.09481)	0.32728 * (0.09481)
Diabetes	-0.00692 (0.07801)				
Alzheimer's	4.25479 ** (0.11695)	4.25477 ** (0.11695)	4.25468 ** (0.11695)	4.25359 ** (0.11695)	4.25424 ** (0.11695)
Parkinson's	1.57446 ** (0.22896)	1.57244 ** (0.22895)	1.57239 ** (0.22895)	1.575 ** (0.22896)	1.57322 ** (0.22896)
Hours social care/ population	-0.79263 ** (0.05934)	-0.79207 ** (0.05932)	-0.7872 ** (0.05903)	-0.75177 ** (0.05879)	-0.77704 ** (0.05905)
Total NH beds/ population	0.01261 ** (0.00140)	0.01259 ** (0.00140)	0.01253 ** (0.00139)	0.0114 ** (0.00138)	0.01226 ** (0.00139)
Year dummy 2009	1.41197 ** (0.11198)	1.35584 ** (0.09843)			0.4182 ** (0.09489)
Year dummy 2010	1.2045 ** (0.11157)	1.14806 ** (0.09796)			0.21019 * (0.09434)
Year dummy 2011	0.99463 ** (0.11063)	0.93805 ** (0.09693)			
Year dummy 2012	0.88488 ** (0.11009)	0.82821 ** (0.09631)			
Year dummy 2013	0.71481 ** (0.10928)	0.6581 ** (0.09542)			
Year dummy 2014	0.58963 ** (0.10851)	0.53294 ** (0.09457)			
Year dummy 2015	0.39038 * (0.10744)	0.33382 * (0.09342)			
Year dummy 2016	0.1138 (0.10666)				
Linear trend			-0.17380** (0.01042)		
Logarithmic trend				-0.63042 ** (0.03976)	-0.49584 ** (0.04415)
Logarithmic trend 2012- 2017					
R-square	0.0188	0.0188	0.0188	0.0187	0.0187
N	749 244	749 244	749 244	749 244	749 244

\*\*  $p < 0.0001$  \*  $p < 0.05$

Implementing the model with year dummies basically means that we put the residual trend from 2017 onwards equal to zero. Both for the full model and the backward model, the evolution of the other

variables then leads to the prediction of an increase in the number of days in category O in 2018 and 2019. This is definitely not observed in reality, where the steady decline since 2009 continues. Figure 22, in which the predicted values are extended beyond 2019, indeed suggests that the model without a trend is not at all in line with the observations, in that it imposes a structural break for which there is no evidence.<sup>1</sup>

In fact, as was mentioned in our discussion of the estimation results, the pattern of the dummies suggests that there is a trend. The fourth column in Table 21 shows that the estimate of a linear trend is indeed highly significant and strongly negative. As table 22 shows, however, it is much too strong in the predictions for 2018-2019. This brings us back to the suggestion that the negative trend in the data seems to become less pronounced in later years.

Table 22 Comparison simulations results (2018-2019) with real data from VAZG and RIZIV – care category O

Type of OLS model Care category O	Year	OLS	VAZG	RIZIV	model/VAZG	model/RIZIV
Full model with year dummies	2018	2 019 821	1 993 878	1 986 096	101.30%	101.70%
	2019	2 080 812	1 943 854		107.05%	
Backward model with year dummies	2018	2 148 716	1 993 878	1 986 096	107.77%	108.19%
	2019	2 211 926	1 943 854		113.79%	
Backward model with linear trend	2018	1 631 968	1 993 878	1 986 096	81.85%	82.17%
	2019	1 281 223	1 943 854		65.91%	
Backward model with logarithmic trend	2018	2 471 851	1 993 878	1 986 096	123.97%	124.46%
	2019	2 383 635	1 943 854		122.62%	
<b>Backward model with logarithmic trend (2012-on) and year dummies 2009-2011</b>	2018	2 073 315	1 993 878	1 986 096	103.98%	104.39%
	2019	1 980 652	1 943 854		101.89%	

One possibility is then to opt for a logarithmic trend, which would make the projected number of days decrease faster in the beginning of the period and slower at the end. The estimate of such a logarithmic trend (in the fifth column of table 21) is indeed significantly negative, but it does not improve the overall predictive performance of the model (see table 22) as the predicted number of days is much too large.

<sup>1</sup> The method to derive the long-term projections will be explained in more detail in section 5. The figures here show what is called there the "reference simulation".

Note that the nice feature of OLS that it perfectly predicts the mean value of the dependent variable in each period, only holds if year-specific constants are introduced, and does no longer hold automatically with a trend in the model. In this case, we start from a too large predicted number of days in 2017 and the logarithmic trend effect is after 10 years so small that it does not make up for this too high level.

All this suggests that we should look for a specification with a rather strong negative trend in the beginning of the period, which then slows down towards 2019. An attempt to specify the model as such is reported in the sixth column of table 21. We now have two (highly significant) positive year dummies for 2009 and 2010 and let the logarithmic trend start from 2012 onwards. Table 22 shows that this model has a very satisfactory performance for 2018 and 2019. Figure 23 also suggests an acceptable smooth decline in the number of days in category O in the longer run. Because the logarithmic trend falters over time, the decline stops around 2028 and the evolution of the other variables then leads to a slight increase. We will in the remainder of this chapter work with this so-called "alternative" scenario.

The adjustment of the trend in this alternative scenario may make a rather ad hoc impression and is not very elegant from a theoretical point of view. It was, however, the most natural solution to reach a model with a satisfactory predictive performance. In the following sections, it will become clear that the model selection was much more straightforward for the other categories.

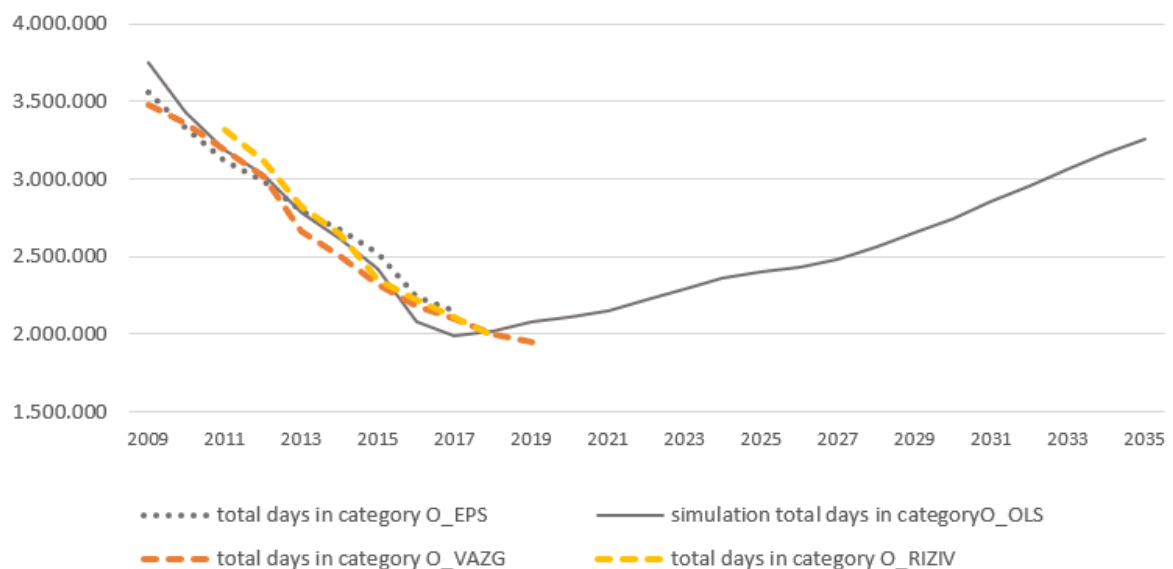


Figure 22 Comparisons for days in care category O

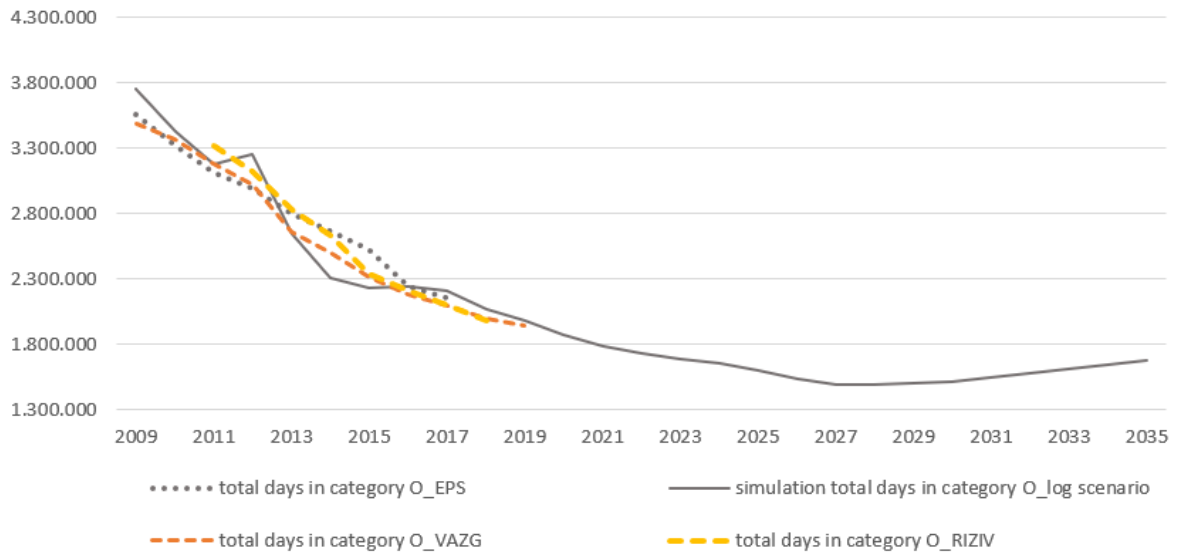


Figure 23 Comparisons for days in care category O (alternative scenario)

## 1.2 Category A

We now turn to the results for category A. Table 23 gives the estimation results, table 24 the predictive performance, figure 24 an illustrative figure. The four columns with results in table 23 give the same information as the corresponding columns in table 21. The special "alternative scenario" is here not needed. The direction of the estimated effects is the same as for category O, with as only difference that now also the morbidity indicators for cardiovascular problems and for diabetes are significant. The time dummies again suggest a faltering trend. Indeed, both the estimated linear and logarithmic trends are significantly negative.

Table 23 Estimation results of OLS models for days in care category A

Days in Category A	Full pooled model with year dummies	Backward model with year dummies	Backward model with trend	Backward model with logarithmic trend
Intercept	0.66751 * (0.18800)	0.65100 ** (0.16610)	1.57653 **	1.63515 ** (0.16027)
Man-5564	-0.17648 (0.11023)			
Man-6574	0.9244 ** (0.10390)	1.01178 ** (0.08830)	1.01234 ** (0.08830)	1.01151 ** (0.08830)
Woman-6574	0.6156 ** (0.10232)	0.70287 ** (0.08650)	0.70316 ** (0.08650)	0.70288 ** (0.08650)
Man-7584	1.37538 ** (0.11663)	1.46309 ** (0.10301)	1.46205 ** (0.10301)	1.46373 ** (0.10301)
Woman 7584	1.66968 ** (0.10916)	1.75827 ** (0.09425)	1.75682 ** (0.09425)	1.75917 ** (0.09424)
Man-85plus	6.41556 ** (0.16560)	6.50322 ** (0.15620)	6.50348 ** (0.15620)	6.50218 ** (0.15620)
Woman 85plus	9.53540 ** (0.13723)	9.62425 ** (0.12546)	9.62412 ** (0.12546)	9.62402 ** (0.12546)
Handicap	1.87958 ** (0.07657)	1.87575 ** (0.07653)	1.87595 ** (0.07653)	1.87572 ** (0.07653)
Low income	1.04092 ** (0.06967)	1.04561 ** (0.06961)	1.04632 ** (0.06961)	1.046 ** (0.06961)
Informal care	-2.28546 ** (0.05968)	-2.28174 ** (0.05964)	-2.2819 ** (0.05964)	-2.28156 ** (0.05964)
Deceased	-2.54544 ** (0.16082)	-2.54577 ** (0.16082)	-2.54753 ** (0.16082)	-2.54549 ** (0.16082)
Cardiovascular-problems	0.26126 ** (0.06101)	0.25966 ** (0.06101)	0.25948 ** (0.06100)	0.25999 ** (0.06101)
COPD	0.62056 ** (0.10025)	0.62106 ** (0.10025)	0.62217 ** (0.10025)	0.62029 ** (0.10025)

Days in Category A	Full pooled model with year dummies	Backward model with year dummies	Backward model with trend	Backward model with logarithmic trend
Diabetes	0.19276 * (0.08229)	0.19032* (0.08228)	0.18985 * (0.08228)	0.19043 * (0.08228)
Alzheimer's	5.5774 ** (0.12338)	5.57757 ** (0.12338)	5.57801 ** (0.12338)	5.57739 ** (0.12338)
Parkinson's	5.11402 ** (0.24155)	5.11256 ** (0.24154)	5.1122 ** (0.24154)	5.11393 ** (0.24154)
Hours social care/ population	-0.53129 ** (0.06260)	-0.52775 ** (0.06244)	-0.54052 ** (0.06244)	-0.51873 ** (0.06203)
Total NH beds/ population	0.00651 ** (0.00148)	0.00642 ** (0.00147)	0.00669 ** (0.00147)	0.00603 ** (0.00146)
Year dummy 2009	0.912 ** (0.11814)	0.84045 ** (0.09823)		
Year dummy 2010	0.76196 ** (0.11770)	0.69045 ** (0.09767)		
Year dummy 2011	0.66955 ** (0.11671)	0.59829 ** (0.09660)		
Year dummy 2012	0.58728 ** (0.11614)	0.5161 ** (0.09589)		
Year dummy 2013	0.26794 * (0.11528)	0.19683 * (0.09495)		
Year dummy 2014	0.27272 * (0.11447)	0.20171 * (0.09407)		
Year dummy 2015	0.10795 (0.11334)			
Year dummy 2016	0.10406 (0.11252)			
Linear trend			-0.11744 ** (0.01099)	
Logarithmic trend				-0.43857 ** (0.04195)
R-square	0.0279	0.0279	0.0279	0.0279
N	749 244	749 244	749 244	749 244

\*\* p<0.0001 \* p<0.05

Table 24 shows that the decline in the number of days for category A is not predicted by the models with year dummies. As for category O, the linear trend is too strong. In this case the model with the logarithmic trend is performing in a satisfactory way: it predicts a decline from 2018 to 2019 and is close to the level of the VAZG-data. It is the model that we will use in the simulations. In fact, figure 24 shows that the rather volatile pattern of changes over time is captured reasonably well by the model.

Table 24 Comparison simulations results (2018-2019) with real data from VAZG and RIZIV – care category A

Type of OLS model Care category A	Year	OLS	VAZG	RIZIV	model/VAZG	model/RIZIV
Full model with year dummies	2018	3 199 583	3 394 435	3 378 962	94.26%	94.69%
	2019	3 276 643	3 319 958		98.70%	
Backward model with year dummies	2018	3 360 167	3 394 435	3 378 962	98.99%	99.44%
	2019	3 439 825	3 319 958		103.61%	
Backward model with linear trend	2018	2 795 484	3 394 435	3 378 962	82.35%	82.73%
	2019	2 591 683	3 319 958		78.06%	
Backward model with logarithmic trend	2018	3 239 050	3 394 435	3 378 962	95.42%	95.86%
	2019	3 218 034	3 319 958		96.93%	

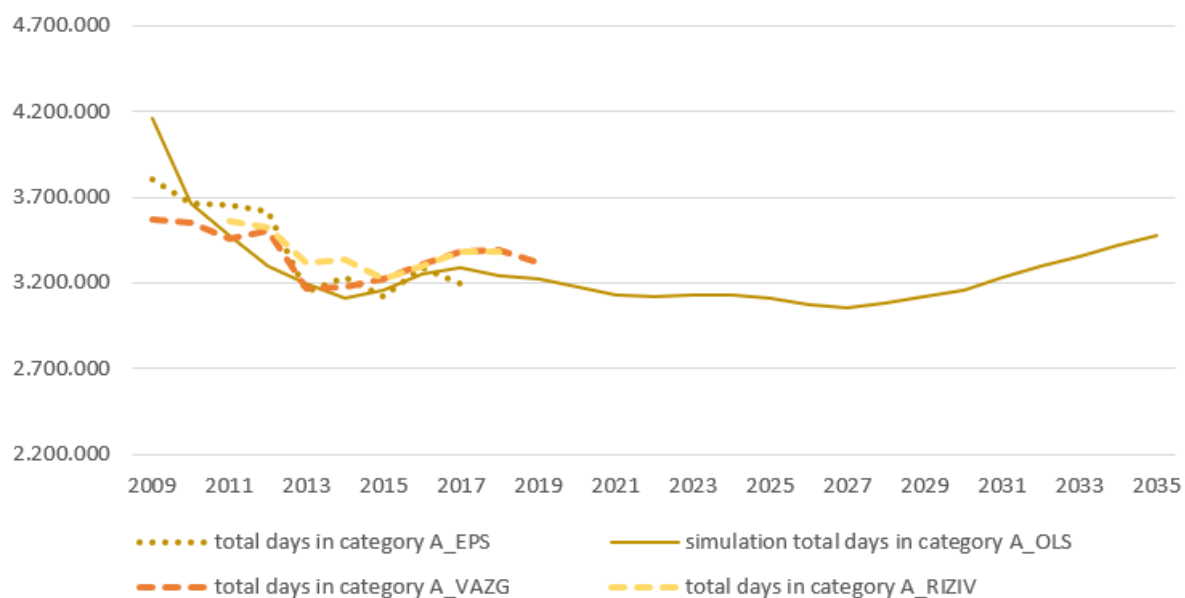


Figure 24 Comparisons for days in care category A



### 1.3 Category B

Category B is a larger category and the number of days can be explained better by the OLS model: the R-squared is still small, but much larger than for categories O and A. The estimated coefficients go in the same direction, with one noteworthy exception: the density of social care services in the region does not significantly affect the number of residential days in category B. If our hypothesis holds that this density has an influence mainly through the decision to be taken up or not in a nursing home, this is what could have been expected. For the more severe cases, social care is no viable alternative for a residential stay. We will indeed see in the following sections that the social care supply is not significant for categories C and Cd either, which seems to confirm this interpretation.

Table 25 Estimation results of OLS models for days in care category B

Days in Category B	Full pooled model with year dummies	Backward model with year dummies	Backward model with trend
Intercept	0.81079 * (0.26915)	0.50817 ** (0.09732)	0.30292 * (0.12516)
Man-5564	-0.20684 (0.15782)		
Man-6574	1.71406 ** (0.14874)	1.81962 ** (0.12640)	1.81586 ** (0.12641)
Woman-6574	1.27425 ** (0.14649)	1.37725 ** (0.12382)	1.3743 ** (0.12382)
Man-7584	2.23641 ** (0.16697)	2.33773 ** (0.14745)	2.33668 ** (0.14745)
Woman 7584	3.84917 ** (0.15627)	3.94826 ** (0.13488)	3.94919 ** (0.13488)
Man-85plus	10.59192 ** (0.23708)	10.70381 ** (0.22350)	10.68986 ** (0.22356)
Woman 85plus	21.43795 ** (0.19647)	21.546 ** (0.17951)	21.53698 ** (0.17954)
Handicap	5.42469 ** (0.10962)	5.42473 ** (0.10948)	5.42354 ** (0.10948)
Low income	1.64297 ** (0.09974)	1.63806 ** (0.09941)	1.65107 ** (0.09953)
Informal care	-4.24706 ** (0.08543)	-4.24699 ** (0.08529)	-4.24047 ** (0.08533)
Deceased	-2.56858 ** (0.23024)	-2.57562 ** (0.23022)	-2.56995 ** (0.23023)
Cardiovascular-problems	0.23932 * (0.08735)	0.2414 * (0.08732)	0.23986 * (0.08732)
COPD	0.86692 ** (0.14353)	0.87433 ** (0.14350)	0.86841 ** (0.14351)

Days in Category B	Full pooled model with year dummies	Backward model with year dummies	Backward model with trend
Diabetes	0.24859 * (0.11781)	0.24804 * (0.11777)	0.24429 * (0.11778)
Alzheimer's	17.02252 ** (0.17663)	17.02458 ** (0.17663)	17.02291 ** (0.17663)
Parkinson's	11.25309 ** (0.34581)	11.25004 ** (0.34574)	11.24754 ** (0.34574)
Hours social care/ population	0.06994 (0.08962)		
Total NH beds/ population	-0.00222 (0.00211)		
Year dummy 2009	-0.30984 (0.16913)		
Year dummy 2010	-0.32719 (0.16850)		
Year dummy 2011	-0.19473 (0.16708)		
Year dummy 2012	-0.08952 (0.16627)		
Year dummy 2013	-0.04536 (0.16504)		
Year dummy 2014	-0.09546 (0.16388)		
Year dummy 2015	-0.02176 (0.16226)		
Year dummy 2016	0.03297 (0.16109)		
Linear trend			0.03957 * (0.01517)
R-square	0.0709	0.0709	0.0709
N	749 244	749 244	749 244

\*\*  $p < 0.0001$  \*  $p < 0.05$

The raw data (see figure 25) and the pattern of time dummies suggest the existence of a small positive residual trend. This is confirmed by the estimated value of the linear trend in the last column of table 25. Table 26 shows that the predictions for 2018 and 2019 of the backward model with a linear trend are excellent.

Table 26 Comparison simulations results (2018-2019) with real data from VAZG and RIZIV – care category B

Type of OLS model Care category B	Year	OLS	VAZG	RIZIV	model/VAZG	model/RIZIV
Full model with year dummies	2018	8 713 007	8 905 227	8 705 659	97.84%	100.08%
	2019	8 937 585	9 314 526		95.95%	
Backward model with year dummies	2018	8 510 520	8 905 227	8 705 659	95.57%	97.76%
	2019	8 736 199	9 314 526		93.79%	
Backward model with linear trend	2018	8 952 400	8 905 227	8 705 659	100.53%	102.83%
	2019	9 277 660	9 314 526		99.60%	

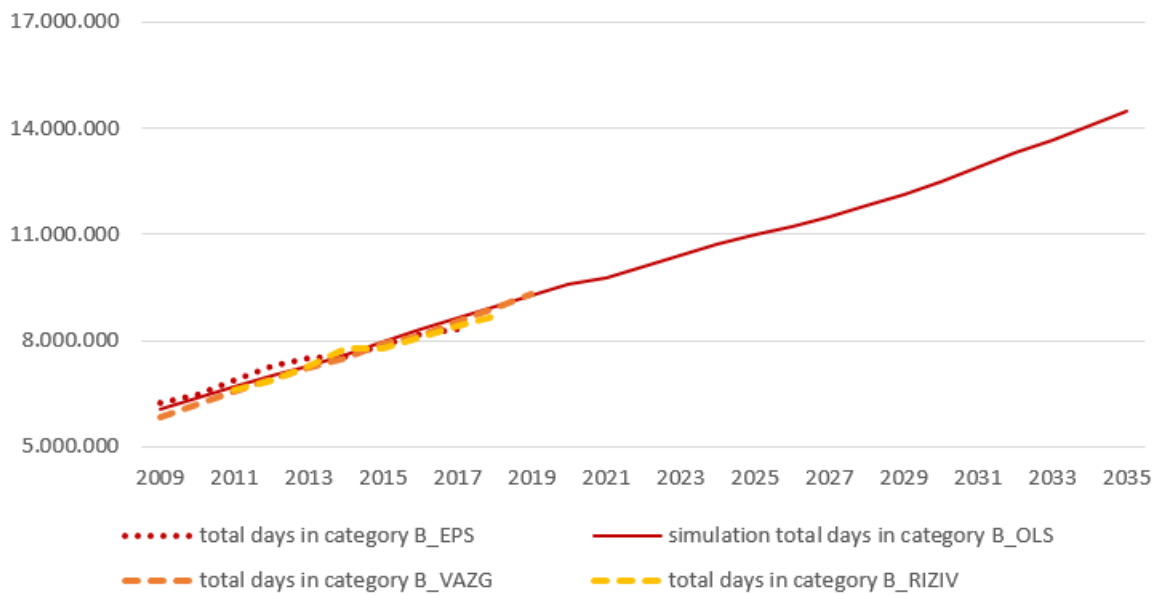


Figure 25 Comparisons for days in care category B

## 1.4 Category C

The results for category C are comparable to those for category B. The main difference is the sign switch for the deceased. We are now in the more severe categories and it is no surprise that the "severity" effect (those dying during the year are in a worse health condition) is now stronger than the "incomplete period" effect. While the effect of the regional density of social care remains insignificant, there is now a small and hardly significant effect of the regional supply of nursing home beds.

Table 27 Estimation results of OLS models for days in care category C

Days in Category C	Full pooled model with year dummies	Backward model with year dummies	Backward model with trend	Backward model with logarithmic trend
Intercept	-0.60979 * (0.18373)	-0.52786 * (0.14412)	-0.47049 * (0.14635)	-0,45661 * (0.14789)
Man-5564	-0.15759 (0.10773)			
Man-6574	0.69524 ** (0.10154)	0.7715 ** (0.08629)	0.7734 ** (0.08630)	0.77317 ** (0.08629)
Woman-6574	0.64549 ** (0.10000)	0.72188 ** (0.08453)	0.72300 ** (0.08453)	0.72284 ** (0.08453)
Man-7584	0.85734 ** (0.11398)	0.93437 ** (0.10066)	0.93434 ** (0.10066)	0.93458 ** (0.10066)
Woman 7584	1.65115 ** (0.10668)	1.72955 ** (0.09209)	1.72829 ** (0.09209)	1.72866 ** (0.09209)
Man-85plus	4.48259 ** (0.16184)	4.5526 ** (0.15260)	4.55961 ** (0.15263)	4.55898 ** (0.15262)
Woman 85plus	8.92665 ** (0.13412)	9.00045 ** (0.12257)	9.00451 ** (0.12258)	9.00421 ** (0.12258)
Handicap	3.15724 ** (0.07483)	3.15508 ** (0.07474)	3.15562 ** (0.07474)	3.15578 ** (0.07474)
Low income	0.84141 ** (0.06809)	0.8555 ** (0.06786)	0.84774 ** (0.06795)	0.84811 ** (0.06795)
Informal care	-1.79542 ** (0.05832)	-1.78767 ** (0.05823)	-1.79120 ** (0.05825)	-1.79091 ** (0.05825)
Deceased	2.68784 ** (0.15717)	2.68993 ** (0.15716)	2.68669 ** (0.15716)	2.6871 ** (0.15716)
Cardiovascular-problems	0.26498 ** (0.05963)	0.26291 ** (0.05961)	0.26418 ** (0.05961)	0.26432 ** (0.05961)
COPD	1.68125 ** (0.09798)	1.67832 ** (0.09796)	1.68217 ** (0.09797)	1.68168 ** (0.09797)
Diabetes	0.40228 ** (0.08043)	0.39808 ** (0.08041)	0.39971 ** (0.08041)	0.39975 ** (0.08041)

Days in Category C	Full pooled model with year dummies	Backward model with year dummies	Backward model with trend	Backward model with logarithmic trend
Alzheimer's	4.46293 ** (0.12058)	4.46248 ** (0.12058)	4.46342 ** (0.12058)	4.46328 ** (0.12058)
Parkinson's	9.16027 ** (0.23606)	9.15977 ** (0.23606)	9.15903 ** (0.23606)	9.15944 ** (0.23606)
Hours social care/ population	0.03847 (0.06118)			
Total NH beds/ population	0.00288 * (0.00144)	0.00289 * (0.00109)	0.00345 * (0.00112)	0.00337 * (0.00111)
Year dummy 2009	0.15136 (0.11546)			
Year dummy 2010	0.16068 (0.11503)			
Year dummy 2011	0.12553 (0.11406)			
Year dummy 2012	0.11551 (0.11350)			
Year dummy 2013	0.08597 (0.11267)			
Year dummy 2014	-0.01598 (0.11187)			
Year dummy 2015	-0.00639 (0.11077)			
Year dummy 2016	0.03251 (0.10996)			
Linear trend			-0.02393 * (0.01063)	
Logarithmic trend				-0.08745 * (0.04072)
R-square	0.0308	0.0308	0.0308	0.0308
N	749 244	749 244	749 244	749 244

\*\* p<0.0001 \* p<0.05

The dummies and the raw data in figure 26 suggest a small negative trend, which seems becoming weaker at the end of the period. In fact, in the prediction period (2018-2019) there is an increase in the observed number of days in category C. We estimated the model both with a linear and with a logarithmic trend. On the basis of the predictive performance we finally preferred the model with the linear trend.

The estimation of the model for category C is somewhat tricky, because the individual EPS data show a strange pattern with an unexpected dip in 2014 and a much stronger increase than observed in the real-world data afterwards. The results should therefore be interpreted with more caution than those for the other categories.

Table 28 Comparison simulations results (2018-2019) with real data from VAZG and RIZIV – care category C

Type of OLS model Care category C	Year	OLS	VAZG	RIZIV	model/VAZG	model/RIZIV
Full model with year dummies	2018	3 700 060	3 353 387	3 346 514	110.34%	110.56%
	2019	3 809 014	3 376 876		112.80%	
Backward model with year dummies	2018	3 857 190	3 353 387	3 346 514	115.02%	115.26%
	2019	3 964 738	3 376 876		117.41%	
Backward model with linear trend	2018	3 602 256	3 353 387	3 346 514	107.42%	107.64%
	2019	3 652 692	3 376 876		108.17%	
Backward model with logarithmic trend	2018	3 719 155	3 353 387	3 346 514	110.91%	111.14%
	2019	3 805 492	3 376 876		112.69%	

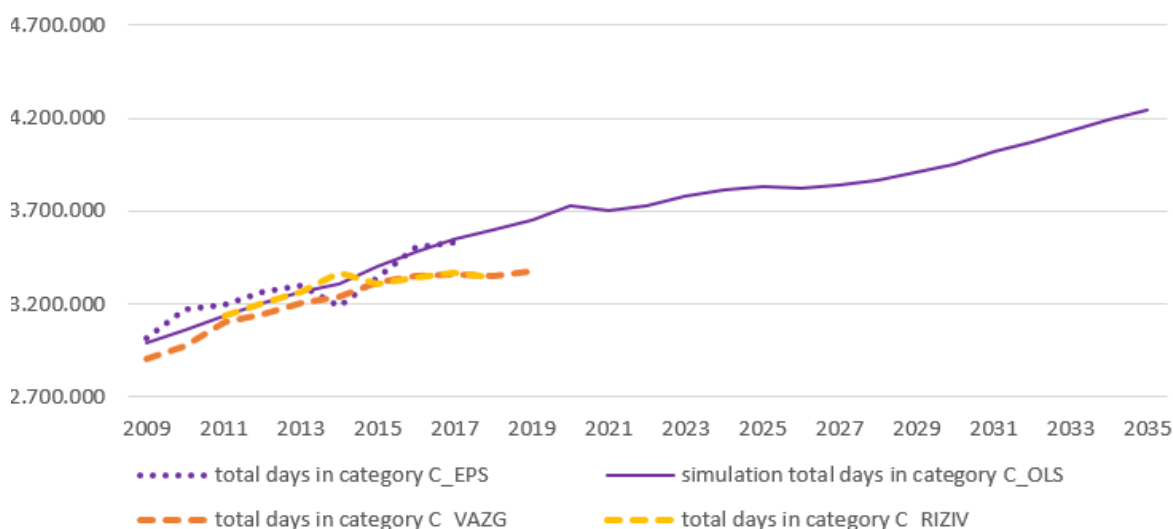


Figure 26 Comparisons for days in care category C

## 1.5 Category Cd

Category Cd is the largest category and is explained the best by our estimated model with a proportion of explained variance of more than 9%. In the light of what was said before, it should come as no surprise that the coefficient of the deceased here is strongly positive. Even less of a surprise is the very large effect of the variable for Alzheimer's and (somewhat less trivial) for Parkinson's. The large positive effects for these three variables are compensated to some extent by the small negative effects for COPD and cardiovascular problems. Surely, these five variables have to be interpreted together.

Table 29 Estimation results of OLS models for days in care category Cd

Days in Category Cd	Full pooled model with year dummies	Backward model with year dummies or linear trend (year dummies or trends not significant)
Intercept	-0.51564 (0.29895)	-0.70428 * (0.25104)
Man-5564	-0.40621 * (0.17529)	-0.40621 * (0.17529)
Man-6574	1.91529 ** (0.16521)	1.91715 ** (0.16521)
Woman-6574	1.6315 ** (0.16271)	1.63515 ** (0.16270)
Man-7584	2.42093 ** (0.18545)	2.42483 ** (0.18544)
Woman 7584	4.17441 ** (0.17358)	4.1791 ** (0.17354)
Man-85plus	9.05388 ** (0.26333)	9.06722 ** (0.26325)
Woman 85plus	24.19481 ** (0.21823)	24.20542 ** (0.21817)
Handicap	6.93555 ** (0.12176)	6.92728 ** (0.12166)
Low income	1.3377 ** (0.11079)	1.32146 ** (0.11050)
Informal care	-4.00991 ** (0.09489)	-4.01827 ** (0.09480)
Deceased	9.55057 ** (0.25573)	9.55063 ** (0.25571)
Cardiovascular-problems	-1.57976 ** (0.09702)	-1.5815 ** (0.09700)
COPD	-1.09365 ** (0.15942)	-1.08973 ** (0.15939)

<b>Days in Category Cd</b>	<b>Full pooled model with year dummies</b>	<b>Backward model with year dummies or linear trend (year dummies or trends not significant)</b>
Diabetes	0.50549 ** (0.13086)	0.5086 ** (0.13085)
Alzheimer's	27.40086 ** (0.19619)	27.40079 ** (0.19619)
Parkinson's	17.31192 ** (0.38410)	17.30991 ** (0.38409)
Hours social care/ population	-0.17922 (0.09954)	
Total NH beds/ population	0.01665 ** (0.00235)	0.01446 ** (0.00177)
Year dummy 2009	-0.10135 (0.18786)	
Year dummy 2010	-0.00429 (0.18716)	
Year dummy 2011	-0.0033 (0.18558)	
Year dummy 2012	-0.20395 (0.18468)	
Year dummy 2013	0.11461 (0.18332)	
Year dummy 2014	0.03811 (0.18203)	
Year dummy 2015	0.03905 (0.18023)	
Year dummy 2016	0.05274 (0.17892)	
Linear trend		
Logarithmic trend		
R-square	0.0949	0.0949
N	749 244	749 244

\*\* p<0.0001 \* p<0.05



There is no indication of a trend in the estimated time dummies and, when we try to introduce a linear or a logarithmic trend in the estimation, these are not significant. Indeed, the backward model (in which the year dummies are dropped, because they are insignificant) predicts the observations for 2018 and 2019 very well.

Table 30 Comparison simulations results (2018-2019) with real data from VAZG and RIZIV – care category Cd

Type of OLS model Care category Cd	Year	OLS	VAZG	RIZIV	model/VAZG	model/RIZIV
Full model with year dummies	2018	10 419 423	10 226 698	10 066 246	101.88%	103.51%
	2019	10 721 158	10 357 844		103.51%	
Backward model	2018	10 359 159	10 226 698	10 066 246	101.30%	102.91%
	2019	10 667 005	10 357 844		102.98%	

Figure 27 illustrates well the interpretation of trends and residual trends in these exercises. There is a clear positive trend in the raw data, but this trend is almost perfectly captured by the evolution of the explanatory variables in the model (mainly the age effects and the effect of the increase in persons suffering from Alzheimer's). Therefore, there is no "residual" trend left.

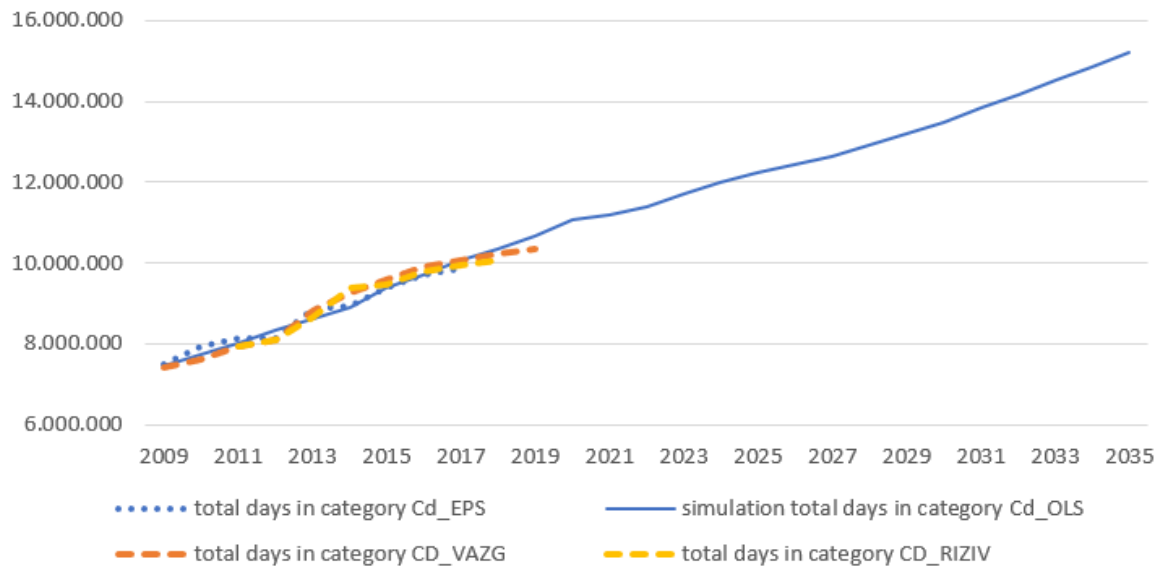


Figure 27 Comparisons for days in care category Cd

## 1.6 Category Short stay

The results for the last category, number of days in short stay, are again similar. The explanatory power of the model is limited, but most of the explanatory variables are significant. It is interesting to note that the regional density of nursing home beds has a positive effect on the number of short stay days. The social care supply has a negative effect on the number of days in short stay, but the effect is small and hardly significant. Moreover, it disappears from the model as soon as we estimate a linear or a logarithmic trend. These trends are small but significant. The predictive performance is best with the logarithmic trend.

Table 31 Estimation results of OLS models for days in care category Short stay

Days in Category Short stay	Full pooled model with year dummies	Backward model with year dummies	Backward model with linear trend	Backward model with logarithmic trend
Intercept	-0.21113 ** (0.03766)	-0.23220 ** (0.03238)	-0.39119 ** (0.2999)	-0.38555 ** (0.03210)
Man-5564	-0.01277 (0.02208)			
Man-6574	0.08675 ** (0.02081)	0.09377 ** (0.01768)	0.09374 ** (0.01768)	0.09371 ** (0.01768)
Woman-6574	0.05839 * (0.02050)	0.06489 * (0.01733)	0.06529 * (0.01733)	0.06491 * (0.01733)
Man-7584	0.23454 ** (0.02336)	0.24199 ** (0.02061)	0.24303 ** (0.02061)	0.24226 ** (0.02061)
Woman 7584	0.34534 ** (0.02187)	0.35158 ** (0.01888)	0.35284 ** (0.01888)	0.35183 ** (0.01888)
Man-85plus	0.77338 ** (0.03317)	0.7808 ** (0.03128)	0.78185 ** (0.03127)	0.78076 ** (0.03128)
Woman 85plus	1.19884 ** (0.02749)	1.20503 ** (0.02513)	1.20613 ** (0.02512)	1.20504 ** (0.02513)
Handicap	0.35237 ** (0.01534)	0.36245 ** (0.01533)	0.35117 ** (0.01532)	0.35227 ** (0.01533)
Low income	0.16308 ** (0.01396)	0.16405 ** (0.01393)	0.16237 ** (0.01391)	0.16401 ** (0.01393)
Informal care	-0.13359 ** (0.01195)	-0.13345 ** (0.01195)	-0.13431 ** (0.01194)	-0.13349 ** (0.01195)
Deceased	0.16974 ** (0.03222)	0.17036 ** (0.03221)	0.17118 ** (0.03221)	0.17062 ** (0.03221)
Cardiovascular-problems	0.10035 ** (0.01222)	0.10109 ** (0.01219)	0.10085 ** (0.01219)	0.10105 ** (0.01219)
COPD	0.02172 (0.02008)			

Days in Category Short stay	Full pooled model with year dummies	Backward model with year dummies	Backward model with linear trend	Backward model with logarithmic trend
Diabetes	0.03779 * (0.01649)	0.03773 * (0.01648)	0.03814 * (0.01648)	0.03777 * (0.01648)
Alzheimer's	0.50594 ** (0.02472)	0.50604 ** (0.02472)	0.5058 ** (0.02472)	0.50594 ** (0.02472)
Parkinson's	0.59494 ** (0.04839)	0.59459 ** (0.04839)	0.59458 ** (0.04839)	0.59454 ** (0.04839)
Hours social care/ population	-0.02763 * (0.01254)	-0.02794 * (0.01241)		
Total NH beds/ population	0.00226 ** (0.00029564)	0.00228 ** (0.00029080)	0.00182 ** (0.00022865)	0.00224 ** (0.00029165)
Year dummy 2009	-0.14739 ** (0.02367)	-0.13258 ** (0.01865)		
Year dummy 2010	-0.14169 ** (0.02358)	-0.12685 ** (0.01853)		
Year dummy 2011	-0.10500 ** (0.02338)	-0.09013 ** (0.01833)		
Year dummy 2012	-0.06113 * (0.02327)	-0.04623 * (0.01818)		
Year dummy 2013	-0.01855 (0.02309)			
Year dummy 2014	-0.01645 (0.02293)			
Year dummy 2015	-0.00517 (0.02270)			
Year dummy 2016	-0.0348 (0.02254)			
Linear trend			0.0198 ** (0.00218)	
Logarithmic trend				0.07619 ** (0.00840)
Logarithmic trend 2012-2017				
R-square	0.0117	0.0117	0.0116	0.0117
N	749 244	749 244	749 244	749 244

\*\*  $p < 0.0001$  \*  $p < 0.05$

Table 32 Comparison simulations results (2018-2019) with real data from VAZG and RIZIV – care category Short stay

Type of OLS model Care category Short stay	Year	OLS	VAZG	RIZIV	model/VAZG	model/RIZIV
Full model with year dummies	2018	756 438	796 423	703 577	94.98%	107.51%
	2019	779 894	803 264		97.09%	
Backward model with year dummies	2018	733 586	796 423	703 577	92.11%	104.27%
	2019	756 706	803 264		94.20%	
Backward model with linear trend	2018	838 172	796 423	703 577	105.24%	119.13%
	2019	909 589	803 264		113.24%	
Backward model with logarithmic trend	2018	776 527	796 423	703 577	97.50%	110.37%
	2019	817 280	803 264		101.74%	

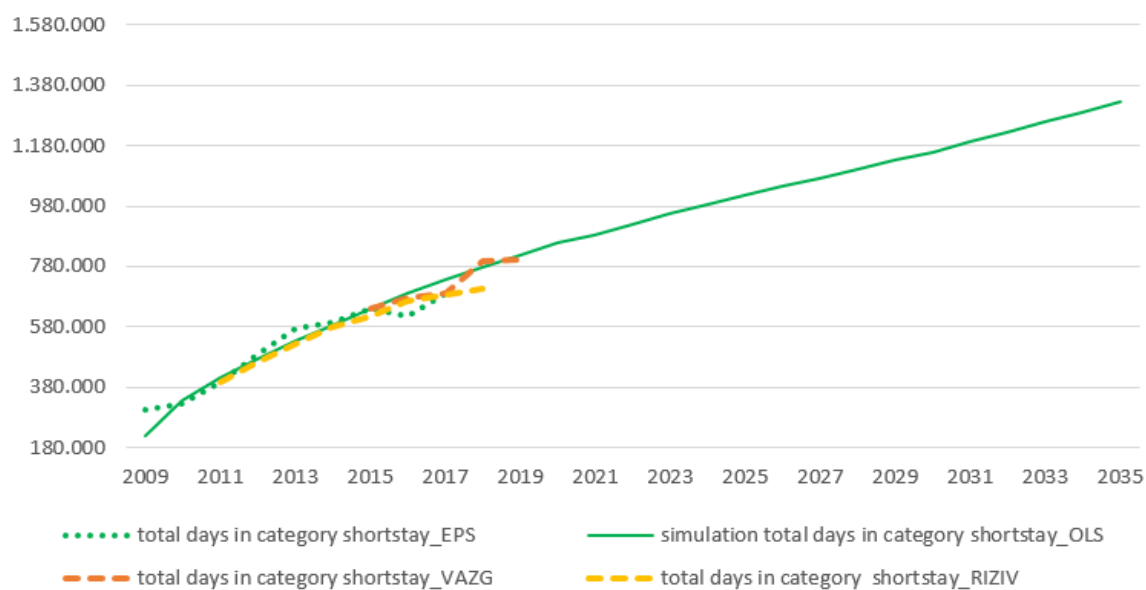


Figure 28 Comparisons for days in care category Short stay

## 2 Estimations of the pooled OLS models for home care and the results from the simulations

The setup of the discussion of the estimation results for the different home care services is the same as that for the residential care categories. The number of nursing tasks and the number of hours of social care and logistic help were used as dependent variables and the same variables as in the residential care models were used as explanatory variables. For each category, a full OLS model with year dummies was constructed with 2017 as reference year, to help determine trends. The simulations from the models are then compared with official sources for the years 2018 and 2019. Since home care used is not restricted to older persons, the sample does now include all observations of respondents older than 18. Women between 18 and 39 are the reference category.

### 2.1 Nursing care at home

Table 33 gives the estimates for the number of nursing tasks. The explanatory power of the model is larger than for residential care. The negative coefficients for many of the age-gender groups indicate that these groups use on average less nursing care at home than the reference group of young women. The effect of a disease is dominated by the incomplete period phenomenon. The morbidity categories are all highly significant, with a particularly strong effect of Parkinson's. We find interesting results for the supply variables. An increase in the regional density of nursing home beds is associated with a smaller use of nursing care at home: nursing homes and nursing care at home can be seen as substitutes of each other. An increase in the regional supply of social care, however, is associated with a larger use of home nursing care. These two are complements. An obvious interpretation suggests itself: it is the combination of nursing care at home and social care that helps people to stay at home.

Table 33 Estimation results of OLS models for total tasks of nursing at home

Nurising tasks at home	Full pooled model with year dummies	Backward model with year dummies	Backward model with linear trend	Backward model with logarithmic trend
Intercept	0.43427 (0.25615)	0.29583 (0.24407)	-1.99920 ** (0.21347)	-2.00223 ** (0.21541)
Man-1839	-0.20974 (0.14730)			
Man-4054	-1.70022 ** (0.15707)	-1.54691 ** (0.13327)	-1.54832 ** (0.13327)	-1.55357 ** (0.13327)
Woman-4054	-1.44368 ** (0.15774)	-1.29180 ** (0.13451)	-1.29319 ** (0.13451)	-1.29842 ** (0.13452)
Man-5564	-2.74559 ** (0.18800)	-2.57253 ** (0.16449)	-2.57202 ** (0.16449)	-2.57004 ** (0.16450)
Woman-5564	-1.57048 ** (0.18833)	-1.39713 ** (0.16481)	-1.39650 ** (0.16481)	-1.39442 ** (0.16481)
Man-6574	-0.31607 (0.17995)			
Woman-6574	2.71015 ** (0.17557)	2.90172 ** (0.14429)	2.90283 ** (0.14429)	2.90509 ** (0.14429)

<b>Nursing tasks at home</b>	<b>Full pooled model with year dummies</b>	<b>Backward model with year dummies</b>	<b>Backward model with linear trend</b>	<b>Backward model with logarithmic trend</b>
Man-7584	8.89592 ** (0.20893)	9.10043 ** (0.17944)	9.09647 ** (0.17944)	9.09326 ** (0.17945)
Woman 7584	18.43362 ** (0.19154)	18.62926 ** (0.16200)	18.62481 ** (0.16200)	18.61847 ** (0.16201)
Man-85plus	35.34465 ** (0.30844)	35.54711 ** (0.28969)	35.54716 ** (0.28969)	35.55637 ** (0.28970)
Woman 85plus	46.30771 ** (0.24833)	46.50066 ** (0.22697)	46.49979 ** (0.22697)	46.50299 ** (0.22697)
Handicap	13.87737 ** (0.10446)	13.88002 ** (0.10432)	13.88093 ** (0.10432)	13.8832 ** (0.10432)
Low income	10.61435 ** (0.10606)	10.60962 ** (0.10592)	10.61283 ** (0.10592)	10.61127 ** (0.10592)
Informal care	-1.87775 ** (0.08598)	-1.91008 ** (0.08285)	-1.90958 ** (0.08285)	-1.91238 ** (0.08285)
Deceased	-6.57794 ** (0.30468)	-6.59756 ** (0.30431)	-6.60155 ** (0.30431)	-6.60926 ** (0.30431)
Cardiovascular-problems	5.27864 ** (0.10254)	5.23451 ** (0.09650)	5.23309 ** (0.09650)	5.23521 ** (0.09650)
COPD	9.08846 ** (0.18787)	9.06878 ** (0.18725)	9.07172 ** (0.18725)	9.07981 ** (0.18725)
Diabetes	9.02797 ** (0.15032)	9.01646 ** (0.15006)	9.01451 ** (0.15006)	9.01605 ** (0.15006)
Alzheimer's	3.61195 ** (0.23809)	3.60271 ** (0.23797)	3.6042 ** (0.23798)	3.60641 ** (0.23798)
Parkinson's	35.57246 ** (0.46201)	35.55805 ** (0.46187)	35.55574 ** (0.46187)	35.55167 ** (0.46188)
Hours social care/ population	3.6243 1 ** (0.08667)	3.62474 ** (0.08667)	3.57683 ** (0.08625)	3.51784 ** (0.08591)
Total NH beds/ population	-0.09036 ** (0.00204)	-0.09038 ** (0.00204)	-0.08937 ** (0.00203)	-0.08729 ** (0.00201)
Year dummy 2009	-1.77551 ** (0.16455)	-1.7734 ** (0.16454)		
Year dummy 2010	-1.82745 ** (0.16416)	-1.82519 ** (0.16415)		
Year dummy 2011	-1.55998 ** (0.16313)	-1.55801 ** (0.16313)		
Year dummy 2012	-1.5943 ** (0.16274)	-1.59256 ** (0.16274)		

<b>Nurising tasks at home</b>	<b>Full pooled model with year dummies</b>	<b>Backward model with year dummies</b>	<b>Backward model with linear trend</b>	<b>Backward model with logarithmic trend</b>
Year dummy 2013	-1.55752 ** (0.16188)	-1.55565 ** (0.16188)		
Year dummy 2014	-1.17722 ** (0.16114)	-1.17583 ** (0.16114)		
Year dummy 2015	-0.89922 ** (0.15998)	-0.89806 ** (0.15998)		
Year dummy 2016	-0.33943 * (0.15921)	-0.33871 * (0.15921)		
Linear trend			0.22104 ** (0.01531)	
Logarithmic trend				0.7132 ** (0.05808)
R-square	0.1336	0.1336	0.1336	0.1335
N	1 439 385	1 439 385	1 439 385	1 439 385

\*\*  $p < 0.0001$  \*  $p < 0.05$

The pattern of the time dummies is somewhat erratic, although there seems to be a positive trend towards the end of the estimation period. This is also what we find when we include a linear or a logarithmic trend variable in the model. Table 34 shows, however, that the inclusion of a trend does not improve the predictions for 2018 and 2019. We therefore work further with the backward model with year dummies, which means that we do not assume a residual trend for the future. The long run increase in home nursing care (see figure 29) is then ascribed fully to the development of the explanatory variables.

Table 34 Comparison simulations results (2018-2019) with real data from RIZIV – Nursing at home

Type of OLS model	Year	OLS	RIZIV	model/RIZIV
<b>Nursing tasks at home</b>				
Full model with year dummies	2018	36 721 392	35 355 949	103.86%
	2019	37 496 933	36 274 145	103.37%
<b>Backward model with year dummies</b>	2018	36 685 362	35 355 949	103.76%
	2019	37 462 332	36 274 145	103.28%
Backward model with linear trend	2018	36 279 741	35 355 949	102.61%
	2019	38 249 583	36 274 145	105.45%
Backward model with logarithmic trend	2018	33 839 849	35 355 949	95.71%
	2019	34 972 075	36 274 145	96.41%

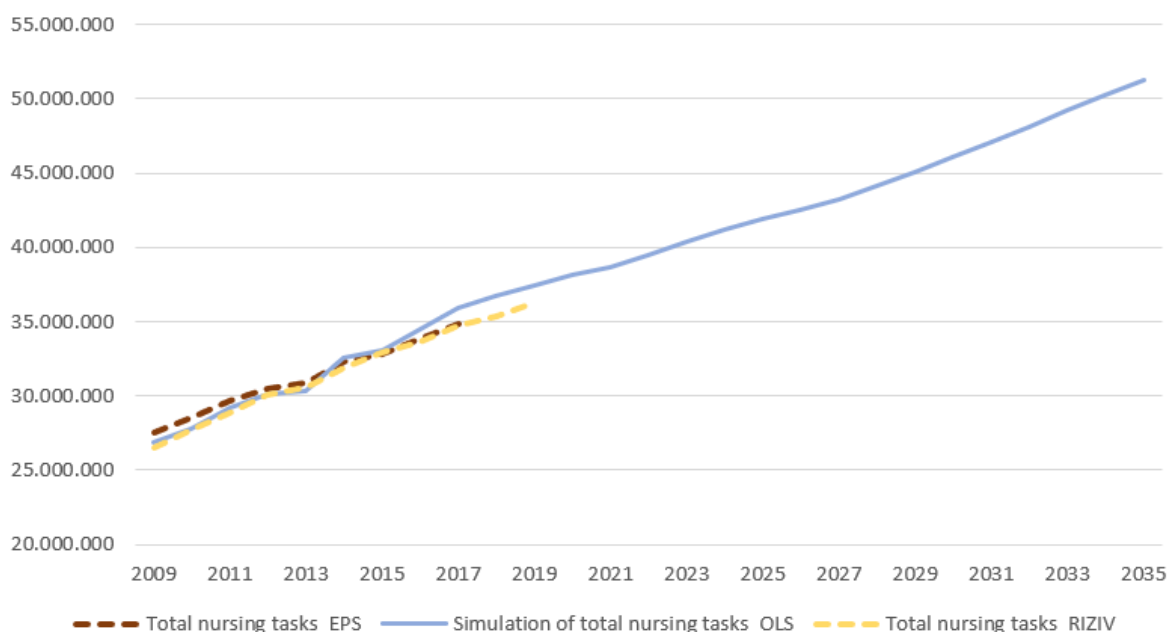


Figure 29 Comparisons for nursing tasks at home



## 2.2 Hours social care at home

Use of social care at home is measured by the number of hours. The estimates in table 35 show a pattern which is (not surprisingly) highly similar to the one in table 33 for nursing care. The results for the time dummies are erratic. A linear trend is barely significant, a logarithmic trend is significant. It is not easy to choose between the different models on the basis of their predictive performance (table 36). We opted for the model without a trend. As figure 30 shows, we then predict an increase in the future number of hours of social care that is stronger than what was observed in the past. This prediction has to be interpreted with caution.

Table 35 Estimation results of OLS models for hours social care at home

Hours of social care at home	Full pooled model with year dummies	Backward model with year dummies	Backward model with linear trend	Backward model with logarithmic trend
Intercept	-0.34518 (0.22888)	-0.07521 (0.19421)	0.15586 (0.19697)	0.18967 (0.19865)
Man-1839	-0.49739 * (0.13162)	-0.5335 ** (0.12089)	-0.5346** (0.12089)	-0.53459 ** (0.12089)
Man-4054	-1.13558 ** (0.14034)	-1.17115 ** (0.12940)	-1.17447** (0.12941)	-1.17420 ** (0.12941)
Woman-4054	-0.83096 ** (0.14095)	-0.86603 ** (0.13032)	-0.8694** (0.13032)	-0.86913 ** (0.13032)
Man-5564	-0.49221 * (0.16798)	-0.53713 * (0.15665)	-0.53527 * (0.15665)	-0.53559 * (0.15665)
Woman-5564	0.12023 (0.16828)			
Man-6574	1.52624 ** (0.16080)	1.47418 ** (0.14606)	1.47831** (0.14606)	1.47773 ** (0.14606)
Woman-6574	2.50028 ** (0.15688)	2.45073 ** (0.14224)	2.45316** (0.14226)	2.45271 ** (0.14225)
Man-7584	5.04095 ** (0.18669)	4.99104 ** (0.17291)	4.99083** (0.17291)	4.99115 ** (0.17291)
Woman 7584	8.42764 ** (0.17115)	8.38204 ** (0.15706)	8.37934** (0.15707)	8.37984 ** (0.15706)
Man-85plus	21.50705 ** (0.27561)	21.44936 ** (0.26654)	21.457** (0.26655)	21.45657 ** (0.26655)
Woman 85plus	21.87814 ** (0.22189)	21.8266 ** (0.21133)	21.8299** (0.21134)	21.82976 ** (0.21134)
Handicap	6.83596 ** (0.09334)	6.83593 ** (0.09330)	6.83755** (0.09330)	6.83743 ** (0.09330)
Low income	6.62335 ** (0.09477)	6.6263 ** (0.09475)	6.62451** (0.09476)	6.62404 ** (0.09476)

Hours of social care at home	Full pooled model with year dummies	Backward model with year dummies	Backward model with linear trend	Backward model with logarithmic trend
Informal care	-4.45507 ** (0.07682)	-4.44536 ** (0.07626)	-4.44822** (0.07627)	-4.44821 ** (0.07627)
Deceased	-4.90697 ** (0.27225)	-4.89903 ** (0.27221)	-4.9045** (0.27222)	-4.90395 ** (0.27222)
Cardiovascular-problems	2.08124 ** (0.09163)	2.09149 ** (0.09017)	2.09243** (0.09017)	2.09282 ** (0.09017)
COPD	2.90512 ** (0.16787)	2.90567 ** (0.16769)	2.91057** (0.16770)	2.91003 ** (0.16770)
Diabetes	3.14157 ** (0.13432)	3.14085 ** (0.13432)	3.14191** (0.13432)	3.14225 ** (0.13432)
Alzheimer's	2.60771 ** (0.21274)	2.60725 ** (0.21274)	2.60832** (0.21274)	2.60813 ** (0.21274)
Parkinson's	18.48636 ** (0.41282)	18.48883 ** (0.41282)	18.48595** (0.41282)	18.48672 ** (0.41282)
Hours social care/ population	1.36105 ** (0.07745)	1.39562 ** (0.07628)	1.36129** (0.07707)	1.36894 ** (0.07676)
Total NH beds/ population	-0.0276 ** (0.00182)	-0.02886 ** (0.00176)	-0.02754** (0.00181)	-0.02775 ** (0.00180)
Year dummy 2009	0.51605 * (0.14703)	0.33353 * (0.11034)		
Year dummy 2010	0.35496 * (0.14669)			
Year dummy 2011	0.23109 (0.14577)			
Year dummy 2012	0.19087 (0.14542)			
Year dummy 2013	0.21727 (0.14465)			
Year dummy 2014	0.22583 (0.14399)			
Year dummy 2015	0.13693 (0.14295)			
Year dummy 2016	0.05018 (0.14226)			
Linear trend			-0.05211 * (0.01368)	
Logarithmic trend				-0.20356 ** (0.05190)

Hours of social care at home	Full pooled model with year dummies	Backward model with year dummies	Backward model with linear trend	Backward model with logarithmic trend
R-square	0.0469	0.0469	0.0469	0.0469
N	1 439 385	1 439 385	1 439 385	1 439 385

\*\*  $p < 0.0001$  \*  $p < 0.05$

Table 36 Comparison simulations results (2018-2019) with real data from VAZG and RIZIV – hours of social care

Type of OLS model Hours of social care	Year	OLS	VAZG	model/VAZG
Full model with year dummies	2018	15 494 139	16 046 011	96.56%
	2019	15 994 861	16 252 556	98.41%
Backward model with year dummies	2018	16 359 259	16 046 011	101.95%
	2019	16 861 769	16 252 556	103.75%
Backward model with linear trend	2018	15 240 240	16 046 011	94.98%
	2019	15 457 390	16 252 556	95.11%
Backward model with logarithmic trend	2018	15 662 268	16 046 011	97.61%
	2019	16 058 435	16 252 556	98.81%

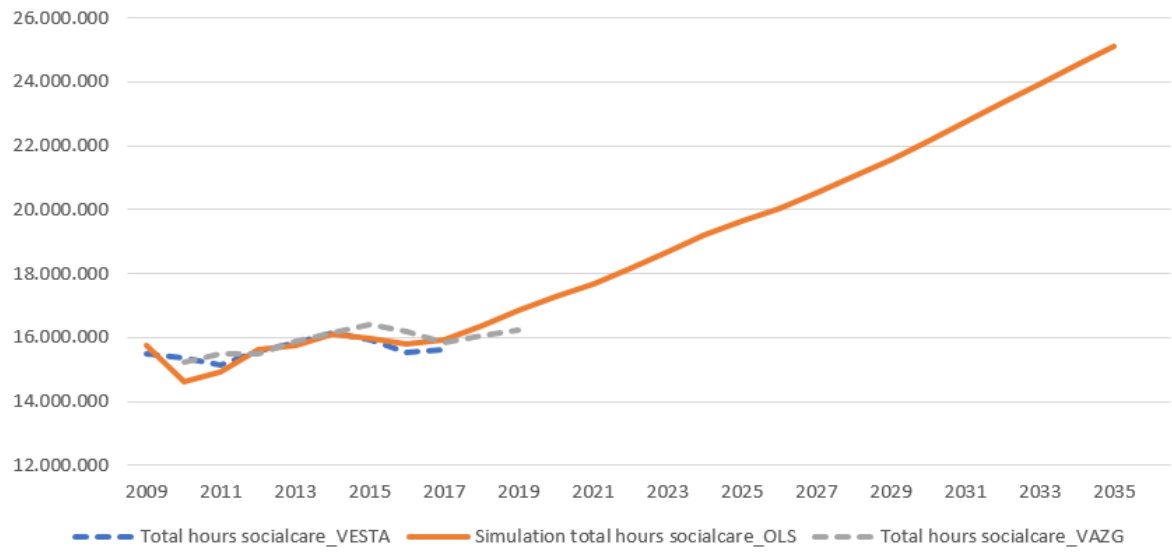


Figure 30 Comparisons for hours social care at home

### 2.3 Hours logistic help at home

For logistic help at home, the picture is again very similar. The regional supply of nursing home beds has a small positive effect, which is barely significant. The negative trend is now much more outspoken and it does improve the predictions. We therefore kept it in the model.

Table 37 Estimation results of OLS models for hours logistic help at home

Hours of logistic help at home	Full pooled model with year dummies	Backward model with year dummies	Backward model with trend	Backward model with logarithmic trend
Intercept	-0,90608 ** (0.08148)	-0,85962 ** (0.07280)	-0,67476** (0.07200)	-0,69018 ** (0.07131)
Man-1839	0,06042 (0.04744)			
Man-4054	-0,06201 (0.05077)	-0,09241 * (0.04335)	-0,09247* (0.04335)	-0,09240 * (0.04335)
Woman-4054	-0,05845 (0.05096)	-0,08873 * (0.04368)	-0,08883* (0.04368)	-0,08875 * (0.04368)
Man-5564	0,03102 (0.06013)			
Woman-5564	0,42304 ** (0.06027)	0,39233 ** (0.05364)	0,39249** (0.05364)	0,39233 ** (0.05364)
Man-6574	0,78200 ** (0.05758)	0,75106 ** (0.04985)	0,75137** (0.04985)	0,75108 ** (0.04985)
Woman-6574	1,30826 ** (0.05622)	1,27744 ** (0.04846)	1,27775** (0.04846)	1,27752 ** (0.04846)
Man-7584	1,91470 ** (0.06708)	1,88394 ** (0.06023)	1,88398** (0.06023)	1,88402 ** (0.06023)
Woman 7584	4,49595 ** (0.06157)	4,46556 ** (0.05432)	4,46537** (0.05432)	4,46558 ** (0.05432)
Man-85plus	4,70235 ** (0.09667)	4,6715 ** (0.09206)	4,67177** (0.09206)	4,67149 ** (0.09206)
Woman 85plus	7,66512 ** (0.07869)	7,63465 ** (0.07314)	7,63477** (0.07314)	7,63467 ** (0.07314)
Handicap	1,03852 ** (0.03348)	1,03948 ** (0.03344)	1,03947** (0.03344)	1,03938 ** (0.03344)
Low income	2,27890 ** (0.03392)	2,27834 ** (0.03391)	2,27839** (0.03391)	2,27837 ** (0.03391)
Informal care	-1,47415 ** (0.02770)	-1,47313 ** (0.02760)	-1,47343** (0.02760)	-1,47319 ** (0.02760)

Deceased	-3,08653 ** (0.09792)	-3,08613 ** (0.09790)	-3,08645** (0.09790)	-3,08636 ** (0.09790)
Cardiovascular-problems	0,61471 ** (0.03291)	0,61739 ** (0.03216)	0,61738** (0.03216)	0,61737 ** (0.03216)
COPD	1,02324 ** (0.05924)	1,02308 ** (0.05919)	1,02340** (0.05919)	1,02317 ** (0.05919)
Diabetes	0,73996 ** (0.04760)	0,73997 ** (0.04758)	0,73996** (0.04758)	0,74001 ** (0.04758)
Alzheimer's	-1,69735 ** (0.07556)	-1,69741 ** (0.07556)	-1,69737** (0.07556)	-1,69747 ** (0.07556)
Parkinson's	1,47408 ** (0.14676)	1,47405 ** (0.14676)	1,47397** (0.14675)	1,47414 ** (0.14675)
Hours social care/ population	0,20938 ** (0.02895)	0,21160 ** (0.02882)	0,20853** (0.02889)	0,21154 ** (0.02878)
Total NH beds/ population	0,00176 * (0.00070498)	0,00171 * (0.000701)	0,00177* (0.00070437)	0,0017 * (0.00070113)
Year dummy 2012	0,16784 ** (0.04334)	0,15243 ** (0.03552)		-0,69018 ** (0.07131)
Year dummy 2013	0,1415 * (0.04300)	0,12612 * (0.03518)		
Year dummy 2014	0,08534 * (0.04272)	0,07006 * (0.03489)		
Year dummy 2015	0,02809 (0.04226)			
Year dummy 2016	0,0168 (0.04196)			
Linear trend			-0,03627** (0.00743)	
Logarithmic trend				-0.10182** (0.02093)
Logarithmic trend 2012- 2017				
R-square	0.0463	0.0463	0.0463	0.0463
N	971 101	971 101	971 101	971 101

\*\*  $p \leq 0.0001$  \*  $p \leq 0.01$

Table 38 Comparison simulations results (2018-2019) with real data from VAZG and RIZIV – hours of logistic help

Type of OLS model Hours of logistic help	Year	OLS	VAZG	model/VAZG
Full model with year dummies	2018	4 670 331	4 456 867	104.79%
	2019	4 838 293	4 446 528	108.81%
Backward model with year dummies	2018	4 757 787	4 456 867	106.75%
	2019	4 926 274	4 446 528	110.79%
Backward model with linear trend	2018	4 386 434	4 456 867	98.42%
	2019	4 356 706	4 446 528	97.98%
Backward model with logarithmic trend	2018	4 595 767	4 456 867	103.12%
	2019	4 689 770	4 446 528	105.47%

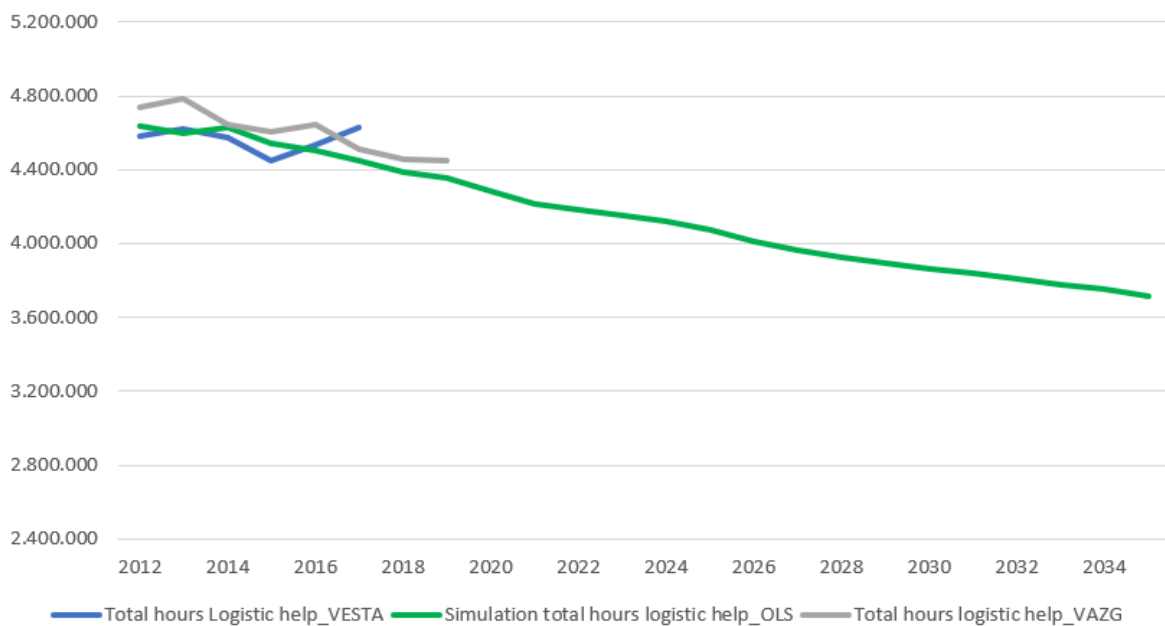


Figure 31 Comparisons for hours logistic help at home

## 2.4 Surveillance help at home

Because of the data problems explained in section 3, we did not estimate a model for surveillance help at home. This is a small category which does not play an important role in the global costs.





## Chapter 5

### Reference simulation

To make projections of the future, we start with a so-called reference simulation. In this simulation all the explanatory variables are assumed to follow the same trend as in the past (see section 5.1) and they are related to the dependent variables with what we considered in the previous section as the best model. Later simulations will always be compared with this reference.

It is important to read correctly the tables and the figures in this section. Because of the many limitations of the data, the relative simplicity of the explanatory model and the difficulties to predict the future path of the explanatory variables, the projections shown should not be seen as real predictions. They are projections into the future of the actual situation under the assumption that there will be no unexpected events in the following decades. Yet, it is clear that unexpected events will happen. The main role of the projection model is not to predict, but rather to compare the results for different alternative scenarios. We will sketch some of these scenarios in sections 6 and 7.

#### 1 Explanatory variables

All the explanatory variables have to be extrapolated for the whole projection period, i.e. until 2035. For the explanatory variables age and gender, we use the projections from Statistics Flanders (Statbel, 2021).

The exogenous variables handicap, availability of informal caregiver, low income, diabetes, COPD, cardiovascular problems, Parkinson's and Alzheimer's, were extrapolated on the basis of time trends. This technique estimates the outcome as a linear function of the time index, assuming that there is a permanent deterministic pattern across time. This calculation is suitable for data not dominated by random fluctuations. The supply of social care and residential care were extrapolated using the demographic growth of the population. The graphs in section 2 showed already the evolution of the explanatory variables in the EPS (2009-2017) and the future projections for the period 2018-2035, as calculated by the time trends. We also experimented with other specifications, e.g. those giving a larger weight to the later observations, but these more complicated extrapolation procedures did not make any difference. It was therefore meaningless to implement them in our projections.

For the supply variables hours of social care and nursing home beds per inhabitant per region, which are related to population totals, we also used the evolution in Statbel to predict the future values for the period 2018-2035. The evolution of these variables can be found in section 2.4.5.

## **2 Reference simulation for residential care: alternative scenario for category O and recalibration for 2019**

Table 39 and figure 30 show the projections of days in each residential care category for the period 2019-2035. These simulations were constructed by applying the coefficients of the chosen OLS models from the previous section to the extrapolated population shares of the explanatory variables (i.e. handicap, low income, etc.) for each year and the Statbel shares of the age/gender groups in the population. Because the choice of the best model for category O was somewhat tricky, we show the results both for the original and for the alternative scenario. Later on, we will only work with the alternative scenario, in which there is a steady decline of the number of days until 2029. The most striking finding in figure 32 is the increase in the number of days in categories B and Cd, and the more stable pattern for the other categories.

The projections in table 39 and figure 32 start in 2018. However, as was shown in the previous section, for 2018 and 2019 we have already data about the number of days from the official source (VAZG). It is natural to use this information to recalibrate our projections. This means that we will start the projections with the values for 2019 set at the level of the VAZG data. After 2019 we then use the growth rates as they are obtained with the model. As it is clear from table 40 and figure 33, this recalibration boils down to a simple vertical shift of the evolution over time.

Our model is formulated in terms of the number of days in the different residential care categories. It is interesting to transform this in the corresponding number of beds that will be needed. We do this by dividing the total number of days by 365 and then by the occupancy rate. The last two columns of table 40 give the results of this exercise, respectively for an assumed occupancy rate of 100% and a more realistic assumption of 85%.

Table 39 Reference simulation for total days in each residential care category

Year	Total days in category O	Total days in category O (alternative scenario)	Total days in category A	Total days in category B	Total days in category C	Total days in category Cd	Total days in category Short stay
2017	2 109 676	2 207 967	3 285 059	8 657 279	3 553 317	10 059 848	734 390
2018	2 148 716	2 073 315	3 239 050	8 952 400	3 602 256	10 359 159	776 527
2019	2 211 926	1 980 652	3 218 034	9 277 660	3 652 692	10 667 005	817 280
2020	2 243 171	1 869 714	3 174 540	9 572 195	3 726 276	11 065 386	858 010
2021	2 286 304	1 783 810	3 129 002	9 786 814	3 705 505	11 171 504	884 907
2022	2 352 639	1 729 983	3 119 489	10 081 290	3 728 706	11 403 800	917 527
2023	2 427 597	1 691 924	3 126 815	10 415 906	3 777 287	11 714 037	953 270
2024	2 496 713	1 654 510	3 129 557	10 734 885	3 817 463	12 006 339	987 169
2025	2 545 020	1 601 433	3 108 997	11 003 474	3 834 480	12 243 667	1 018 026
2026	2 576 228	1 536 706	3 068 626	11 220 755	3 827 970	12 420 970	1 044 836
2027	2 627 245	1 497 022	3 054 386	11 479 542	3 837 008	12 635 154	1 072 744
2028	2 705 782	1 490 217	3 077 121	11 799 493	3 870 248	12 905 652	1 102 073
2029	2 797 106	1 500 618	3 117 240	12 145 333	3 913 126	13 198 595	1 131 848
2030	2 888 820	1 515 701	3 159 864	12 487 117	3 953 105	13 482 174	1 160 388
2031	3 001 401	1 553 579	3 231 230	12 891 103	4 017 775	13 831 735	1 192 707
2032	3 106 615	1 585 590	3 294 652	13 284 181	4 076 221	14 172 080	1 225 030
2033	3 210 456	1 617 560	3 357 495	13 680 889	4 134 672	14 518 016	1 257 989
2034	3 310 819	1 647 436	3 416 675	14 072 715	4 189 601	14 859 120	1 291 069
2035	3 407 770	1 675 483	3 473 137	14 459 972	4 241 444	15 196 475	1 323 616

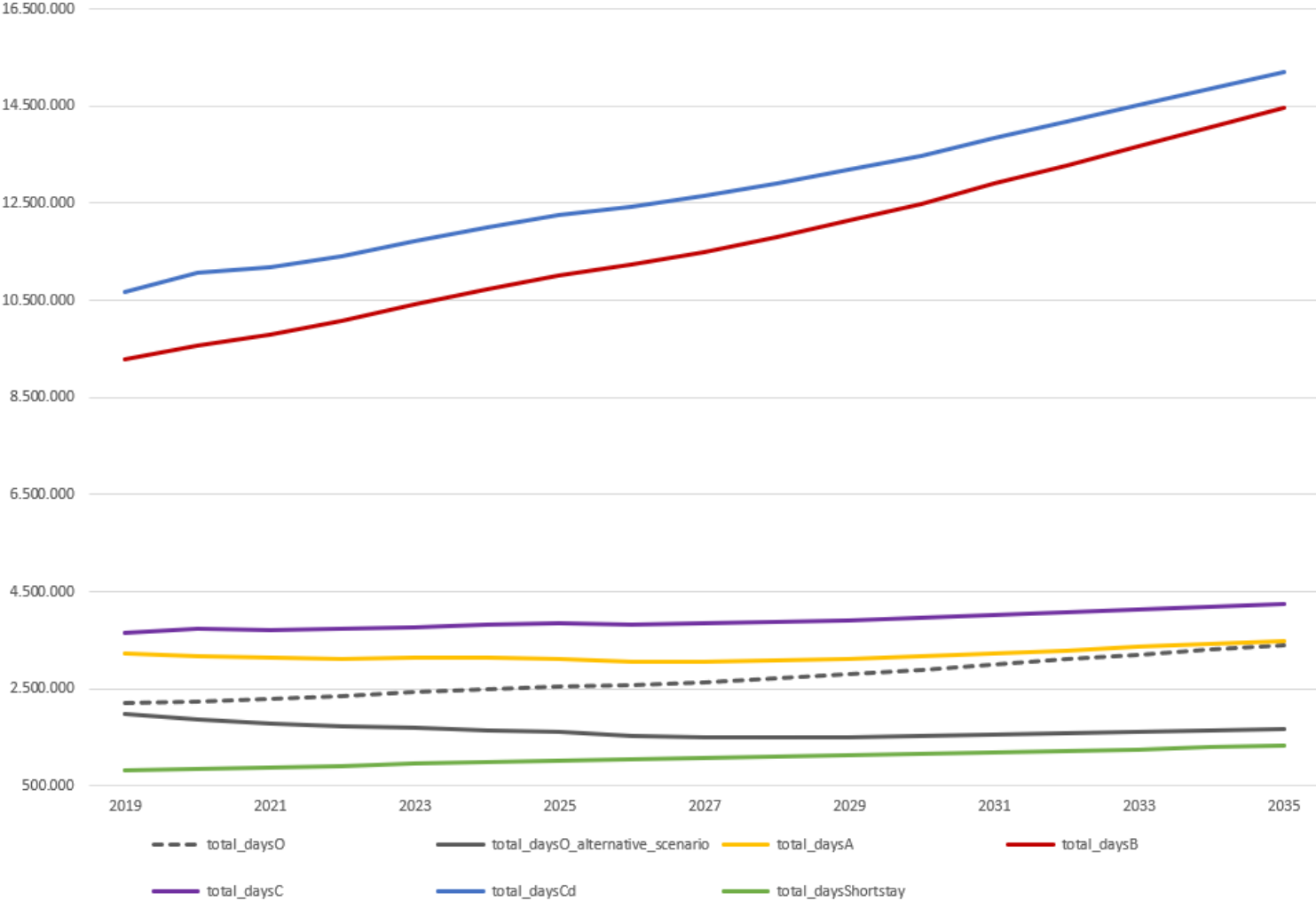


Figure 32 Reference simulation for total days in each residential care category

Table 40 Reference simulation for total days in each residential care category with recalibration on the real data from the VAZG for 2019.

Year	Total days in category O	Total days in category O (alternative scenario)	Total days in category A	Total days in category B	Total days in category C	Total days in category Cd	Total days in category Short stay	Total days in residential care (using alternative scenario for category O)	Total beds at 100% occupancy rate	Total beds at 85% occupancy rate
2019	1 943 854	1 943 854	3 319 958	9 314 526	3 376 876	10 357 844	803 264	29 116 322	79 771	93 848
2020	1 971 312	1 834 977	3 275 086	9 610 232	3 444 904	10 744 679	843 295	29 753 173	81 516	95 901
2021	2 009 218	1 750 670	3 228 105	9 825 703	3 425 701	10 847 720	869 731	29 947 631	82 048	96 527
2022	2 067 514	1 697 843	3 218 291	10 121 349	3 447 150	11 073 284	901 791	30 459 709	83 451	98 178
2023	2 133 387	1 660 490	3 225 849	10 457 294	3 492 062	11 374 529	936 921	31 147 147	85 335	100 394
2024	2 194 126	1 623 772	3 228 678	10 777 541	3 529 205	11 658 360	970 238	31 787 795	87 090	102 459
2025	2 236 579	1 571 681	3 207 467	11 047 197	3 544 937	11 888 810	1 000 567	32 260 659	88 385	103 983
2026	2 264 005	1 508 156	3 165 818	11 265 342	3 538 919	12 060 974	1 026 917	32 566 126	89 222	104 967
2027	2 308 839	1 469 209	3 151 126	11 525 157	3 547 275	12 268 950	1 054 346	33 016 064	90 455	106 418
2028	2 377 858	1 462 531	3 174 582	11 846 380	3 578 005	12 531 608	1 083 173	33 676 278	92 264	108 546
2029	2 458 114	1 472 739	3 215 971	12 193 594	3 617 645	12 816 061	1 112 437	34 428 446	94 325	110 970
2030	2 538 712	1 487 541	3 259 945	12 536 736	3 654 605	13 091 420	1 140 487	35 170 735	96 358	113 363
2031	2 637 649	1 524 716	3 333 572	12 942 328	3 714 391	13 430 851	1 172 252	36 118 109	98 954	116 416
2032	2 730 112	1 556 132	3 399 002	13 336 967	3 768 424	13 761 331	1 204 020	37 025 877	101 441	119 342
2033	2 821 369	1 587 509	3 463 836	13 735 252	3 822 462	14 097 241	1 236 414	37 942 713	103 953	122 297
2034	2 909 568	1 616 829	3 524 890	14 128 635	3 873 243	14 428 459	1 268 927	38 840 982	106 414	125 193
2035	2 994 769	1 644 355	3 583 140	14 517 430	3 921 171	14 756 037	1 300 916	39 723 049	108 830	128 036

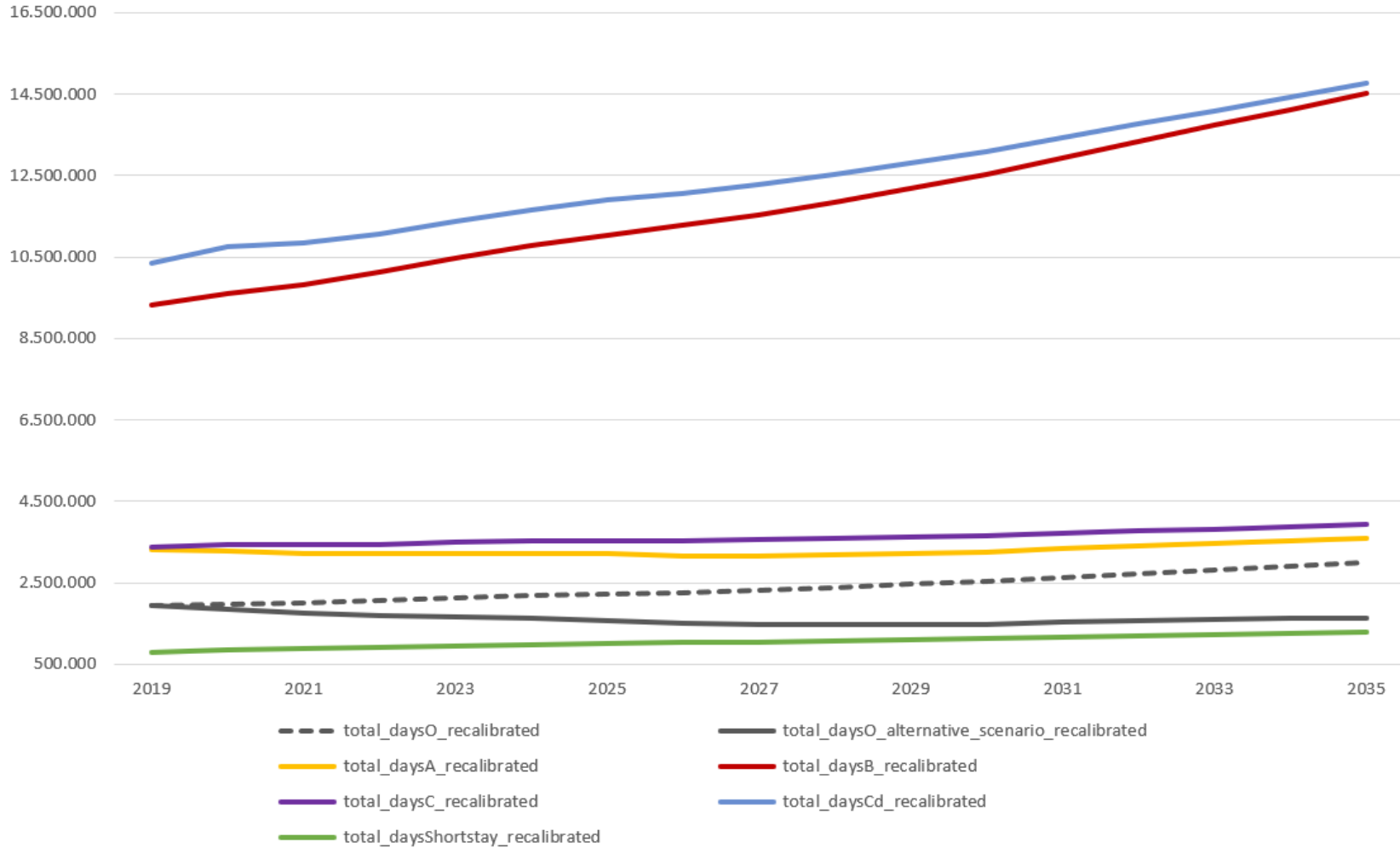


Figure 33 Reference simulation for total days in each residential care category with recalibration for year 2019

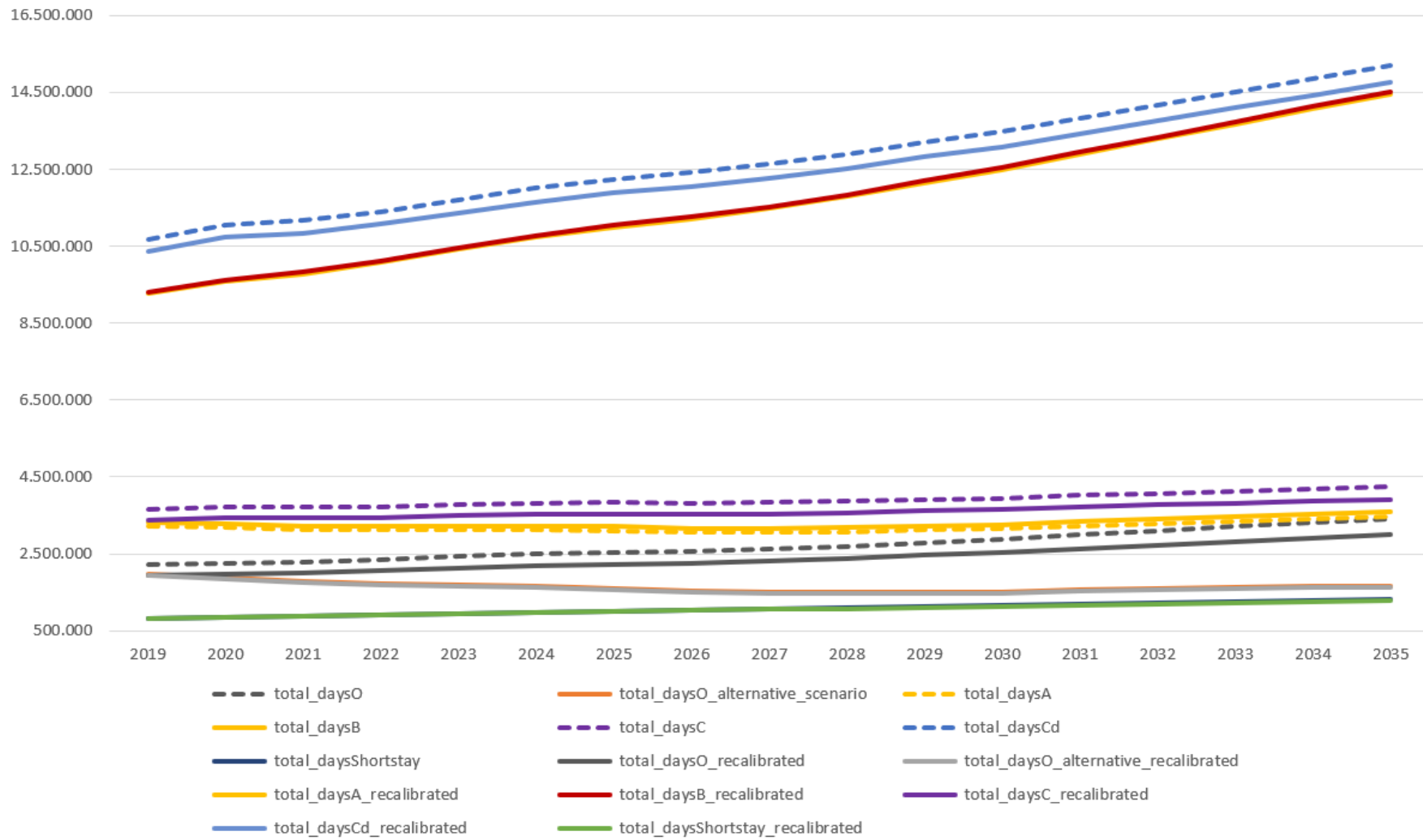


Figure 34 Reference simulation for total days in each residential care category before and after recalibration for year 2019

### 3 Reference simulation for the costs of residential care

In this section we calculate the costs of residential care for the period 2019-2035. As stated before, we did not estimate a model to explain the development of costs, because we did not have the necessary data to do so and, moreover, it seemed better to treat unit costs as a policy variable. We therefore simulated the future with the unit costs for the reference year 2017 kept constant until 2035. This also means that our cost projections are in constant prices and do not consider the future inflation.

Table 41 shows the unit costs used, based on the VAZG data for 2017. For the categories O and A this is the direct cost from the ROB classification, but for the more severe care categories B, C and Cd, we calculated a weighted average of ROB and RVT costs. The same weighted type of calculation was applied for the category short stay. These weighted averages are not perfect and the projections below should therefore be seen as approximations, the more so because we make the implicit assumption that the relative weight ROB/RVT will remain the same in the future. Note, however, that we will show in section 7 how to introduce other assumptions about the costs in the simulation results.

Table 42 and figure 35 show the development of the total costs over time and the distribution of this total over the different care categories. For obvious reasons, we believe that these are the most interesting results. As announced in the previous section, we only show the results with the so-called alternative scenario for category O.

Table 41 Costs in each residential care category – reference year 2017

Year	Costs in category O	Costs in category A	Costs in category B	Costs in category C	Costs in category Cd	Costs in category Short stay
2017	3.08	17.34	66.45	74.19	74.46	45.46



Table 42 Total costs for the reference simulation in each residential care category with recalibration on the real data from the VAZG for 2019.

Year	Total costs in category O	Total costs in category A	Total costs in category B	Total costs in category C	Total costs in category Cd	Total costs in category Short stay	Total costs in residential care after recalibration
2019	5 987 070	57 568 072	618 950 253	250 530 430	771 245 064	36 516 381	1 740 797 271
2020	5 651 730	56 789 995	638 599 900	255 577 420	800 048 775	38 336 192	1 795 004 013
2021	5 392 063	55 975 347	652 917 981	254 152 792	807 721 251	39 537 949	1 815 697 383
2022	5 229 356	55 805 165	672 563 656	255 744 065	824 516 723	40 995 442	1 854 854 407
2023	5 114 310	55 936 228	694 887 219	259 076 115	846 947 436	42 592 437	1 904 553 747
2024	5 001 217	55 985 281	716 167 613	261 831 739	868 081 493	44 107 042	1 951 174 385
2025	4 840 777	55 617 477	734 086 260	262 998 897	885 240 767	45 485 770	1 988 269 948
2026	4 645 121	54 895 283	748 581 994	262 552 389	898 060 114	46 683 636	2 015 418 537
2027	4 525 164	54 640 530	765 846 697	263 172 309	913 546 013	47 930 591	2 049 661 305
2028	4 504 595	55 047 245	787 191 956	265 452 160	933 103 532	49 241 036	2 094 540 524
2029	4 536 035	55 764 941	810 264 339	268 393 072	954 283 887	50 571 373	2 143 813 647
2030	4 581 627	56 527 449	833 066 105	271 135 111	974 787 169	51 846 552	2 191 944 013
2031	4 696 125	57 804 132	860 017 677	275 570 684	1 000 061 137	53 290 567	2 251 440 322
2032	4 792 886	58 938 697	886 241 458	279 579 394	1 024 668 739	54 734 770	2 308 955 944
2033	4 889 526	60 062 916	912 707 475	283 588 421	1 049 680 570	56 207 379	2 367 136 288
2034	4 979 833	61 121 588	938 847 784	287 355 883	1 074 343 043	57 685 411	2 424 333 542
2035	5 064 613	62 131 646	964 683 242	290 911 711	1 098 734 485	59 139 656	2 480 665 353

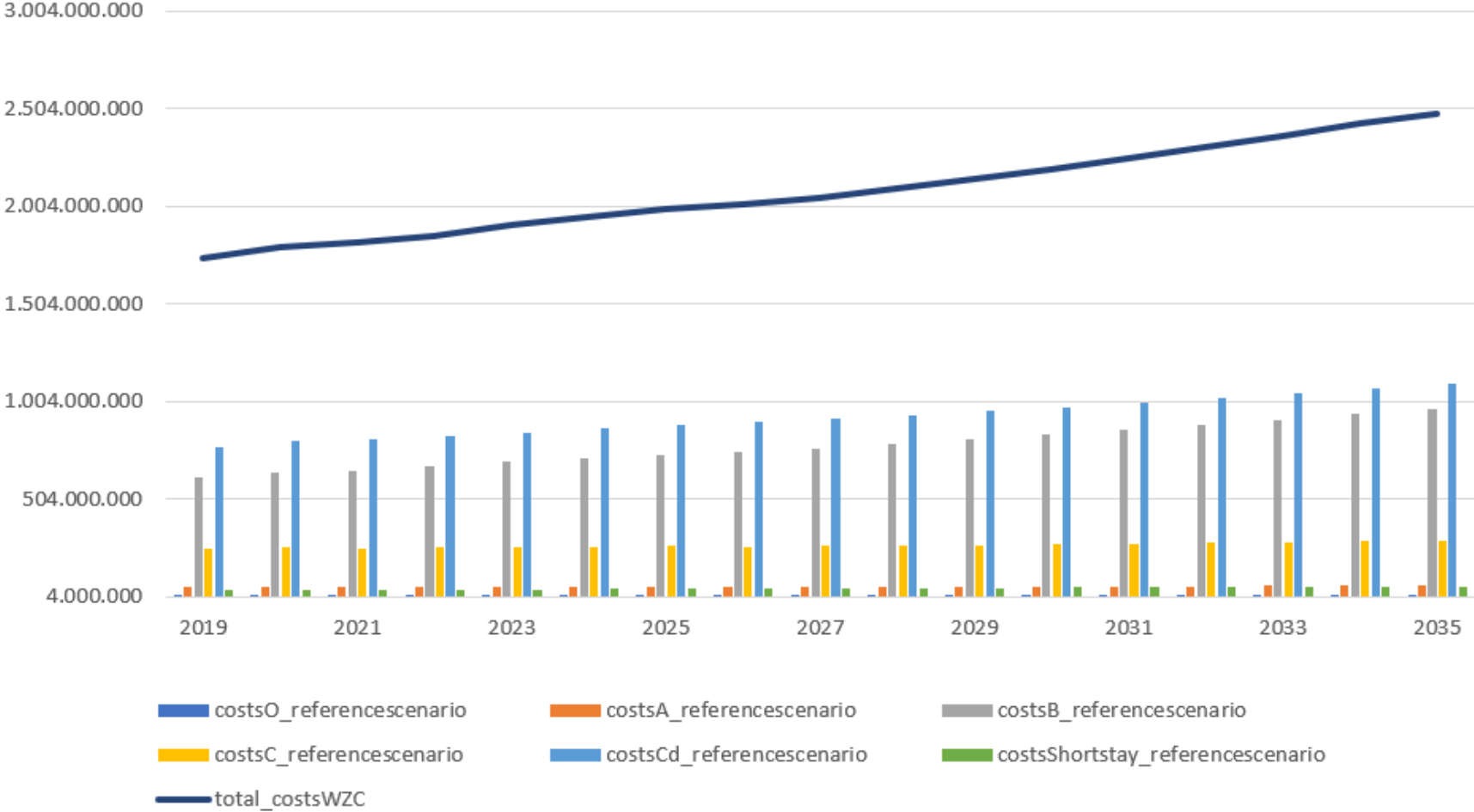


Figure 35 Reference simulation for total days in each residential care category with recalibration for the year 2019

#### 4 Reference simulation for home care services

The following simulations show the forecasts of the number of home nursing tasks and the number of hours of social care and logistic help for the years 2019 until 2035. Similar to the previous simulations, we applied the coefficients of the chosen OLS models to the trends in the explanatory variables for each year and the shares of the age/gender groups from the Statbel projections. We first show the "raw" projections, starting in 2018, and then the projections in which we recalibrated the results to start at the same level as the values from the official source VAZG. We show separate figures for home nursing and for social care, because the units in which these variables are measured are different, and putting them in the same figure could invite interpretations which are not acceptable. The results point to an increase in the use of home nursing and social care and to a slight decrease in the use of logistic help.

Table 43 Reference simulation for total tasks of nursing care, social care and logistic help at home.

Year	Total nursing tasks at home	Total hours social care	Total hours logistic help
2017	35 868 727	15 948 492	4 452 273
2018	36 685 362	16 359 259	4 386 434
2019	37 462 332	16 861 769	4 356 706
2020	38 145 840	17 292 613	4 283 399
2021	38 709 563	17 666 706	4 216 819
2022	39 478 303	18 148 848	4 180 197
2023	40 344 063	18 677 481	4 152 330
2024	41 172 879	19 187 386	4 118 589
2025	41 897 770	19 642 436	4 070 924
2026	42 527 517	20 045 714	4 011 304
2027	43 266 362	20 499 887	3 961 496
2028	44 137 797	21 022 327	3 923 887
2029	45 081 726	21 577 921	3 893 365
2030	46 028 320	22 127 410	3 859 832
2031	47 094 966	22 741 298	3 836 923
2032	48 138 030	23 340 286	3 809 549
2033	49 184 182	23 938 108	3 780 274
2034	50 232 785	24 534 773	3 750 521
2035	51 249 651	25 114 430	3 714 216

Table 44 Reference simulation for total tasks of nursing care at home and for total hours social care and logistic help with recalibration on the real data from the VAZG (social care and logistic help) and RIZIV (nursing tasks) for 2019.

<b>Year</b>	<b>Total nursing tasks at home</b>	<b>Total hours social care</b>	<b>Total hours logistic help</b>
2019	36 274 145	16 252 556	4 446 528
2020	36 935 974	16 667 833	4 371 710
2021	37 481 817	17 028 410	4 303 758
2022	38 226 175	17 493 133	4 266 380
2023	39 064 476	18 002 667	4 237 939
2024	39 867 005	18 494 149	4 203 502
2025	40 568 905	18 932 757	4 154 854
2026	41 178 678	19 321 466	4 094 005
2027	41 894 089	19 759 229	4 043 170
2028	42 737 885	20 262 793	4 004 786
2029	43 651 875	20 798 314	3 973 635
2030	44 568 446	21 327 950	3 939 411
2031	45 601 262	21 919 658	3 916 029
2032	46 611 243	22 497 005	3 888 091
2033	47 624 214	23 073 228	3 858 212
2034	48 639 559	23 648 336	3 827 845
2035	49 624 173	24 207 049	3 790 792

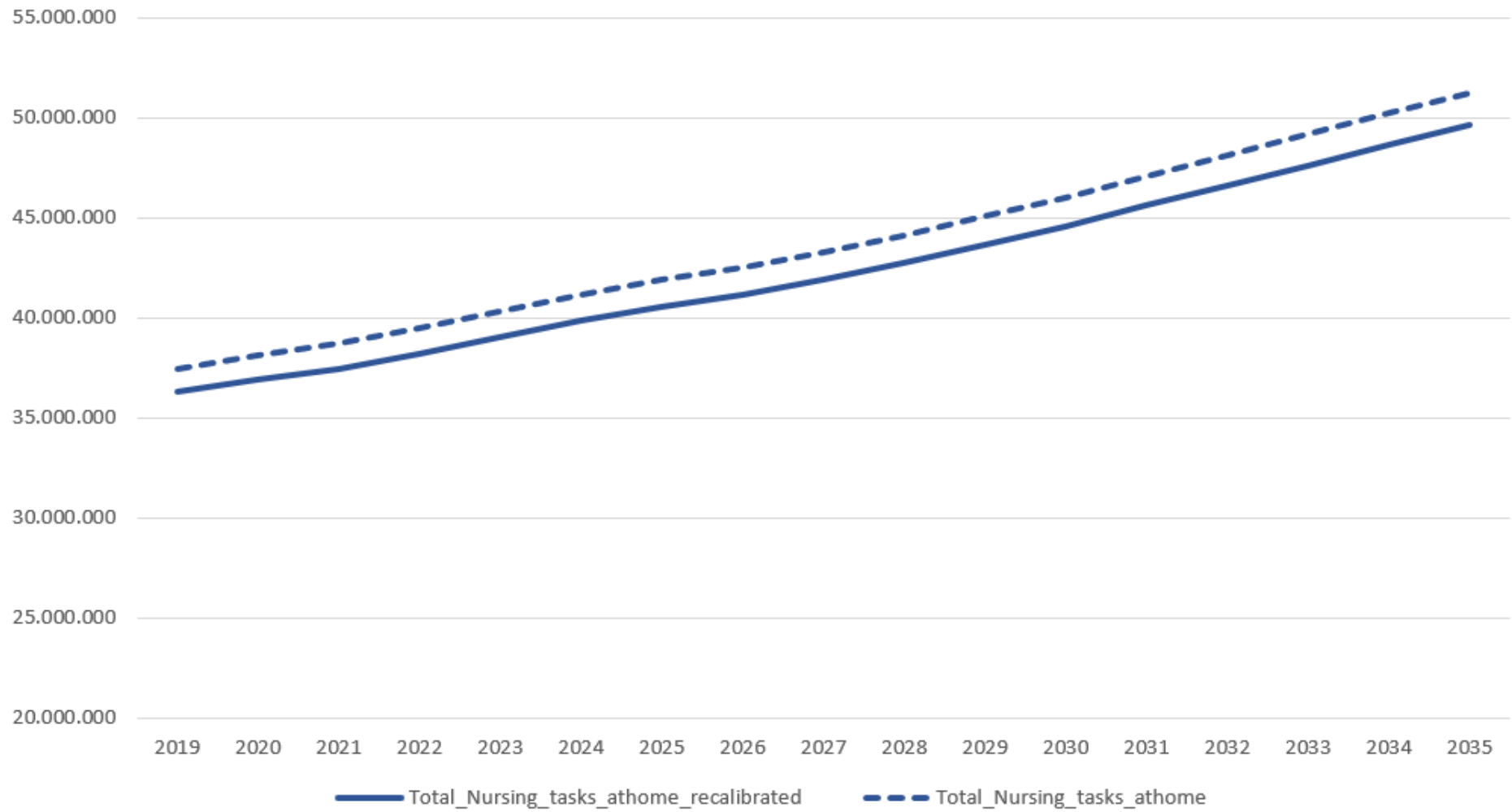


Figure 36 Reference simulation for total nursing tasks at home before and after recalibration

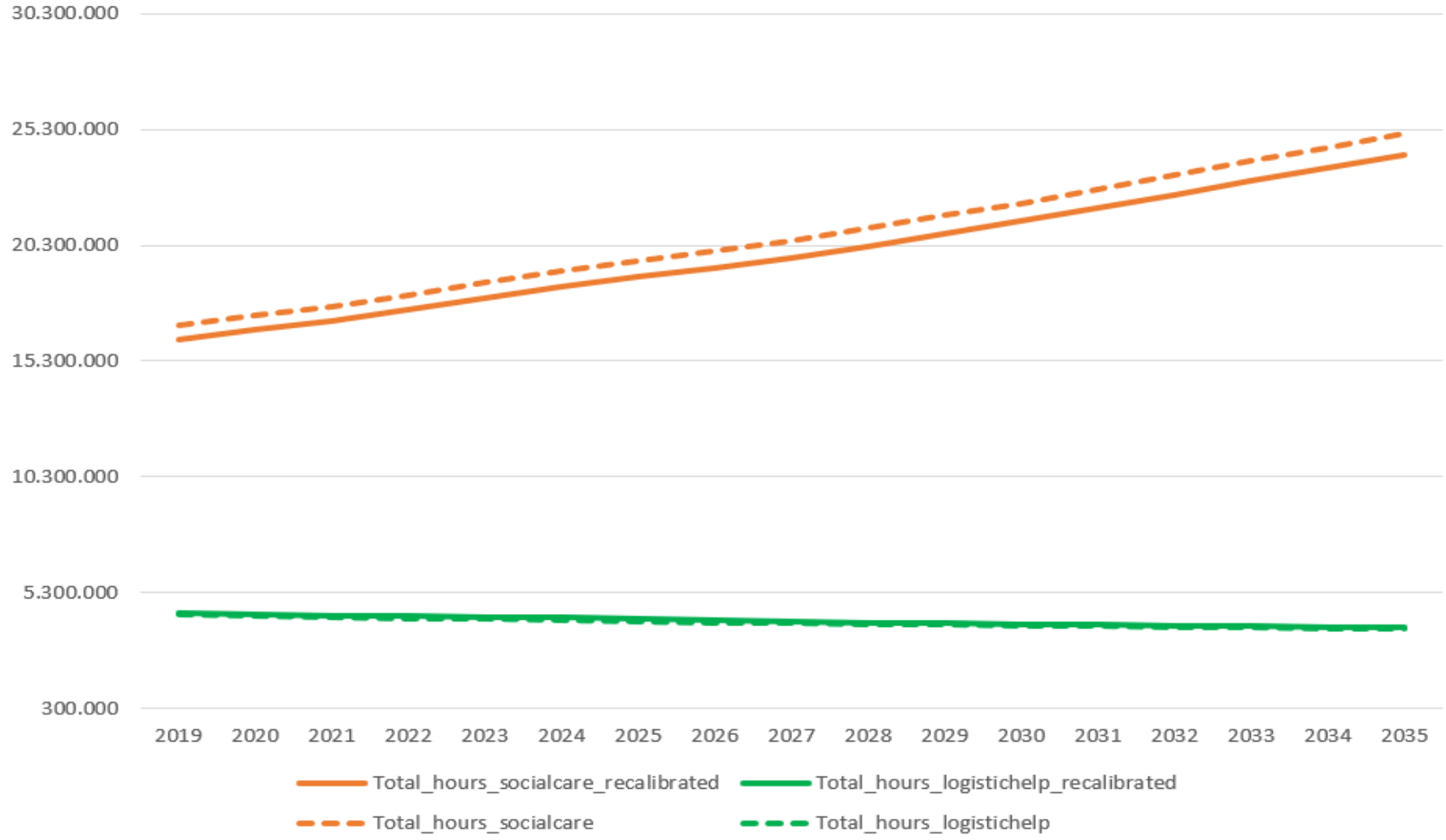


Figure 37 Reference simulation for total hours social care and logistic help at home before and after recalibration

## 5 Reference simulation for the costs of home care

For the simulations of the cost of home care, we follow the same procedure as for the costs of residential care, i.e. we take the unit cost from a recent source and then keep it constant over the complete projection period. Table 45 shows unit costs for 2017-2019. We will use in the projections the 2019 cost. For nursing, only the reimbursed costs by the RIZIV were used, as provided by the Actuarial Department of the RIZIV. The costs for social care and logistic help were provided by the VAZG and consist of all costs covered by the Flemish Administration, such as personnel costs, transportation costs, training and subsidies.

Table 45 Costs for home care services.

Year	Nursing costs (only reimbursed costs from RIZIV)	Social care costs (bron: VAZG)	Logistic help costs (bron: VAZG)
2017	19.40	33.73	25.51
2018	20.07	34.56	26.40
2019	20.80	35.45	27.12

Table 46 and figure 38 show the development of the home care costs in total and of the costs for the different subcategories after recalibration of the projections to the level of the official 2019 use data. As home nursing is financed at the Federal level and therefore is not part of the Flemish Social Protection scheme, we included in table 46 an additional column with the total costs without home nursing, i.e. the sum of the costs for social care and for logistic help.

Table 46 Reference simulation for total costs of home care services for the reference simulation after recalibration for 2019. Total costs and costs for Flemish Social Protection.

Year	Total costs for nursing tasks at home	Total costs for social care	Total costs for logistic help	Total costs home care services	Total cost for Flemish Social Protection – only social care and logistic help
2019	754 502 216	576 153 110	120 589 839	1 451 245 166	696 742 950
2020	768 268 266	590 874 684	118 560 765	1 477 703 716	709 435 449
2021	779 621 801	603 657 151	116 717 906	1 499 996 857	720 375 056
2022	795 104 439	620 131 567	115 704 231	1 530 940 236	735 835 798
2023	812 541 101	638 194 539	114 932 904	1 565 668 544	753 127 443
2024	829 233 708	655 617 578	113 998 988	1 598 850 274	769 616 566
2025	843 833 223	671 166 250	112 679 643	1 627 679 116	783 845 893
2026	856 516 510	684 945 964	111 029 411	1 652 491 885	795 975 375
2027	871 397 050	700 464 663	109 650 777	1 681 512 490	810 115 439
2028	888 948 006	718 316 018	108 609 798	1 715 873 823	826 925 817

2029	907 959 001	737 300 225	107 764 976	1 753 024 202	845 065 201
2030	927 023 679	756 075 840	106 836 824	1 789 936 343	862 912 664
2031	948 506 241	777 051 880	106 202 710	1 831 760 831	883 254 590
2032	969 513 855	797 518 822	105 445 023	1 872 477 699	902 963 844
2033	990 583 661	817 945 933	104 634 715	1 913 164 309	922 580 648
2034	1 011 702 834	838 333 506	103 811 165	1 953 847 504	942 144 670
2035	1 032 182 802	858 139 902	102 806 292	1 993 128 996	960 946 194



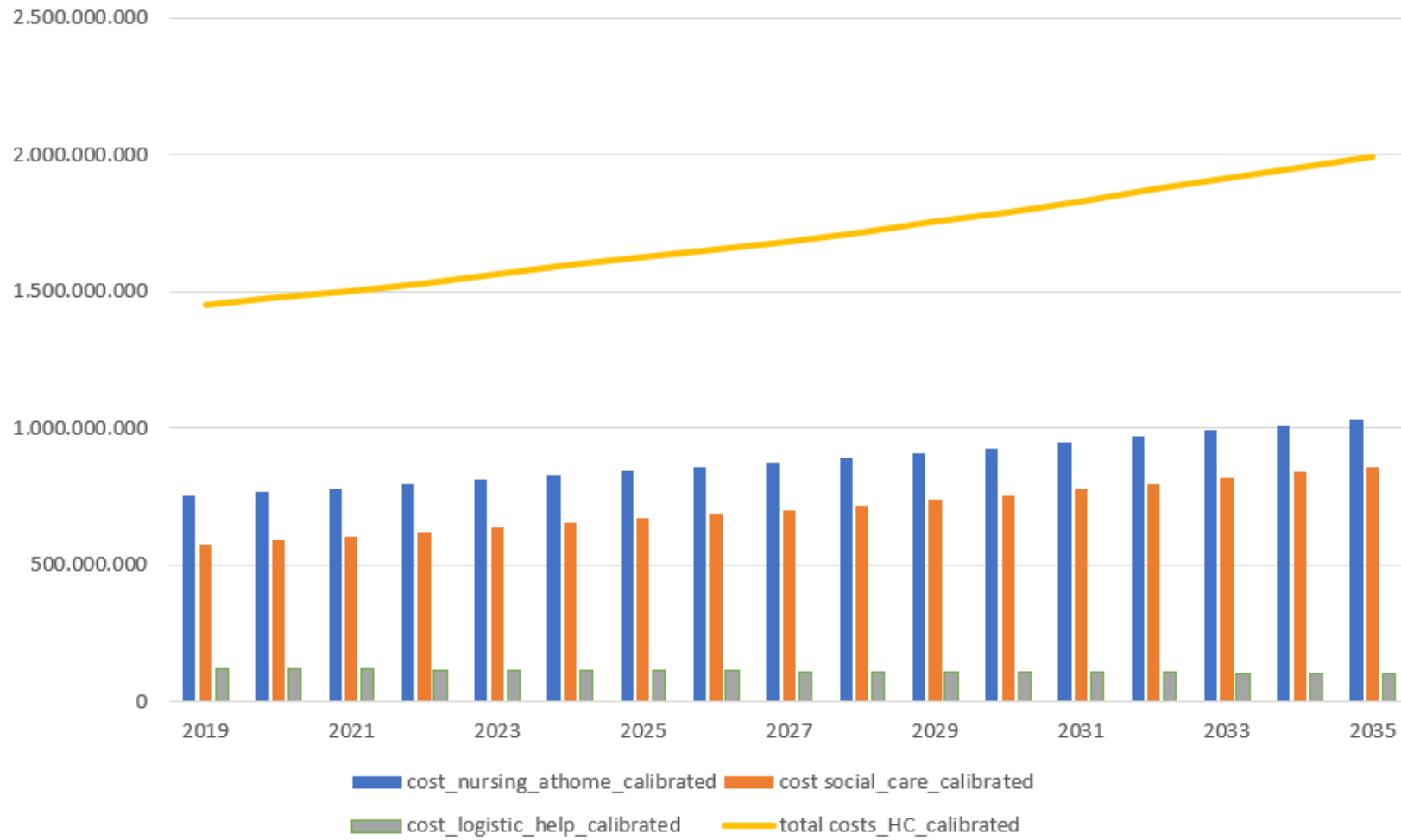


Figure 38 Total costs for the reference simulation for home care (HC) services after recalibration.



## Chapter 6

### Alternative projections

We will now turn to projections with some alternative scenarios. There is of course an infinity of possible scenarios, as one can play with the extrapolations for all the explanatory variables. If this is deemed interesting, one can even calculate scenarios with the coefficients in the regression model fixed at different values than the ones that were estimated. A huge advantage of the fact that we opted for the simple pooled model – and one of the main arguments for our choice – is that running such simulations is technically not difficult.

In this section we illustrate the working of the simulation model for two alternative scenarios: a scenario which only considers demographic changes and one in which we assume that the availability of informal care does not decrease. We first show the projections for the residential care categories and then for home care. In each case, the reference scenario is the one in which the use data are recalibrated to the levels of the official data for 2019.

It is possible, even likely, that the experience with covid-19 will lead to deeper changes in the organization of the care sector and in the behavior of the potential users. At this stage, we have neither the knowledge nor the data to simulate these structural changes. The consequences of the change in the demographic composition of the population can be analyzed through a comparison between the results with the old pre-covid and the new demographic projections. The changes in the demographic composition are not large enough to lead to substantial changes in the projections, however. We therefore did not include them in the report, but results are available on request. All the simulations presented in this section are with the most recent Statbel data, that take into account already the recent excess mortality, mainly among the aged, as a result of the pandemic.

#### **1 Simulation of residential care with the demographic scenario**

In the reference scenario that was presented in the previous section, the extrapolation of the different explanatory variables was based on their evolution in the past. As an example, the population shares of low-income earners and of persons with a potential informal carer decreased over time, while the population share of persons with Alzheimer's increased. Many simpler projection models only consider information about future demographic changes. To get an idea about the "joint" effect of all the explanatory variables in our model in comparison to a more primitive approach which only considers demographics, we simulate a so-called "demographic scenario" in which all explanatory variables grow at the same rate as the population of 55 and older in the Statbel demographic projection. This basically means that all the proportions referred to earlier remain constant.

Table 47 Simulation with the recalibrated demographic scenario for total days in each residential care category.

Year	Total days in category O - demographic scenario	Total days in category A- demographic scenario	Total days in category B- demographic scenario	Total days in category C- demographic scenario	Total days in category Cd- demographic scenario	Total days in category Short stay- demographic scenario
2019	1 943 854	3 319 958	9 314 526	3 376 876	10 357 844	803 264
2020	1 813 794	3 254 869	9 567 548	3 427 651	10 702 397	843 222
2021	1 708 497	3 187 858	9 740 731	3 391 355	10 763 546	869 585
2022	1 634 810	3 158 136	9 994 345	3 395 813	10 947 473	901 574
2023	1 576 697	3 145 882	10 288 459	3 423 817	11 207 280	936 633
2024	1 519 378	3 129 050	10 567 198	3 444 182	11 449 994	969 879
2025	1 446 805	3 088 292	10 795 585	3 443 233	11 639 562	1 000 137
2026	1 363 061	3 027 346	10 972 989	3 420 746	11 771 367	1 026 417
2027	1 304 231	2 993 680	11 192 745	3 412 910	11 939 661	1 053 778
2028	1 278 124	2 998 594	11 474 821	3 427 816	12 163 539	1 082 538
2029	1 269 299	3 021 820	11 783 686	3 451 955	12 410 004	1 111 736
2030	1 265 513	3 048 054	12 089 374	3 473 776	12 648 262	1 139 723
2031	1 284 218	3 104 054	12 457 751	3 518 520	12 950 827	1 171 424
2032	1 297 237	3 151 928	12 815 323	3 557 570	13 244 589	1 203 129
2033	1 310 286	3 199 271	13 176 679	3 596 680	13 543 915	1 235 460
2034	1 321 373	3 242 923	13 533 323	3 632 611	13 838 740	1 267 910
2035	1 330 817	3 283 917	13 885 686	3 665 813	14 130 227	1 299 837

The results for this demographic scenario are shown in table 47 and figure 39. In the figure the full lines refer to the reference scenario, the dotted lines to the demographic scenario. It is clear that the additional explanatory variables in the reference scenario overall lead to an increase in the number of days of residential care, more specifically for categories A and B. Looking only at demographic developments could suggest a too low projection for the residential care needs in the future. As we will see in the following subsection, the decrease in the availability of informal care is an important driver of that result.

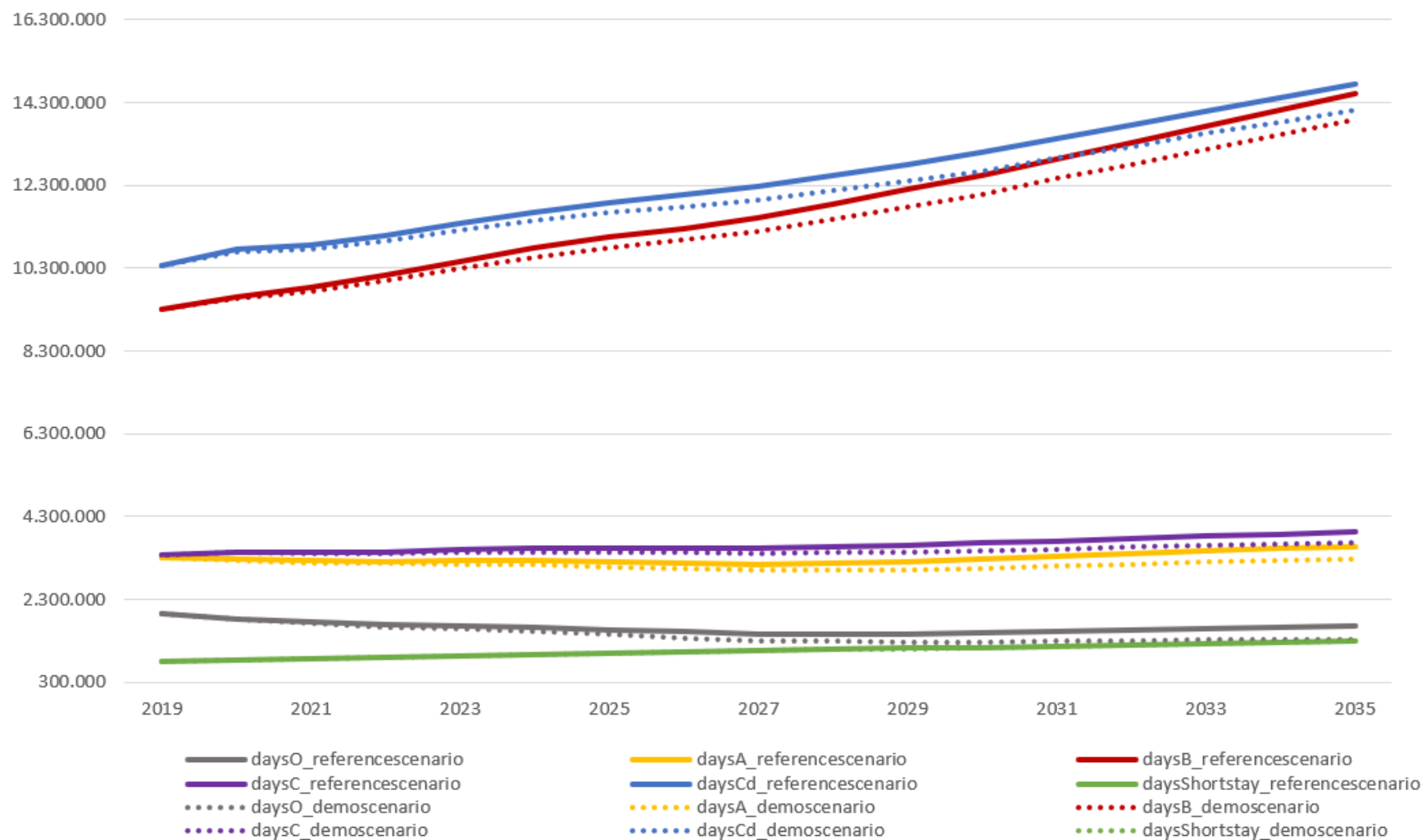


Figure 39 Comparison simulations from the recalibrated demographic scenario and the recalibrated reference scenario.

## 2 Simulation of residential care in the scenario of a constant availability of informal care

We now simulate a hypothetical scenario in which it is assumed that the availability of informal care does not change in the future, but remains until 2035 at the same rate as in the year 2019. All the other variables follow the extrapolated path that was used in the reference scenario. The results in table 48 and figure 40 are striking and show a significant effect. If informal care remained available in the future to the same extent as it is now, the use of residential care would be considerably lower. Of course, this result is not surprising in the light of the very significant negative effects that were estimated for the availability of informal care in the regression model (see chapter 4).

Table 48 Simulation with the recalibrated scenario of constant availability informal care for total days in each residential care category

Year	Total days in category O - constant informal care	Total days in category A- constant informal care	Total days in category B- constant informal care	Total days in category C- constant informal care	Total days in category Cd- constant informal care	Total days in category Short stay- constant informal care
2019	1 943 854	3 319 958	9 314 526	3 376 876	10 357 844	803 264
2020	1 812 139	3 248 883	9 562 838	3 426 469	10 701 243	841 834
2021	1 705 203	3 175 940	9 731 353	3 389 002	10 761 249	866 823
2022	1 629 886	3 140 322	9 980 329	3 392 298	10 944 039	897 446
2023	1 570 151	3 122 200	10 269 826	3 419 144	11 202 716	931 144
2024	1 511 222	3 099 548	10 543 985	3 438 360	11 444 307	963 041
2025	1 437 049	3 053 001	10 767 817	3 436 268	11 632 759	991 957
2026	1 351 725	2 986 341	10 940 725	3 412 654	11 763 464	1 016 913
2027	1 291 342	2 947 055	11 156 056	3 403 708	11 930 671	1 042 972
2028	1 263 717	2 946 478	11 433 812	3 417 530	12 153 492	1 070 458
2029	1 253 405	2 964 325	11 738 445	3 440 608	12 398 919	1 098 410
2030	1 248 167	2 985 305	12 039 999	3 461 392	12 636 164	1 125 179
2031	1 265 430	3 036 086	12 404 270	3 505 106	12 937 724	1 155 670
2032	1 277 011	3 078 760	12 757 751	3 543 130	13 230 483	1 186 170
2033	1 288 628	3 120 923	13 115 031	3 581 218	13 528 812	1 217 300
2034	1 298 290	3 159 422	13 467 620	3 616 132	13 822 643	1 248 556
2035	1 306 322	3 195 307	13 815 963	3 648 326	14 113 146	1 279 299

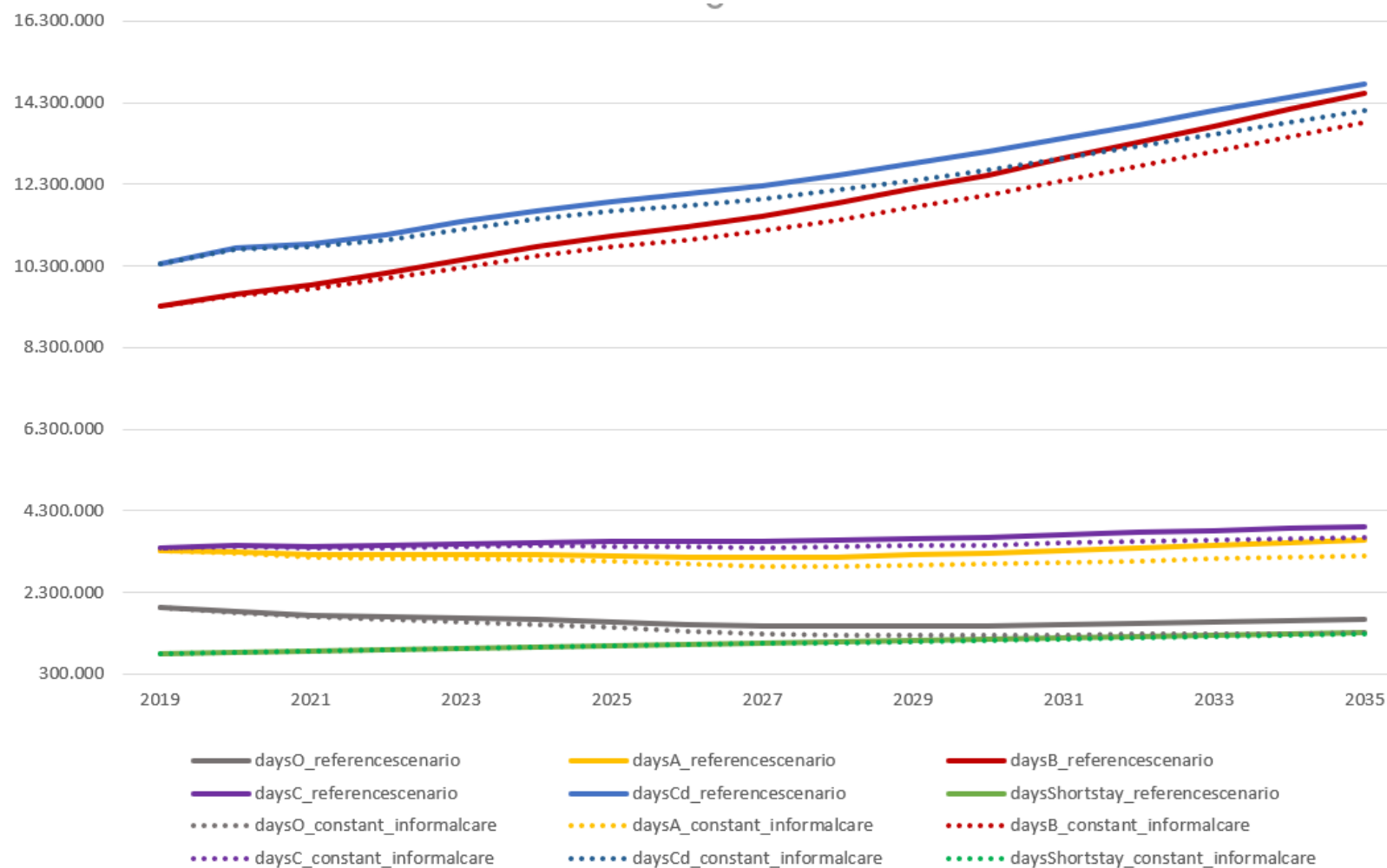


Figure 40 Comparison simulations from the recalibrated scenario of constant availability of informal care and the recalibrated reference scenario.

### 3 Simulation of home care in the demographic scenario

Let us now turn to the results of the same scenarios for home care. Table 49 and figures 41 and 42 show the projections with the demographic scenario, in which all explanatory variables grow at the demographic rate of the Statbel projections for the population of 18 or older. As for residential care, this demographic scenario leads to an underestimate of the future use of home care, when compared to the reference scenario.

Table 49 Simulation with the demographic scenario for total nursing tasks and total hours of social care and logistic help.

Year	Total nursing tasks at home - demographic scenario	Total hours social care - demographic scenario	Total hours logistic help - demographic scenario
2019	36 274 145	16 252 556	4 446 528
2020	36 582 384	16 437 029	4 308 142
2021	36 776 677	16 568 134	4 176 990
2022	37 168 868	16 802 991	4 076 305
2023	37 654 609	17 082 393	3 984 482
2024	38 104 221	17 343 511	3 886 600
2025	38 453 131	17 551 717	3 774 495
2026	38 709 083	17 709 471	3 650 037
2027	39 071 815	17 917 026	3 535 800
2028	39 562 809	18 190 310	3 433 994
2029	40 124 909	18 496 135	3 339 581
2030	40 690 723	18 796 818	3 242 300
2031	41 374 422	19 160 651	3 156 158
2032	42 036 177	19 510 695	3 065 617
2033	42 703 569	19 861 343	2 973 612
2034	43 374 565	20 211 688	2 881 342
2035	44 018 123	20 547 779	2 782 975



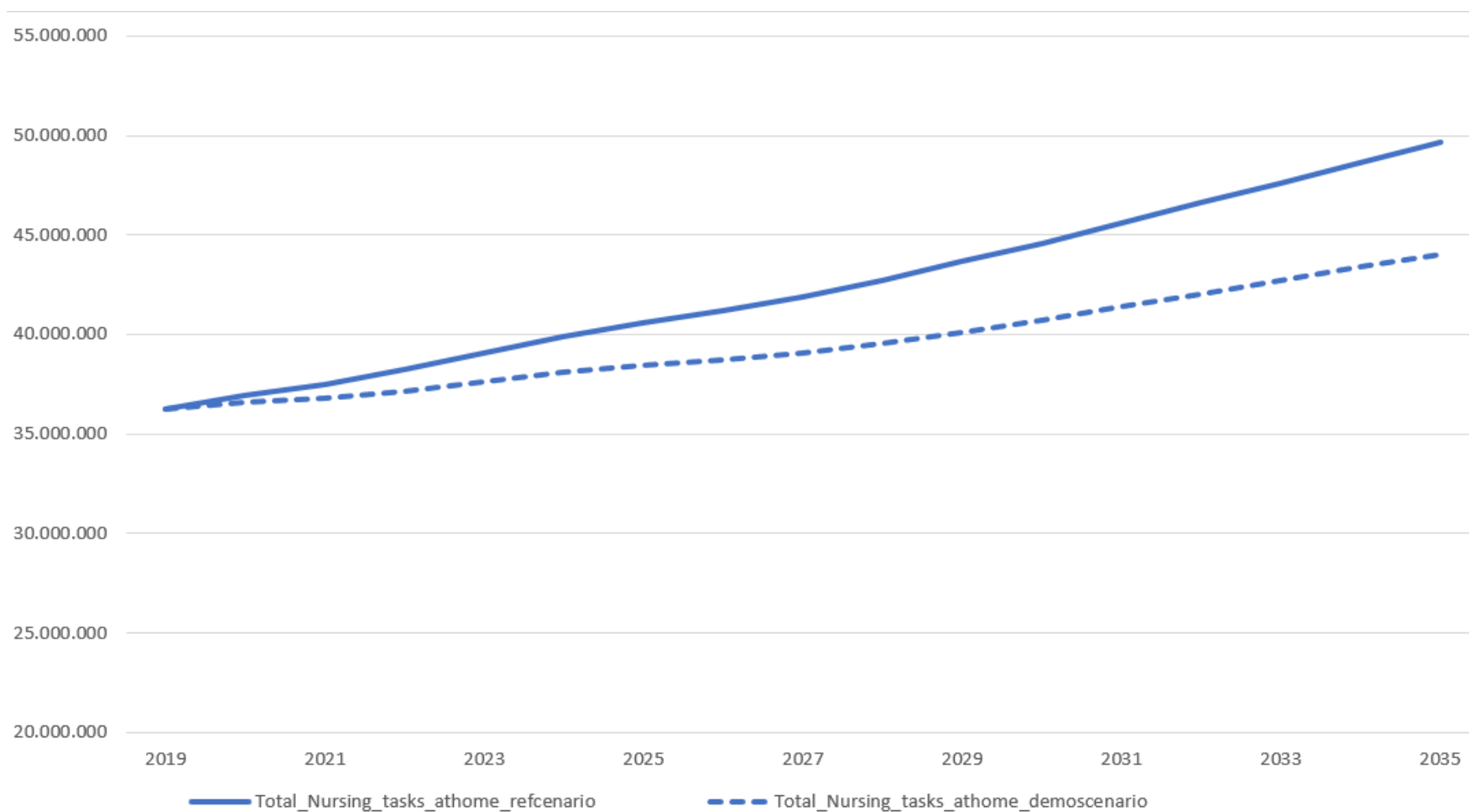


Figure 41 Comparison simulations from recalibrated demographic scenario and recalibrated reference scenario for nursing tasks at home.

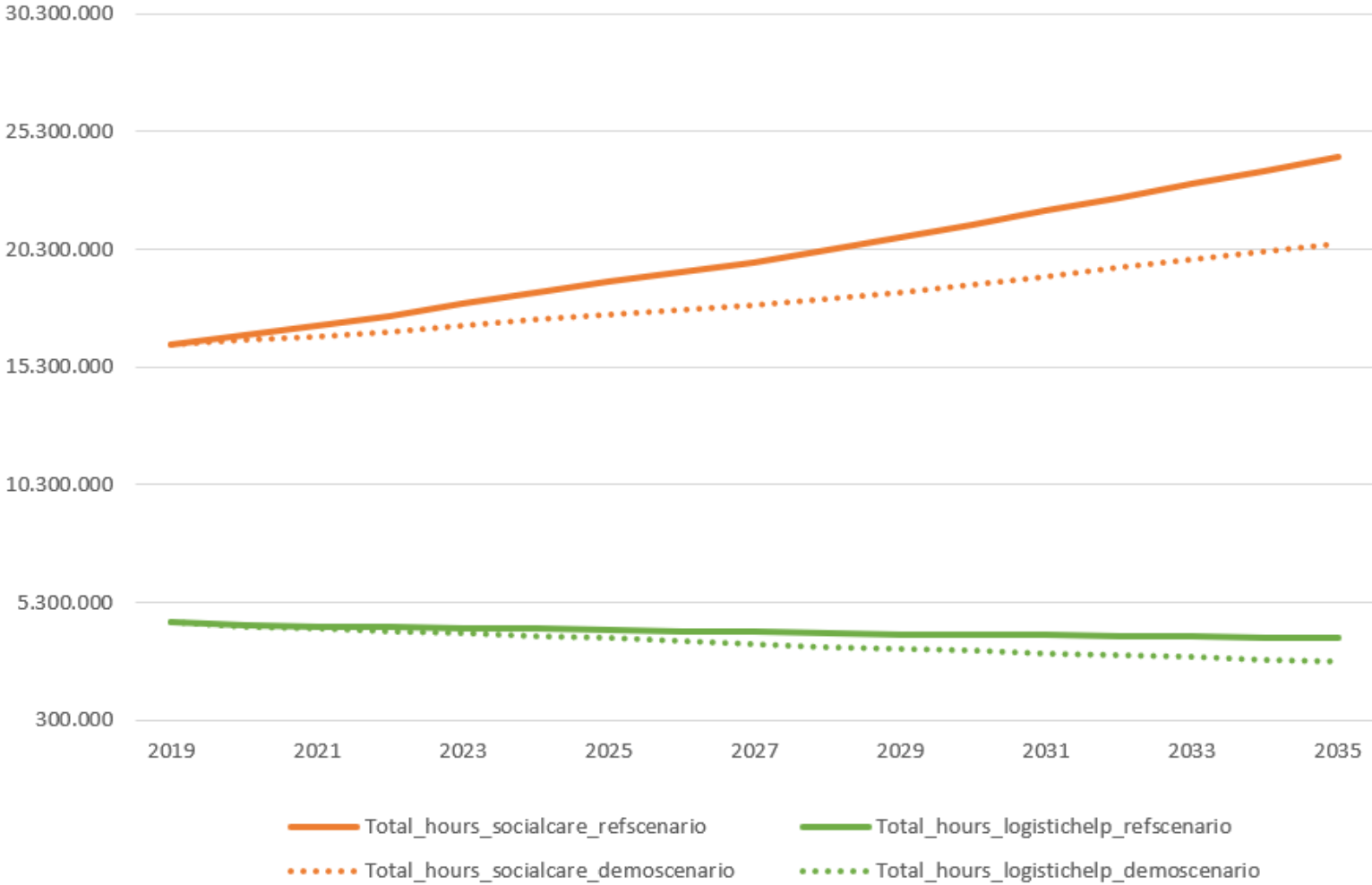


Figure 42 Comparison simulations from recalibrated demographic scenario and recalibrated reference scenario for social care and logistic help at home.

#### 4 Simulation of home care in the scenario of a constant availability of informal care

In the case of residential care, the assumption of constant availability of informal care, had large effects on the projections. As table 50 and figures 43 and 44 show, these effects are also strong for social care and nursing care at home. There can be no doubt that the future availability of informal care is one of the main drivers of the increase in all categories of formal care.

Table 50 Simulation with the scenario of constant availability informal care for total nursing tasks and total hours of social care and logistic help.

Year	Total nursing tasks at home - constant informal care	Total hours social care - constant informal care	Total hours logistic help - constant informal care
2019	36 274 145	16 252 556	4 446 528
2020	36 898 041	16 579 954	4 340 867
2021	37 406 171	16 853 159	4 242 250
2022	38 112 753	17 230 368	4 174 158
2023	38 913 232	17 652 277	4 114 964
2024	39 677 901	18 056 049	4 049 744
2025	40 341 937	18 406 939	3 970 309
2026	40 913 753	18 707 711	3 878 597
2027	41 591 329	19 057 822	3 796 999
2028	42 397 282	19 473 715	3 727 845
2029	43 273 521	19 921 778	3 665 999
2030	44 152 464	20 364 240	3 601 180
2031	45 147 832	20 869 193	3 547 350
2032	46 120 455	21 359 993	3 489 037
2033	47 096 353	21 850 328	3 429 014
2034	48 074 762	22 339 865	3 368 615
2035	49 022 788	22 813 814	3 301 812

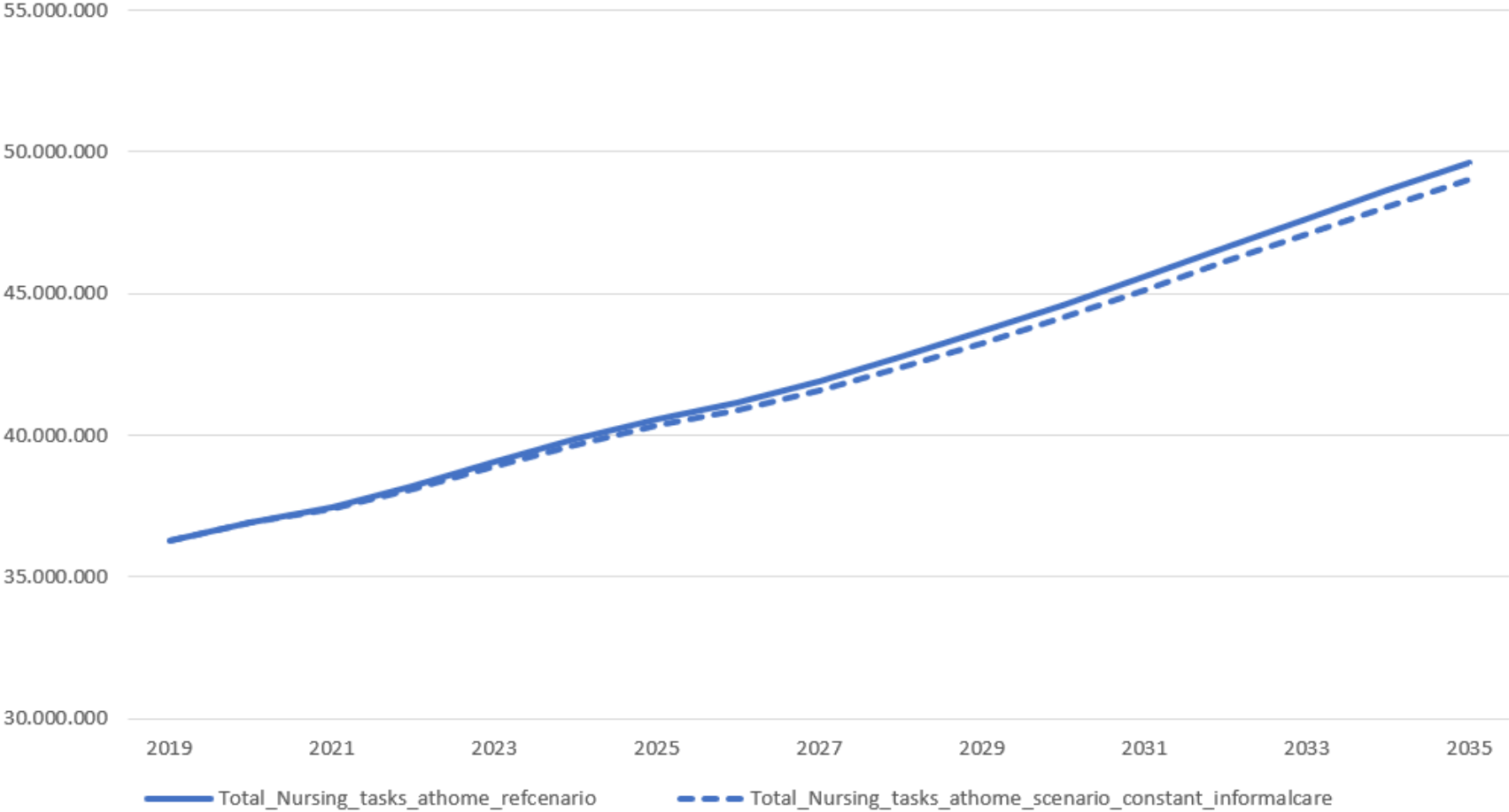


Figure 43 Comparison simulations from the recalibrated scenario with constant availability of informal care and the recalibrated reference scenario for nursing tasks at home.

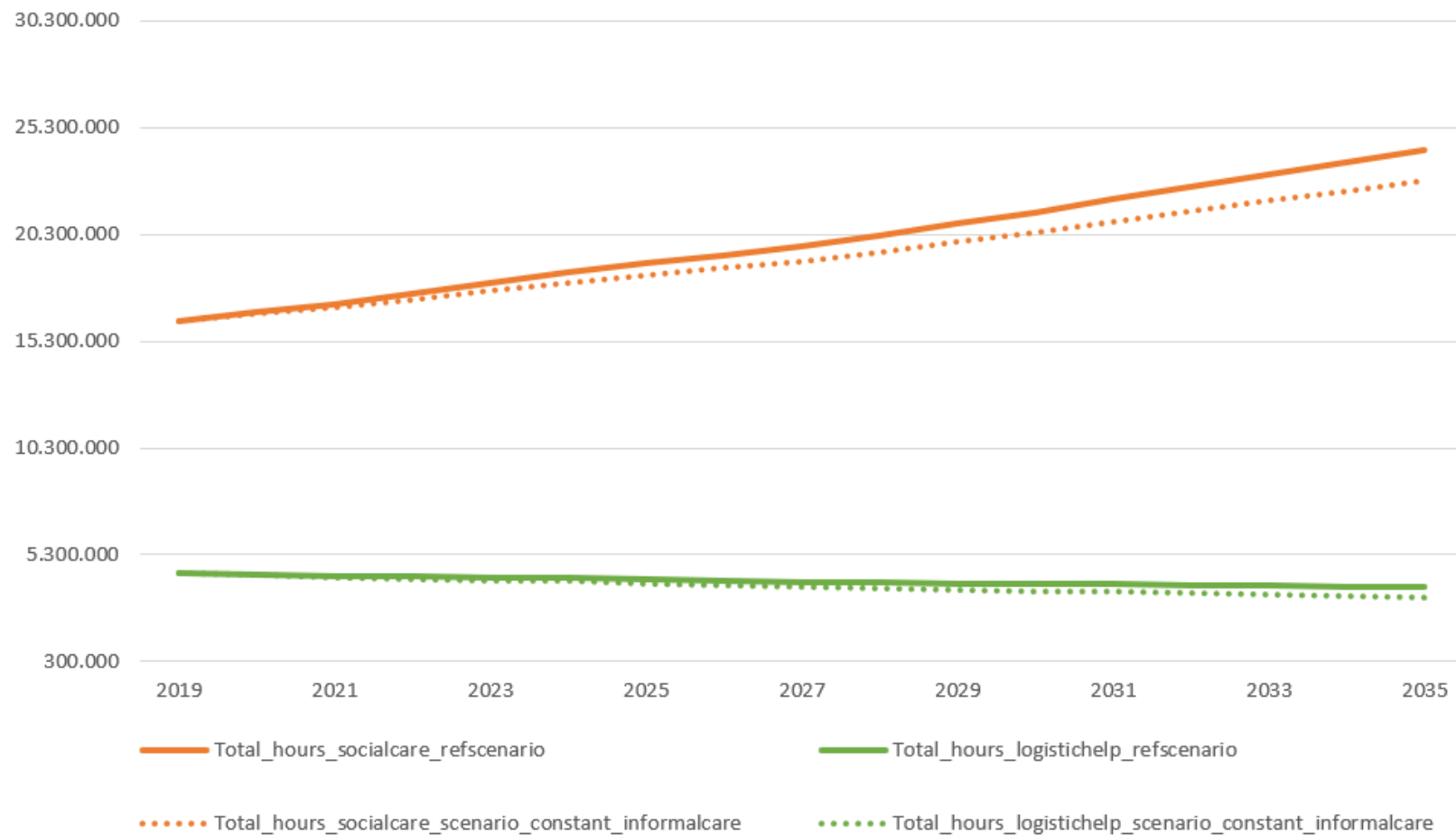


Figure 44 Comparison simulations from the recalibrated scenario with constant availability of informal care and the recalibrated reference scenario for social care and logistic help at home.



## Chapter 7

### Policy simulations

In section 6 we have discussed the results of some counterfactual simulations. The main interest of these counterfactuals lies in their contribution to a better understanding of the relative importance and the interactions between the different explanatory variables. For the policy makers it is perhaps more interesting to simulate the changes induced by policy measures. Again, there is a wide range of possibilities here. We discuss the effects of an increase in the supply of social care, of an increase in the personnel norms and of the conversion of ROB beds into RVT beds in residential care. All these policies have been discussed already by policy makers or are already in the course of implementation.

#### **1 Simulation with the scenario of increase of supply of social care with 2.0%.**

Table 51 shows the results of the simulations when the Flemish government would decide to increase the supply of social care with 2.0% per year, starting in 2020. This action would have an impact on the use of residential care for the lower care categories, as is shown in figure 45. The number of days in categories O and A decreases. This is of course a direct consequence of the fact that the supply of social care had a negative and significant estimated coefficient in the regression model for categories O and A.

This is a good place to repeat that this simulation calls for a cautious interpretation. We have mentioned in our description of the variables in section 2 that the regional variation in the amount of social care is likely to capture not only supply effects, but also other features of the regions. Even more than for some other variables, it is dangerous to ascribe causal value to the strong and significant effect found. The results in this section should therefore be seen as an illustration. While one can be confident that the direction of the effect of an increase in the supply of social care is a robust finding, the numerical magnitude of the effect is less reliable.

Table 51 Simulation of the recalibrated scenario of increase of supply of social care hours with 2.0% per year for total days in each residential care category

<b>Year</b>	<b>Total days in category O - increase social care with 2.0%</b>	<b>Total days in category A- increase social care with 2.0%</b>	<b>Total days in category B- increase social care with 2.0%</b>	<b>Total days in category C- increase social care with 2.0%</b>	<b>Total days in category Cd- increase social care with 2.0%</b>	<b>Total days in category Short stay- increase social care with 2.0%</b>
2019	1 943 854	3 319 958	9 314 526	3 376 876	10 357 844	803 264
2020	1 815 867	3 261 675	9 610 232	3 444 904	10 744 679	842 662
2021	1 685 386	3 182 293	9 825 703	3 425 701	10 847 720	867 566
2022	1 587 984	3 141 197	10 121 349	3 447 150	11 073 284	898 150
2023	1 505 546	3 117 117	10 457 294	3 492 062	11 374 529	931 785
2024	1 418 577	3 084 682	10 777 541	3 529 205	11 658 360	963 437
2025	1 313 420	3 026 231	11 047 197	3 544 937	11 888 810	992 006
2026	1 188 567	2 941 545	11 265 342	3 538 919	12 060 974	1 016 323
2027	1 079 135	2 877 391	11 525 157	3 547 275	12 268 950	1 041 416
2028	991 146	2 843 786	11 846 380	3 578 005	12 531 608	1 067 547
2029	912 439	2 822 779	12 193 594	3 617 645	12 816 061	1 093 864
2030	830 428	2 798 814	12 536 736	3 654 605	13 091 420	1 118 705
2031	770 412	2 804 237	12 942 328	3 714 391	13 430 851	1 147 248
2032	704 141	2 801 115	13 336 967	3 768 424	13 761 331	1 175 779
2033	636 509	2 796 469	13 735 252	3 822 462	14 097 241	1 204 890
2034	564 292	2 786 269	14 128 635	3 873 243	14 428 459	1 234 037
2035	486 379	2 770 527	14 517 430	3 921 171	14 756 037	1 262 532



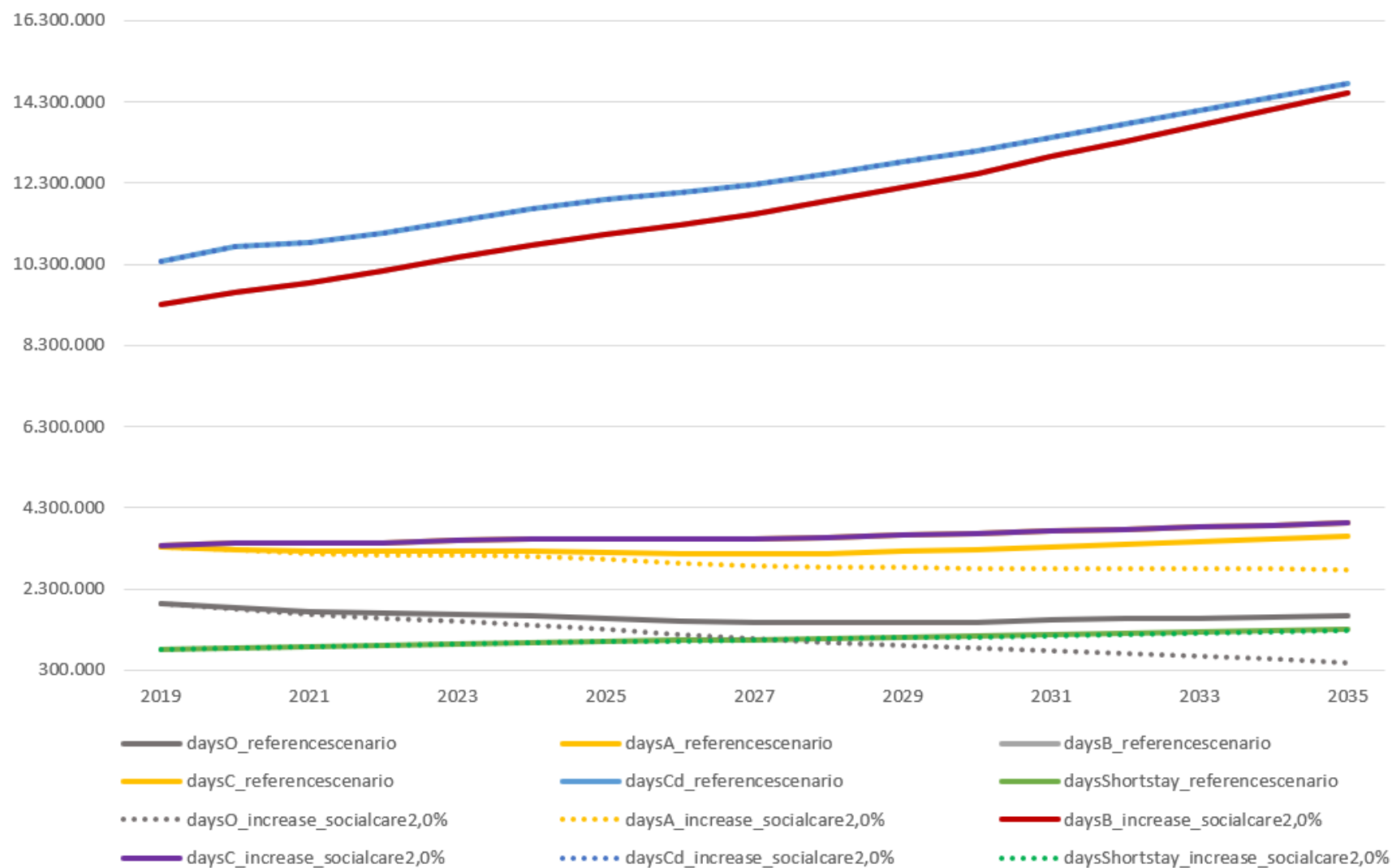


Figure 45 Comparison simulations from the recalibrated scenario of increase in social care of 2.0% per year and the recalibrated reference scenario

Table 52 shows the difference of costs in residential care between the reference scenario and the scenario with 2.0% increase in social care from the year 2020 on, as well as the cost of this increase in social care itself. The first column represents savings, as the increase in social care makes the days in the categories O, A and Short stay decrease, while the days in the other residential care categories remain unchanged. The second column represents the cost of the increase of 2.0% of social care and the third column shows the difference between both costs. Until 2032, this scenario brings an extra cost for the government, as the savings due to the decrease in residential care do not compensate the cost increase in social care. From the year 2033 on, there is a shift, and the savings in residential care surpass the costs of the increase in social care.

Table 52 Simulation of the recalibrated scenario of increase of supply of social care hours with 2.0% per year for total days in each residential care category

<b>Year</b>	<b>Difference of costs of residential care between the reference simulation and the simulation with 2.0% social care (savings in residential care)</b>	<b>Cost for the increase of 2.0% social care</b>	<b>Difference between costs (Extra cost social care – savings in residential care)</b>
2019	-	-	-
2020	320 204	11 523 062	11 202 858
2021	1 093 842	11 753 523	10 659 681
2022	1 840 719	11 988 594	10 147 875
2023	2 596 145	12 228 366	9 632 221
2024	3 438 106	12 472 933	9 034 828
2025	4 327 252	12 722 392	8 395 140
2026	5 354 821	12 976 840	7 622 018
2027	6 535 812	13 236 376	6 700 564
2028	7 898 194	13 501 104	5 602 910
2029	9 387 994	13 771 126	4 383 132
2030	11 010 146	14 046 549	3 036 403
2031	12 638 597	14 327 479	1 688 883
2032	14 275 378	14 614 029	338 651
2033	15 934 295	14 906 310	-1 027 985
2034	17 635 586	15 204 436	-2 431 150
2035	19 402 251	15 508 525	-3 893 726

## **2 Simulation with the scenario of 15% more norm personnel**

The Flemish government has recently decided to increase the financing of personnel "above norm" from 13,5% to 15%. The idea of this measure is of course to help the residential care organizations finance their workforce, after the pandemic had revealed that there were shortages. Because of data limitations, we cannot perfectly simulate the details of this measure, but we can approximate it fairly well. Table 53 and figure 46 show the results of a simulation in which the costs for "personnel above norm" (column C – cost from 2017, about 9.74% of norm personnel) are replaced by "personnel costs after conversion" (column E), amounting to 15% of the cost of the costs for norm personnel in column B. We assume that the conversion starts in 2020.

Table 53 Cost simulation for scenario of conversion for 15% more (norm) personnel from 2020 on, from recalibrated simulations.

Year	Material Costs (A)	Personnel Norm Costs (B)	Personnel above norm (C)	Harmonization Costs (D)	Personnel costs after conversion (Norm*0.15) (E)	Administration Costs (F)	Other costs (palliative and dementia subsidies) (G)	Total costs before conversion (A+B+C+D+F+G)	Total costs after conversion (A+B+D+E+F+G)
2019	18 020 151	1 495 648 687	146 333 573	12 377 180	146 333 573	40 813 851	31 044 925	1 744 238 368	1 744 238 368
2020	18 512 037	1 542 870 739	150 901 818	12 248 902	231 430 611	42 029 835	31 926 226	1 798 489 556	1 879 018 349
2021	18 673 715	1 561 014 209	152 645 860	12 090 983	234 152 131	42 496 400	32 266 012	1 819 187 179	1 900 693 450
2022	19 031 012	1 595 006 610	155 941 903	12 076 074	239 250 991	43 395 403	32 934 794	1 858 385 795	1 941 694 884
2023	19 499 167	1 638 064 389	160 124 454	12 130 591	245 709 658	44 539 335	33 788 493	1 908 146 429	1 993 731 634
2024	19 936 443	1 678 468 591	164 047 969	12 168 726	251 770 289	45 612 066	34 588 971	1 954 822 765	2 042 545 085
2025	20 272 840	1 710 712 925	167 171 107	12 119 884	256 606 939	46 459 201	35 216 758	1 991 952 715	2 081 388 547
2026	20 505 722	1 734 415 795	169 458 083	11 995 983	260 162 369	47 072 819	35 667 013	2 019 115 415	2 109 819 701
2027	20 818 046	1 764 152 062	172 340 238	11 969 770	264 622 809	47 858 967	36 252 917	2 053 391 999	2 145 674 570
2028	21 248 093	1 802 946 642	176 115 093	12 081 053	270 441 996	48 902 719	37 040 024	2 098 333 622	2 192 660 526
2029	21 727 939	1 845 472 311	180 258 474	12 257 269	276 820 847	50 053 899	37 911 988	2 147 681 879	2 244 244 252
2030	22 198 006	1 886 994 177	184 305 366	12 442 100	283 049 127	51 180 568	38 766 923	2 195 887 140	2 294 630 900
2031	22 789 296	1 938 244 988	189 307 037	12 735 693	290 736 748	52 577 374	39 829 800	2 255 484 188	2 356 913 900
2032	23 358 427	1 987 812 061	194 142 464	13 000 736	298 171 809	53 925 979	40 855 100	2 313 094 767	2 417 124 113
2033	23 933 858	2 037 956 945	199 033 836	13 264 802	305 693 542	55 289 574	41 891 581	2 371 370 596	2 478 030 302
2034	24 498 478	2 087 264 248	203 842 629	13 515 954	313 089 637	56 629 436	42 909 842	2 428 660 587	2 537 907 595
2035	25 053 678	2 135 832 440	208 578 755	13 757 240	320 374 866	57 948 730	43 912 101	2 485 082 943	2 596 879 054

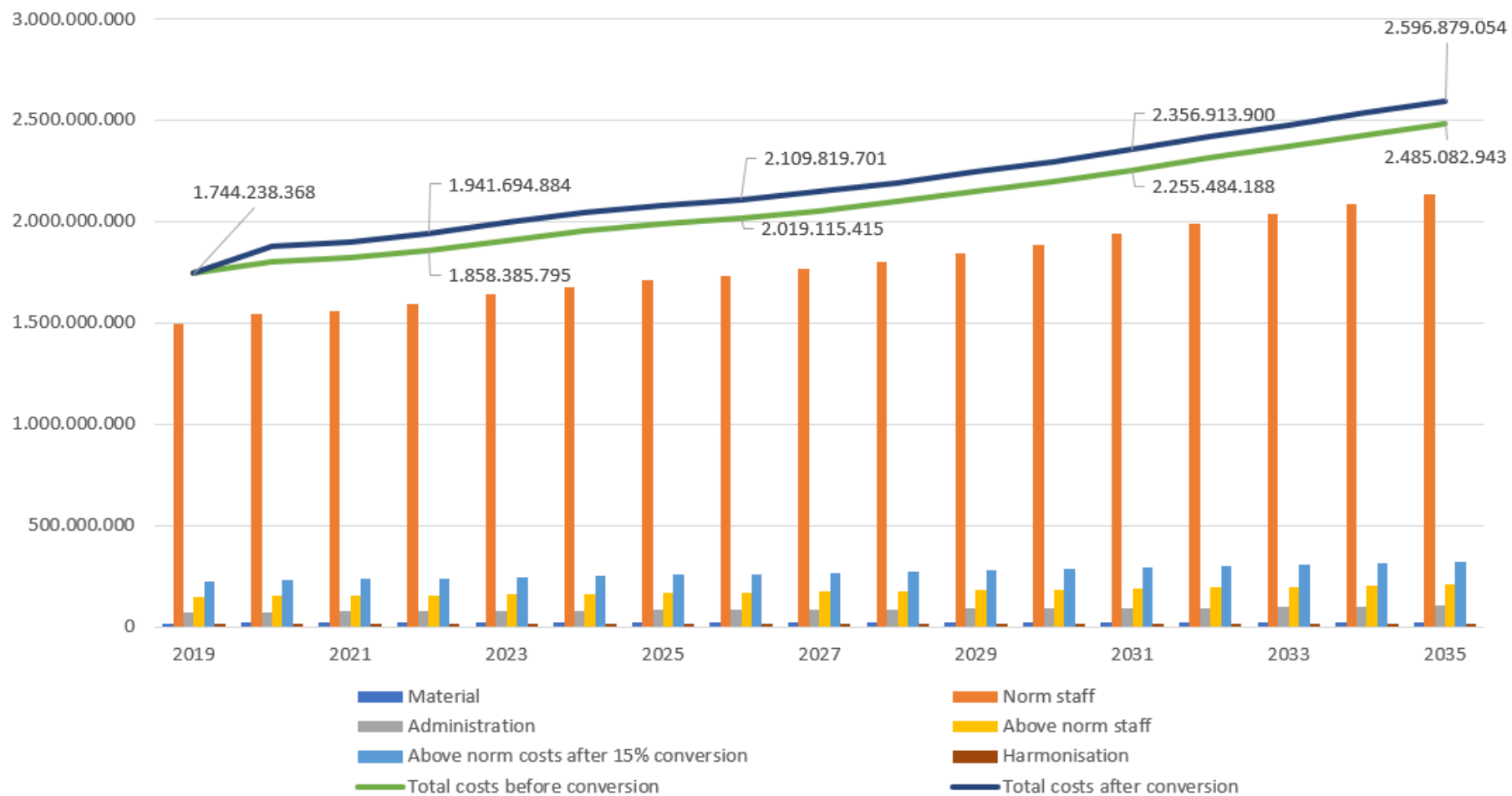


Figure 46 Cost comparison recalibrated simulations from scenario of increase of 15% of personnel in comparison with reference scenario

### **3 Simulation with the scenario of conversion from ROB to RVT for residential care**

In our final simulation, we calculate the costs for the total conversion of ROB beds into RVT beds, a measure which also has been decided by the Flemish government. Until now there was a different financing regime for the residential care categories B, C and Cd between so called "RVT" institutions and "ROB" institutions, where the former have been treated in a more generous way. This situation reflected a historical distinction, in which the ROB-institutions attracted inhabitants with a less severe profile. It is generally accepted, however, that this distinction is no longer meaningful in the present situation.

Table 54 and figure 47 show the results for a simulation in which we did no longer use the weighted average of RVT-costs, but for categories B, C and Cd just used the (higher) RVT-cost. Nothing changes for ROB-categories O and A.

Table 54 Simulation of scenario of conversion from ROB to RVT for residential care from the year 2020, from recalibrated simulations.

Year	Material (A)	Personnel cost ROB and RVT (B)	Personnel cost after conversion to RVT (C)	Administration Costs (D)	Other costs (palliative and dementia subsidies) (E)	Total costs before conversion (A+B+D+E)	Total costs after conversion (A+C+D+E)
2019	18 020 151	1 654 359 441	1 654 359 441	40 813 851	31 044 925	1 744 238 368	1 744 238 368
2020	18 512 037	1 706 021 459	1 809 986 399	42 029 835	31 926 226	1 798 489 556	1 902 454 496
2021	18 673 715	1 725 751 052	1 830 905 908	42 496 400	32 266 012	1 819 187 179	1 924 342 035
2022	19 031 012	1 763 024 587	1 870 469 142	43 395 403	32 934 794	1 858 385 795	1 965 830 351
2023	19 499 167	1 810 319 434	1 920 698 678	44 539 335	33 788 493	1 908 146 429	2 018 525 673
2024	19 936 443	1 854 685 285	1 967 822 553	45 612 066	34 588 971	1 954 822 765	2 067 960 032
2025	20 272 840	1 890 003 917	2 005 358 533	46 459 201	35 216 758	1 991 952 715	2 107 307 332
2026	20 505 722	1 915 869 860	2 032 868 825	47 072 819	35 667 013	2 019 115 415	2 136 114 379
2027	20 818 046	1 948 462 070	2 067 492 065	47 858 967	36 252 917	2 053 391 999	2 172 421 994
2028	21 248 093	1 991 142 787	2 112 788 896	48 902 719	37 040 024	2 098 333 622	2 219 979 732
2029	21 727 939	2 037 988 054	2 162 488 148	50 053 899	37 911 988	2 147 681 879	2 272 181 973
2030	22 198 006	2 083 741 643	2 211 021 137	51 180 568	38 766 923	2 195 887 140	2 323 166 634
2031	22 789 296	2 140 287 718	2 270 990 650	52 577 374	39 829 800	2 255 484 188	2 386 187 121
2032	23 358 427	2 194 955 261	2 328 975 619	53 925 979	40 855 100	2 313 094 767	2 447 115 126
2033	23 933 858	2 250 255 583	2 387 635 955	55 289 574	41 891 581	2 371 370 596	2 508 750 968
2034	24 498 478	2 304 622 831	2 445 309 380	56 629 436	42 909 842	2 428 660 587	2 569 347 135
2035	25 053 678	2 358 168 434	2 502 115 809	57 948 730	43 912 101	2 485 082 943	2 629 030 318

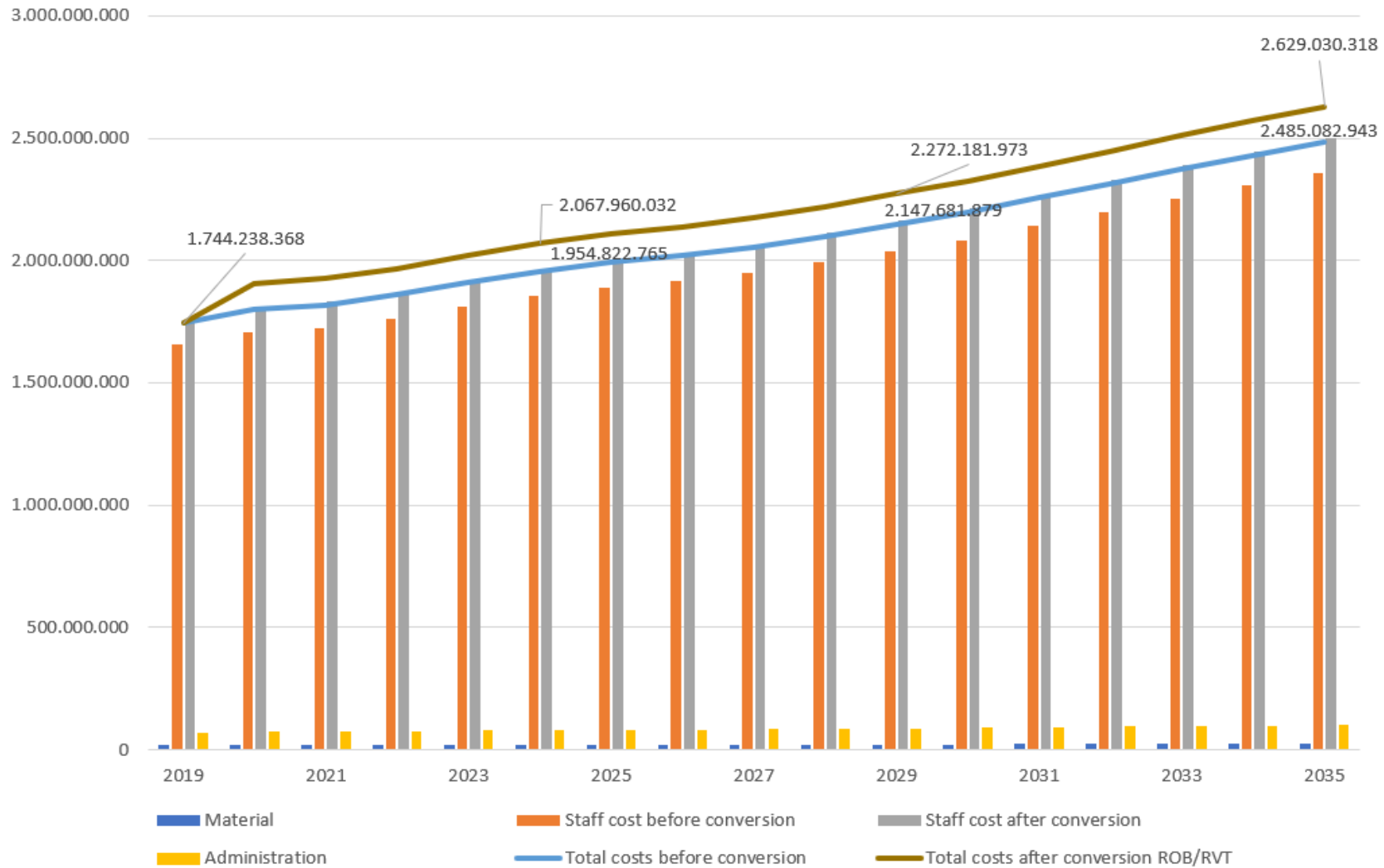


Figure 47 Comparison simulations from scenario of conversion of ROB beds into RVT beds in comparison with reference scenario.



## Chapter 8

### A note on the psychiatric care homes

Psychiatric care homes can also be seen as a form of residential care for older persons, but with specific features that differentiate them from the residential care institutions that have been analysed in the other chapters of this report. A psychiatric care home is a residential care facility for people with a long-term and stabilized psychological disorder or mental disability. Additional criteria for the definition of the target group are:

- Residents do not require permanent physical care, where physical care dominates psychiatric problems;
- Residents may have a daily need for support in the field of general daily life activities, instrumental activities in daily life and daytime activities, due to reduced functioning for psychiatric reasons, without the need for 24-hour medical availability;
- Residents are in need of support to promote inclusion and participation in society;
- Residents are not or not yet able to live independently, but do need guidance in the form of a permanent or on-call duty.

In Flanders, there are 23 official psychiatric care homes divided in 41 campuses located in all Flemish provinces. In 2019, there were a total of 1835 beds in this setting. Since the Sixth State reform, the Flemish government became responsible for the programming, licensing, and financing of the services in the psychiatric care homes.

Psychiatric care homes receive funding for each of their residents. The latter pay also a personal contribution, dependent on their financial and/or handicap status. Another part of the funding fits in the framework of social agreements for personnel with the Flemish government. Finally, funding is possible for furnishing and renovation works. A report from the Flemish inspection agency from 2018 concluded that 55% of the total costs consisted of personnel costs.

Like for the other residential care categories, we have two sources of data available for the psychiatric care homes. At the aggregate level we have the data from the RIZIV, which contain the total number of days invoiced by the psychiatric care homes and the total reimbursed costs. Another source of data is the EPS, which contains data at the client level, but only for a small sample of residents. By using the sampling weights of the EPS, we try to approach the population totals for all people in psychiatric care homes in Flanders. For both the RIZIV and the EPS, the nomenclature codes used are the following: 762510, 762532, 762554, 762591, 762775, 763770, 763792, 763814, 763836, 763851, 763873, 763895, 763910, 791711, 791733, 791755, 791770, 791814, 791836, 791851, 791873. With these codes we can calculate the total costs and the total days in psychiatric care homes from both databases RIZIV and EPS.

Table 55 and figure 48 show the total number of people in psychiatric care homes in the EPS and the totals from the RIZIV. The population estimates, using the EPS weights, differ strongly from the RIZIV totals. The EPS data do not seem representative for the population in psychiatric care homes. Table 56 shows a similar problem for the evolution of the costs. Given the very small number of observations in the EPS (see the last row of Table 55), this lack of representativeness is not surprising.

Since the psychiatric care homes are a rather unimportant component of the FPS, and the number of observations in the EPS is very small and not representative, we decided that it was not meaningful to construct a projection model for this sector. This gives already a taste of what's in store for us in the third part of this report.

Table 55 Comparison of the total number of invoiced days in psychiatric care homes in the EPS and the RIZIV and the total number of people in the EPS.

	2009	2010	2011	2012	2013	2014	2015	2016	2017
Total number of days in PVT - EPS	29 047	29 763	31 290	31 991	33 066	35 306	33 681	29 965	29 193
Total number of days in PVT*weight	856 884	859 141	915 727	925 994	979 255	1 019 143	986 362	865 786	821 106
Total number of days in PVT (RIZIV)	879 728	774 801	786 928	757 647	779 559	782 272	748 743	751 294	801 129
% Total number of days in PVT EPS/RIZIV	97.40%	110.89%	116.37%	122.22%	125.62%	130.28%	131.74%	115.24%	102.49%
Total number of people in PVT - EPS	88	89	91	93	101	106	106	96	90

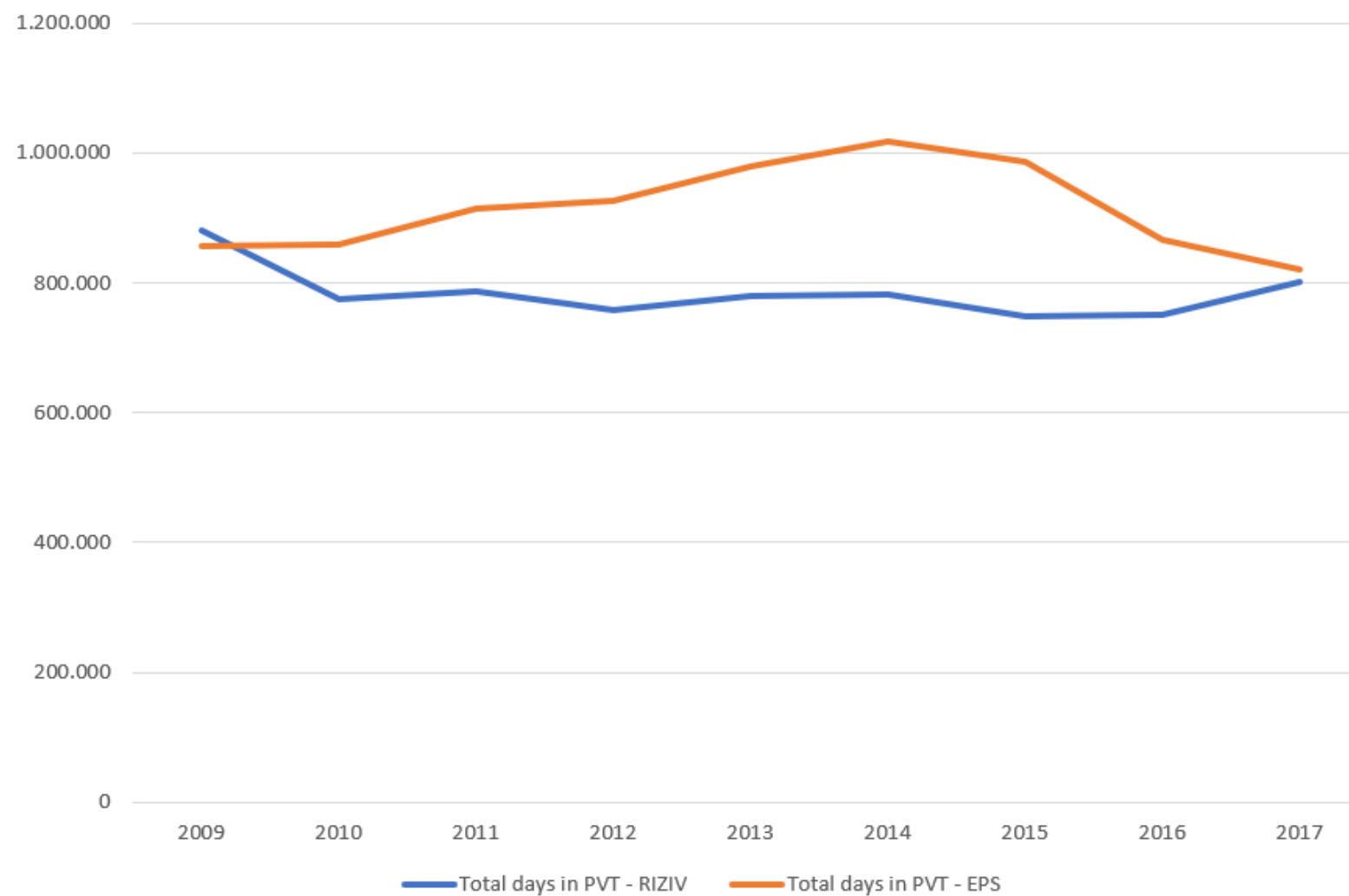


Figure 48 Total days in psychiatric care homes in the EPS and in the RIZIV

Table 56 Total costs in psychiatric care homes

	2009	2010	2011	2012	2013	2014	2015	2016	2017
Costs in PVT - EPS	2 118 432	2 223 377	2559678	2 636 794	2 677 409	2 881 785	2 761 484	2 487 280	2 454 036
Costs in PVT EPS*weight	61 921 939	63 822 554	74 356 068	75 880 470	78 844 186	82 768 279	80 685 752	71 841 428	68 720 327
Costs in PVT - RIZIV	59 061 612	60 005 195	65 220 157	63 727 738	65 450 602	69 158 932	66 433 183	67 095 616	71 926 664
% Costs in PVT – EPS/ RIZIV	104.84%	106.36%	114.01%	119.07%	120.46%	119.68%	121.45%	107.07%	95.54%



## Chapter 9

### Conclusion

In this part of the report we have presented a projection model for residential care and for home care. The estimation is based on the matched EPS-VESTA data for 2009-2017. For the selection of the model we relied on the statistical performance and, more especially, on the out-of-sample predictive performance for the years 2018-2019. The available data are not perfect, but our projection model is comparable to the examples for other countries that we have described in the first part of this report.

We experimented with sophisticated hierarchical models but at the end it turned out that the predictive performance of a simple OLS model was at least equally good and usually better. We therefore continued with this model. This has the additional advantage that it is rather simple to understand and to apply for policy simulations.

The ultimate aim of a projection model is creating the possibility to perform such policy simulations. "Projections" should not be seen as "predictions", since it is clear that in the future societal changes will occur that we could not detect in the data from the past. However, comparing the reference projection with the simulation results for alternative assumptions, gives useful insights into the relative importance of the different explanatory variables and in the likely effects of policy changes. As illustrations of this possibility, we have shown the budgetary consequences of converting ROB into RVT beds and of financing more personnel "above norm". Another simulation suggests that increasing the supply of social care at home will reduce the number of persons moving into residential care and that it is even possible that this shift has a positive effect on the government budget in the long run. We also substantiated the (not really surprising) claim that the decreasing availability of informal care is one of the main challenges in this context. Of course, these are only illustrations of the usefulness of the projection tool, and there are many other possibilities. These are left to the user.

Since the model is estimated with data until 2017, regular updating is necessary. This is even more the case since we can assume that the covid-19-crisis may have led to some structural changes in the system and in the behavior, that cannot be analyzed on the basis of the pre-covid data.





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## Appendix 1 – Results of the OLS models with annualized data.

Table 1 shows the estimates from the OLS models for residential care with the annualized data. These models were constructed with the same exogenous variables as in the preferred models presented in section 3.1.1 in the main text, but without the dummy 'deceased'. As could be expected, the results with the annualized data are very similar to the ones that have been presented in the main text for the models with 'deceased' as an explanatory variable. It is interesting to see that the differences are largest for the number of days in categories C and Cd. These were the cases where we found a positive effect for the variable 'deceased'. We interpreted this positive effect as an indication that the morbidity effect of dying dominated the correction for the shorter period. It is not surprising that in this case the coefficients of the other variables capturing morbidity, are more strongly affected.

Table 1 Estimation results of the OLS models for days in residential care – annualized data

	Model for days in category O	Model for days in category A	Model for days in category B	Model for days in category C	Model for days in category Cd	Model for days in category Short stay
Intercept	1.68056 ** (0.15262)	1.74196 ** (0.16438)	0.41035 * (0.12593)	-0.4171 * (0.15474)	-0.05256 (0.28284)	-0.40643 ** (0.03543)
Man-5564					-0.41483 * (0.18878)	
Man-6574	0.83924 ** (0.08402)	1.01357 ** (0.09051)	1.93365 ** (0.12979)	0.97599 ** (0.0914)	2.63124 ** (0.17783)	0.1138 ** (0.0195)
Woman-6574	0.73659 ** (0.08254)	0.7185 ** (0.08872)	1.47195 ** (0.12728)	0.87624 ** (0.08964)	2.12845 ** (0.17521)	0.07703 ** (0.01912)
Man-7584	1.57485 ** (0.0969)	1.45447 ** (0.10536)	2.56799 ** (0.14963)	1.33135 ** (0.10538)	3.79212 ** (0.19925)	0.30217 ** (0.02268)
Woman 7584	1.87598 ** (0.08822)	1.74957 ** (0.09658)	4.1114 ** (0.13624)	2.00648 ** (0.09595)	5.07163 ** (0.18679)	0.38881 ** (0.02082)
Man-85plus	5.32155 ** (0.14754)	6.72469 ** (0.15876)	11.81065 ** (0.22741)	6.06507 ** (0.16015)	13.29687 ** (0.28123)	0.95118 ** (0.03421)
Woman 85plus	8.18257 ** (0.11748)	9.83567 ** (0.1276)	22.97702 ** (0.18108)	10.63608 ** (0.12754)	29.4895 ** (0.23331)	1.34156 ** (0.02751)
Handicap	0.54906 ** (0.07359)	1.89709 ** (0.0784)	5.63696 ** (0.11336)	3.56568 ** (0.07983)	8.17491 ** (0.13095)	0.38384 ** (0.0169)
Low income	0.46609 ** (0.06692)	1.04621 ** (0.07139)	1.73006 ** (0.10312)	0.92552 ** (0.07262)	1.56504 ** (0.11917)	0.18314 ** (0.01537)
Informal care	-2.12271 ** (0.05741)	-2.36264 ** (0.06115)	-4.48086 ** (0.08843)	-2.01448 ** (0.06227)	-4.66693 ** (0.10214)	-0.14879 ** (0.01318)
Cardiovascular-problems		0.27053 ** (0.0625)			-2.78375 ** (0.10434)	0.07684 ** (0.01344)
COPD	0.31713 * (0.09632)	0.61332 ** (0.10281)	0.91957 ** (0.14846)	1.77655 ** (0.10456)	-1.25592 ** (0.17163)	

Diabetes		0.17128 * (0.0844)	0.26553 * (0.11955)	0.38717 ** (0.08419)	0.56564 ** (0.14093)	0.03644 * (0.01819)
Alzheimer's	4.25777 ** (0.11865)	5.73689 ** (0.12636)	17.96099 ** (0.18285)	5.31342 ** (0.12877)	31.43037 ** (0.21096)	0.54518 ** (0.02724)
Parkinson's	1.53474 ** (0.23265)	5.03831 ** (0.24777)	11.24169 ** (0.35849)	9.27874 * (0.25249)	17.02566 ** (0.41367)	0.59344 ** (0.05341)
Hours social care/ population	-0.80288 ** (0.06)	-0.55864 ** (0.06363)			-0.29578 * (0.10552)	-0.03002 * (0.01372)
Total NH beds/ population	0.01253 ** (0.00142)	0.00633 ** (0.00149)		0.00427 * (0.00119)	0.01974 ** (0.00243)	0.00247 ** (0.0003219)
Year dummy 2009	0.43215 ** (0.09642)					
Year dummy 2010	0.20653 * (0.09586)					
Year dummy 2011						
Year dummy 2012						
Year dummy 2013						
Year dummy 2014						
Year dummy 2015						
Year dummy 2016						
Linear trend			0.04418 * (0.01573)	-0.02947 * (0.01137)		
Logarithmic trend		-0.4553 *** (0.04303)				0.08462 ** (0.00927)
Logarithmic trend 2012- 2017	-0.49659 ** (0.04486)					
R-square	0.0188	0.0287	0.0746	0.0332	0.1036	0.0112
N	749,244	749,244	749,244	749,244	749,244	749,244

\*\* p<0.0001 \* p<0.05

Table 2 shows the simulation results obtained for 2018 and 2019 with the model in which the data are annualized and compares these simulation results with the actual administrative data for these years. The results are mixed, but overall they are not better than the results reported in the main text for the models without annualization.

Table 2 Comparison of simulations results for residential care (2018-2019) with real data from VAZG and RIZIV

<b>Independent variable</b>	<b>Year</b>	<b>OLS simulations</b>	<b>VAZG</b>	<b>RIZIV</b>	<b>Model/VAZG</b>	<b>Model/RIZIV</b>
Days in category O	2018	1 878 847	1 993 878	1 986 096	94.23%	94.60%
	2019	1 797 580	1 943 854		92.48%	
Days in category A	2018	2 969 855	3 394 435	3 378 962	87.49%	87.89%
	2019	2 962 203	3 319 958		89.22%	
Days in category B	2018	8 204 215	8 560 817	8 705 659	95.83%	94.24%
	2019	8 482 994	8 905 227		95.26%	
Days in category C	2018	3 513 846	3 353 387	3 346 514	104.78%	105.00%
	2019	3 545 996	3 376 876		105.01%	
Days in category Cd	2018	10 454 557	10 226 698	10 066 246	102.23%	103.86%
	2019	10 723 545	10 357 844		103.53%	
Days in category Short stay	2018	766 320	796 423	703 577	96.22%	108.92%
	2019	799 963	803 264		99.59%	

Table 3 shows the estimates from the OLS models for home care services with the annualized data. Table 4 compares the simulation results for 2018 and 2019 with the actual observations from the official sources VAZG and RIZIV. The conclusion can be the same as for the residential care models: both the estimated coefficients and the simulation results are very similar to those obtained with the non-annualized data and the variable 'deceased'. The projections are not better.

Table 3 Estimation results of the OLS models for home care services – annualized data

	<b>Model for nursing tasks</b>	<b>Model for hours social care</b>	<b>Model for hours logistic care</b>
Intercept	0,26765 (0,25025)	-0,09437 (0,20262)	-0,65234 (0,06513)
Man-1839		-0,55992 ** (0,12613)	
Man-4054	-1,60657 ** (0,13664)	-1,19608 ** (0,13501)	
Woman-4054	-1,32879 ** (0,13791)	-0,87951 ** (0,13596)	
Man-5564	-2,59821 ** (0,16865)	-0,51103 * (0,16342)	
Woman-5564	-1,42192 ** (0,16898)		0,42852 ** (0,05418)
Man-6574		1,55738 ** (0,15224)	0,75029 ** (0,05009)
Woman-6574	3,04538 ** (0,14793)	2,55886 ** (0,14836)	1,30764 ** (0,04862)
Man-7584	9,92717 ** (0,1835)	5,22328 ** (0,1798)	1,86108 ** (0,06103)
Woman 7584	19,16828 ** (0,16597)	8,69141 ** (0,16365)	4,50925 ** (0,05473)
Man-85plus	38,5947 ** (0,29437)	23,15757 ** (0,27541)	4,62918 ** (0,09392)
Woman 85plus	48,25155 ** (0,23059)	22,90589 ** (0,21834)	7,62237 ** (0,074)
Handicap	14,3795 ** (0,10688)	7,16463 ** (0,09727)	1,03392 ** (0,03475)
Low income	10,85333 ** (0,10855)	6,82528 ** (0,09882)	2,29617 ** (0,0353)
Informal care	-1,72033 ** (0,08494)	-4,43384 ** (0,07955)	-1,46401 ** (0,02869)

Cardiovascular-problems	5,03703 ** (0,0989)	1,93086 ** (0,094)	0,60825 ** (0,03344)
COPD	9,27077 ** (0,19193)	2,85448 ** (0,17492)	0,98691 ** (0,0617)
Diabetes	9,13354 ** (0,15385)	3,14943 ** (0,14013)	0,72688 ** (0,04961)
Alzheimer's	3,44022 ** (0,24358)	2,53285 ** (0,2216)	-1,79164 ** (0,07863)
Parkinson's	35,38323 ** (0,47355)	18,41639 ** (0,43071)	1,41108 ** (0,15301)
Hours social care/ population	3,74298 ** (0,08886)	1,46513 ** (0,07958)	0,25948 ** (0,2273)
Total NH beds/ population	-0,09313 ** (0,00209)	-0,0306 ** (0,00183)	
Year dummy 2009	-1,83494 ** (0,1687)	0,35092 * (0,11512)	
Year dummy 2010	-1,85532 ** (0,1683)		
Year dummy 2011	-1,63278 ** (0,16725)		
Year dummy 2012	-1,62209 * (0,16685)		
Year dummy 2013	-1,58364 ** (0,16597)		
Year dummy 2014	-1,22659 ** (0,16522)		
Year dummy 2015	-0,87674 ** (0,16403)		
Year dummy 2016	-0,32569 ** (0,16324)		
Linear trend			
Logarithmic trend			-0,09723 ** (0,02108)
R-square	0.1368	0.0472	0.0438
N	1,439,385	1,439,385	971,101

\*\* p<0.0001 \* p<0.05

Table 4 Comparison of simulations results for home care services (2018-2019) with real data from VAZG and RIZIV

<b>Independent variable</b>	<b>Year</b>	<b>OLS simulations</b>	<b>VAZG</b>	<b>RIZIV</b>	<b>Model/VAZG</b>	<b>Model/RIZIV</b>
Nursing tasks	2018	35.477.559		35.355.949		100,34%
	2019	36.357.538		36.274.145		100,23%
Hours of social care	2018	15.585.305	16.046.011		97,13%	
	2019	16.093.448	16.252.556		99,02%	
Hours of logistic help	2018	4.252.490	4.514.221		94,20%	
	2019	4.263.984	4.456.867		95,67%	



## Appendix 2 – Results from the fixed effects models with the panel data.

Tables 5 and 6 show the estimates from the panel models using fixed effects. As described in the text, introducing fixed effects has the advantage that one controls for all the constant (observable and unobservable) features of the individuals. This also means, however, that one can no longer identify the separate effects of these constant characteristics. As an example, gender remain fixed during the whole observation period and therefore the effect of gender is taken up in the fixed effect. Age is a somewhat different case, since individuals can move from one age group into another, but these age effects were difficult to identify in our models, given the small number of observations for which this occurs, the impossibility to identify the gender effect and the presence of trends (or dummies) in the model.

The effects of the other variables are identified on the basis of changes. As an example, the coefficient of 'low income' has to be interpreted as the effect of a change in the income position from "high" to "low". Some variables that were significant in the pooled model, lose their significance in the fixed effects model, but this was exactly what could be expected. It is reassuring that most of the coefficients in these fixed effect models have the same sign as in the pooled model. We explain in the main text why these fixed effects approach is less suited for the construction of our projection model.

Table 5 Estimation results of fixed effects models for days in residential care

	Fixed effects model for days in Category O	Fixed effects model for days in Category A	Fixed effects model for days in Category B	Fixed effects model for days in Category C	Fixed effects model for days in Category Cd	Fixed effects model for days in Category Short stay
Intercept	1.814506 (4.9579)	-3.00887 (5.6922)	3.5888 (8.2778)	2.529713 (5.0166)	3.502715 (7.7428)	0.032076 (1.4354)
Handicap	1.403222** (0.1404)	2.714992** (0.1614)	10.65006** (0.2347)	3.577482** (0.1422)	8.723652** (0.2195)	1.068876** (0.0407)
Low income	0.537237** (0.1127)	0.742186** (0.1295)	1.771855** (0.1883)	0.530045** (0.1141)	0.864284** (0.1762)	0.339189** (0.0326)
Informal care	-1.2076** (0.0967)	-1.6196** (0.1112)	-3.79215** (0.1617)	-1.47627** (0.0980)	-4.21181** (0.1512)	-0.15289** (0.0280)
Deceased	-3.7397** (0.3263)	-3.3756** (0.3746)	-7.22013** (0.5456)	1.735967** (0.3307)	5.342334** (0.5104)	0.255253* (0.0945)
Cardiovascular-problems	-0.23399* (0.0922)	0.023717 (0.1060)	-0.77909** (0.1541)	-0.29658* (0.0934)	-1.65825** (0.1482)	0.080496* (0.0267)
COPD	0.183148 (0.1507)	0.729283** (0.1732)	1.162787** (0.2520)	1.759418** (0.1527)	0.610658* (0.1527)	0.060099 (0.0437)

					(0.2357)	
Diabetes	-0.41022* (0.1604)	-1.0948** (0.1844)	-1.25122** (0.2682)	-1.26173** (0.1625)	-2.93939** (0.2508)	0.057438 (0.0465)
Alzheimer's	1.743048** (0.1758)	5.323177** (0.2019)	17.71118** (0.2939)	4.039695** (0.1781)	18.45394** (0.2749)	0.815214** (0.0509)
Parkinson's	1.093979* (0.3629)	2.872712** (0.4171)	5.800974** (0.6067)	3.088697** (0.3677)	7.164782** (0.5675)	0.345202* (0.1052)
Hours social care/ population	-0.52454 (0.3002)	0.127098 (0.3259)	-2.34002** (0.4765)	-2.53167** (0.2888)	-4.11564** (0.4457)	-0.22502* (0.0822)
Total NH beds/ population	-0.00056 (0.00465)	0.023803** (0.00462)	-0.00213 (0.00769)	0.00733 (0.00466)	0.036595** (0.00719)	0.002545* (0.00117)
Year dummy 2009	-0.37867** (0.0846)					
Year dummy 2010	-0.22138* (0.0829)					
Year dummy 2011	-0.13628 (0.0846)					
Year dummy 2012						
Year dummy 2013						
Year dummy 2014						
Year dummy 2015						
Year dummy 2016						
Linear trend			0.668571** (0.0215)	0.272439** (0.0131)	0.752047** (0.0201)	
Logarithmic trend		0.454519** (0.0496)				0.153348** (0.0125)
Logarithmic trend (vanaf 2012)	0.253578 (0.0557)					
R-square	0.5533	0.4427	0.4361	0.4492	0.5016	0.2095
N	56330	56330	56330	56330	56330	56330

\*\* p<0.0001 \* p<0.05

Table 6 Estimation results of the fixed effects models for home care services

	Fixed effects model for nursing tasks	Fixed effects model for hours social care	Fixed effects model for hours logistic help
Intercept	1.827888 (9.2879)	2.781668 (7.3978)	0.527395 (2.6464)
Handicap	11.53627** (0.1654)	5.047606** (0.1317)	0.351591** (0.0551)
Low income	5.666995** (0.1534)	2.980136** (0.1222)	0.490527** (0.0488)
Informal care	-1.89531** (0.1041)	-2.39978** (0.0829)	-0.42002** (0.0339)
Deceased	-16.8729** (0.5973)	-10.3753** (0.4757)	-3.56937** (0.1424)
Cardiovascular- problems	1.888457** (0.1331)	1.04299** (0.1060)	0.265173** (0.0426)
COPD	2.299532 (0.2480)	0.135417 (0.1975)	0.112555 (0.0739)
Diabetes	3.542193** (0.2575)	1.11207** (0.2051)	0.428749** (0.0829)
Alzheimer's	11.59534** (0.3267)	5.633308** (0.2602)	-0.90952** (0.1009)
Parkinson's	24.66529** (0.6645)	8.832641** (0.5293)	0.631981* (0.2097)
Hours social care/ population	-1.59157** (0.3123)	-0.56912* (0.2487)	-0.05494 (0.0934)
Total NH beds/ population	0.056546** (0.00546)	0.016034* (0.00435)	-0.00187 (0.00166)
Year dummy 2009	-6.46827** (0.1405)	-2.39459** (0.1119)	
Year dummy 2010	-5.86737** (0.1405)	-2.18549** (0.1119)	
Year dummy 2011	-5.29331** (0.1348)	-2.00955** (0.1074)	
Year dummy 2012	-4.56271** (0.1344)	-1.66707** (0.1070)	
Year dummy 2013	-3.80318** (0.1293)	-1.2525** (0.1030)	
Year dummy 2014	-2.84542** (0.1259)	-0.79856** (0.1002)	
Year dummy 2015	-2.07038** (0.1169)	-0.52269** (0.0931)	
Year dummy 2016	-0.98523** (0.1110)	-0.2807* (0.0884)	
Logarithmic trend			0.258495** (0.0177)
R-square	0.6422	0.6502	0.7818
N	127,422	127,422	127,422

\*\* p&lt;0.0001 \* p&lt;0.05

### **Appendix 3 – Results of the multinomial models**

In the main text we explained the theoretical advantages of a hierarchical approach in which different states are distinguished. In our case, it seems natural to distinguish four states (or categories of care):

1= people needing no care

2= people using only home care: they receive care at home (social care, logistic help, surveillance help or nursing), or are in short stay or get care in a day center, but are still living at home

3 = people who are admitted into nursing home during the year.

4 = people who stay in a nursing home during the whole year.

The first step is then the explanation of the allocation of individuals to a specific state. The results for this first step are shown in this section. The following step is the explanation of the use of care, conditional on the fact that we know the state in which individuals find themselves, e.g., we explain the use of different categories of home care based only on the observations of persons in state 2. These results will be shown in Appendix 4.

We first look at the results for the model with all four care categories. We then turn to a simplified approach in which states 3 and 4 are merged.

#### **Multinomial model with four categories of care**

The results for the multinomial model with four categories are in table 7. The interpretation of such a multinomial model is a bit complicated. We have chosen as the reference the situation in which people do not need care. The coefficients on the explanatory variables for the other categories then indicate the direction of the change in the probability that an individual belongs to that latter category, compared to the situation in which (s)he needs no care. Let us illustrate for the supply variable "social care". The positive effect for the category "home care" suggests that the availability of social care increases the chance that the individual will use home care, rather than do without it. The negative effects for the categories 3 and 4 indicate that the availability of social care lowers the chances that an individual moves into residential care or stays in a nursing home for the complete period. The coefficients for the other variables have to be interpreted in a similar way.

The results in table 7 are in line with the theoretical expectations. Note that the estimated coefficients for states 3 and 4 are similar, suggesting that it will not be easy to distinguish between these two states.

Table 7 Estimates from the multinomial model with four categories of care

<b>Reference= No care (1)</b>	<b>Multinomial model with 4 categories of care</b>
<b>Category: Only home care (2)</b>	
Intercept	-4.2159** (0.02995)
Man-5564	-0.511** (0.30895)
Man-6574	0.531231** (0.024123)
Man-7584	1.568084** (0.022835)
Man-85plus	2.744339** (0.02507)
Woman-6574	0.998199** (0.022556)
Woman 7584	1.919102** (0.021597)
Woman 85plus	3.036044** (0.023201)
Handicap	1.080627** (0.010016)
Informal care	-0.74498** (0.00885)
Low income	0.680088** (0.009393)
Parkinson's	1.473043** (0.028121)
Alzheimer's	0.649272** (0.015368)
Cardiovascular-problems	0.534458** (0.010659)
Diabetes	0.476367** (0.010705)
COPD	0.500399** (0.0130431)
Hours social care/ population	0.242633** (0.0095578)
Total NH beds/ population	-0.00356** (0.0002146)
<b>Category: Admission to residential care (3)</b>	
Intercept	-7.89834** (0.1649058)

Man-5564	0.232833* (0.2042232)
Man-6574	2.273178** (0.1639512)
Man-7584	3.797103** (0.1592573)
Man-85plus	5.428429** (0.1590724)
Woman-6574	2.207995** (0.1635956)
Woman 7584	3.942107** (0.1581769)
Woman 85plus	5.659943** (0.1580181)
Handicap	1.48018** (0.0236258)
Informal care	-0.96853** (0.0221327)
Low income	0.53866** (0.0245438)
Parkinson's	1.948397** (0.0478611)
Alzheimer's	1.611253** (0.0241949)
Cardiovascular- problems	0.237118** (0.0260105)
Diabetes	0.351922** (0.026162)
COPD	0.330573** (0.0323267)
Hours social care/ population	-0.16017** (0.0224963)
Total NH beds/ population	0.000995* (0.0005275)
<b>Category: Only residential care (4)</b>	
Intercept	-7.19839** (0.1046936)
Man-5564	0.374093* (0.1237451)
Man-6574	2.382405** (0.1037052)
Man-7584	3.723034** (0.1005864)
Man-85plus	5.450133** (0.1003458)

Woman-6574	2.325664** (0.1030367)
Woman 7584	3.980991** (0.0991169)
Woman 85plus	5.958536** (0.0990051)
Handicap	1.722497** (0.0171629)
Informal care	-2.08017** (0.0190934)
Low income	0.50642** (0.0177394)
Parkinson's	2.257575** (0.0369892)
Alzheimer's	2.031357** (0.0181367)
Cardiovascular- problems	-1.70078** (0.017537)
Diabetes	0.355166** (0.0195712)
COPD	0.469079** (0.0233112)
Hours social care/ population	-0.08866** (0.0166459)
Total NH beds/ population	0.003012** (0.0003846)
Pseudo R- squared	0.3081
N	748,893

Table 8 gives some insight into the explanatory power of the model. It shows for the year 2017 the allocation of persons in the different age-gender categories over the four states, as predicted by the model, and compares this allocation with the actual allocation in the EPS data. Some of these predictions are very poor. The model underestimates for all age-gender groups the share of persons that use home care and overestimates for all groups, except the males aged 55-64, the share of persons that are admitted to residential care. Except for some very small groups, it also underestimates the share of persons in residential care. All this strongly suggests that we do not have enough observations to differentiate the group of individuals moving into residential care from the other groups. This was the reason to also estimate a model in which groups 3 and 4 are merged.

Table 8 Results from the multinomial model for 4 categories of care compared to EPS data in 2017

Profile	Allocation of type of care				Total	Type of care category in EPS				Total	Percentage of agreement			
	No care	Home care	Admitted to residential care	Residential care during whole year		No care	Home care	Admitted to residential care	Residential care during whole year		No care	Home care	Admitted to residential care	Residential care during whole year
Man - 5564	10675	228	8	24	10935	10655	251	8	21	10935	100,19%	90,83%	95,64%	114,71%
Man - 6574	15643	730	54	117	16544	15592	799	49	104	16544	100,32%	91,33%	110,90%	112,86%
Man - 7584	8101	1314	166	269	9851	7993	1417	154	287	9851	101,35%	92,75%	107,92%	93,87%
Man-85 plus	1948	1150	259	547	3904	1848	1254	247	555	3904	105,42%	91,74%	104,76%	98,49%
Woman - 5564	10479	340	5	14	10838	10458	369	4	7	10838	100,20%	92,05%	131,25%	200,01%
Woman - 6574	15759	1216	54	120	17149	15681	1317	45	106	17149	100,49%	92,36%	119,14%	113,63%
Woman - 7584	9016	2598	287	668	12568	8831	2791	254	692	12568	102,10%	93,07%	112,85%	96,48%
Woman - 85	2246	2414	550	1906	7116	2063	2633	509	1911	7116	108,89%	91,68%	108,01%	99,73%
Total	73867	9990	1382	3665	88905	73121	10831	1270	3683	88905	101,02%	92,23%	108,84%	99,52%



### Multinomial model with three categories of care

The estimates for the multinomial model with three categories can be found in table 9, the predictive performance of this model in table 10. Overall, it is clear that merging categories 3 and 4 is not a solution to our problems. The model still underestimates considerably the share of persons that use only home care and, with only one exception, overestimates the number of persons who do not need care or who are admitted to residential care. Moreover, merging categories 3 and 4 in the estimation step, raises some difficult issues for the simulation step, since group 3 by construction uses only home care for part of the year and is staying in a nursing home for the rest of the year.

Table 9 Estimates from the multinomial model with three categories of care

Reference= No care (1)	Multinomial model with 3 categories of care
<b>Category: Only home care (2)</b>	
Intercept	-4.21493** (0.0299483)
Man-5564	-0.51094** (0.308946)
Man-6574	0.529778** (0.024121)
Man-7584	1.567604** (0.0228315)
Man-85plus	2.744428** (0.0250658)
Woman-6574	0.996868** (0.0225559)
Woman 7584	1.918325** (0.0215942)
Woman 85plus	3.033059** (0.0231979)
Handicap	1.079125** (0.0100135)
Informal care	-0.74194** (0.0088492)
Low income	0.681198** (0.0093924)
Parkinson's	1.469777** (0.0281151)
Alzheimer's	0.643102** (0.015366)
Cardiovascular-problems	0.537283** (0.0106571)
Diabetes	0.476341** (0.0107013)
COPD	0.499364** (0.0130397)
Hours social care/ population	0.241953** (0.0095546)
Total NH beds/ population	-0.00358** (0.0002145)

<b>Category: Admission to residential care and residential care all year long (3)</b>	
Intercept	-6.77606** (0.0893241)
Man-5564	0.336431* (0.1059167)
Man-6574	2.349755** (0.0878)
Man-7584	3.756709** (0.0852434)
Man-85plus	5.444886** (0.0853396)
Woman-6574	2.289554** (0.0873548)
Woman 7584	3.967733** (0.0842021)
Woman 85plus	5.871198** (0.084241)
Handicap	1.647357** (0.0150715)
Informal care	-1.67628** (0.0151111)
Low income	0.514339** (0.0152632)
Parkinson's	2.155495** (0.0338705)
Alzheimer's	1.90468** (0.0166277)
Cardiovascular-problems	-0.04964** (0.0155611)
Diabetes	0.354737** (0.0170718)
COPD	0.426868** (0.0205306)
Hours social care/ population	-0.11095** (0.0145219)
Total NH beds/ population	0.002405** (0.0003368)
Pseudo R-square	0.3222
N	748,893

Table 10 Results from the multinomial models for 3 categories of care compared to EPS data in 2017

Profile	Allocation of type of care by the model			Total	Type of care category in EPS			Total	Percentage of agreement		
	No care	Home care	Residential care		No care	Home care	Residential care		No care	Home care	Residential care
Man - 5564	10675	228	32	10935	10655	251	29	10935	100.19%	90.80%	109.36%
Man - 6574	15643	730	172	16544	15592	799	153	16544	100.33%	91.33%	112.15%
Man - 7584	8101	1314	436	9851	7993	1417	441	9851	101.35%	92.75%	98.79%
Man- 85 plus	1949	1150	805	3904	1848	1254	802	3904	105.44%	91.71%	100.37%
Woman - 5564	10479	340	19	10838	10458	369	11	10838	100.20%	92.04%	174.93%
Woman - 6574	15759	1216	174	17149	15681	1317	151	17149	100.49%	92.35%	115.34%
Woman - 7584	9016	2597	955	12568	8831	2791	946	12568	102.10%	93.06%	100.90%
Woman - 85	2246	2413	2457	7116	2063	2633	2420	7116	108.87%	91.66%	101.51%
Total	73868	9989	5048	88905	73121	10831	4953	88905	101.02%	92.23%	101.93%

#### Appendix 4 – Results of the OLS models for the residential care categories.

As described in the previous appendix, the second step in the hierarchical model is the explanation of the use of care only with the observations for individuals in the relevant state. Table 11 shows the estimates of a pooled OLS model for the days of care in the different residential categories, estimated on the sample of individuals staying in a nursing home.

When interpreting the results, we have to take into account the new setting. Note, e.g., the much larger values for the intercepts. Let us illustrate the interpretation further for the results of the age-groups. All the age-effects are negative for categories O and A. This implies here that, compared to the reference group of women aged between 55 and 64, the older a person becomes, the smaller the number of days in O and A, because older individuals move into the more severe categories (for which all age effects are positive). Or look at handicap: *within the group of individuals that are staying in a nursing home*, being handicapped lowers the number of days in the less severe categories and increases the number of days in categories B, C and Cd.

Table 31 Estimation results of OLS models for days in residential care

	Model for days in category O	Model for days in category A	Model for days in category B	Model for days in category C	Model for days in category Cd
Intercept	68,58397** (3,31685)	68,52137** (3,56688)	56,89283** (4,0051)	15,9555** (2,68267)	84,31185** (4,51912)
Man-5564		-14,4757* (6,89815)	44,27993** (8,82373)		-29,3414* (9,84597)
Man-6574	-6,76462* (3,3206)				
Woman-6574		-8,87095* (3,59705)		8,37434* (2,91329)	
Man-7584	-8,98877* (2,61181)	-11,8466** (2,98709)			
Woman 7584	-11,3479** (2,36425)	-13,9082** (2,75238)	10,93871** (2,12307)	4,84357* (1,70018)	7,48461* (2,36595)
Man-85plus	-10,8137** (2,49608)	-6,14938* (2,87519)	6,2489* (2,37702)	7,27832* (1,88167)	-6,81856* (2,65883)
Woman 85plus	-13,8699** (2,27847)	-12,9503** (2,67056)	11,20659** (1,91673)	7,39404** (1,5618)	14,42895** (2,12062)
Handicap	-17,843** (0,92726)	-9,82402** (1,24159)	4,56061* (1,32409)	11,46896** (0,99668)	25,72992** (1,87139)
Low income	-13,7294** (1,1691)	7,83674** (1,34673)			-12,2669** (2,00669)
Informal care		-13,6917** (1,25214)	-20,1353** (1,66737)	-5,77431** (1,25756)	
Cardiovascular- problems	5,28147** (1,1051)	12,69955** (1,15887)	16,36678** (1,55492)	6,95061** (1,19578)	-40,3064** (1,74855)
COPD		3,99196* (1,5429)		20,09563** (6,9506)	-22,615** (2,32929)
Diabetes	-3,38769* (1,21458)			3,00712* (1,30949)	
Alzheimer's	-8,19907** (0,97287)	-7,87685** (1,02922)	4,06017* (1,39007)	-10,1351** (1,04832)	39,43989** (1,5522)

Parkinson's	-12,8666** (1,88642)			16,36211** (2,03286)	15,68522** (3,01038)
Hours social care/ population	-10,0358** (1,04851)	-5,5635** (0,83809)	9,08764** (1,49861)	2,77171* (0,85401)	6,55606** (1,66584)
Total NH beds/ population	0,1411** (0,02496)		-0,22292** (0,03567)		0,12115* (0,03943)
Year dummy 2009	6.60414** (1.66614)				-11.23429** (2.46644)
Year dummy 2010	3.38365* (1.65741)				-9.22542* (2.45311)
Year dummy 2011					-7.27378* (2.43283)
Year dummy 2012					-8.36260* (2.39923)
Year dummy 2013					
Year dummy 2014					
Year dummy 2015					
Year dummy 2016					
Linear trend			1,81581** (0,25912)		
Logarithmic trend		-6,61413** (0,7178)			
Logarithmic trend 2012- 2017	-7,91624** (0,76972)				
R-square	0.0238	0.0130	0.0115	0.0145	0.0434
N	41192	41192	41192	41192	41192

\*\*  $p < 0.0001$  \*  $p < 0.05$

Table 12 shows the projections for 2018 and 2019 and compares these projections with the real data. These projection results are not better than the ones that we have given for the full pooled model in the main text.

Table 4 Comparison simulations results for residential care (2018-2019) with real data from VAZG

<b>Category and type of OLS model</b>	<b>Year</b>	<b>OLS</b>	<b>VAZG</b>	<b>model/VAZG</b>
Category O - Backward model with logarithmic trend (2012-on) and year dummies 2009-2011	2018	1 395 292	1 993 878	69.98%
	2019	1 340 256	1 943 854	68.95%
Category A- Backward model with logarithmic trend	2018	2 724 070	3 394 435	80.25%
	2019	2 718 995	3 319 958	81.90%
Category B- Backward model with linear trend	2018	7 759 854	8 905 227	87.14%
	2019	8 102 018	9 314 526	86.98%
Category C- Backward model with linear trend	2018	3 320 137	3 353 387	99.01%
	2019	3 413 620	3 376 876	101.09%
Category Cd- Backward model with year dummies	2018	9 391 299	10 226 698	91.83%
	2019	9 674 721	10 357 844	93.40%
Category Short stay - Backward model with logarithmic trend	2018	572 141	796 423	71.84%
	2019	600 857	803 264	74.80%

**Appendix 5 – Results of the OLS for the home care categories.**

Tables 13 and 14 give analogous results for the home care categories. For each category we estimate two models: one for the sample of persons who are in home care for the whole year, another for the sample of persons who are admitted to residential care and therefore use home care for part of the year. In the projection, the results for these two groups have to be added. We have estimated these regressions only on the sample of the older persons. The administrative data in Table 14 are therefore also those for the older population.

Table 5 Estimation results of OLS models for home care

	<b>Model for nursing tasks at home (people in home care)</b>	<b>Model for nursing tasks at home (people being admitted to nursing home)</b>	<b>Model for social care hours (people in home care)</b>	<b>Model for social care hours (people being admitted to nursing home)</b>	<b>Model for logistic help hours (people in home care)</b>	<b>Model for logistic help hours (people being admitted to nursing home)</b>
Intercept	33,36324** (2,74838)	56,72702** (9.96185)	20,93652** (1,41728)	37,82639** (5,51602)	13,58876** (0,56974)	7,46258** (1.06708)
Man-5564	15,28954* (4,03344)		8,09105* (3,71421)		-6,47137** (1,27696)	
Man-6574	34,47866** (3,08118)				-3,84744** (0,76583)	
Woman-6574	31,29667** (2,86745)					
Man-7584	44,0325** (2,84466)				-1,81077* (0,60400)	
Woman 7584	44,74591** (2,71152)		4,07816* (1,30083)	14,16523* (6,47725)	6,12239** (0,49252)	
Man-85plus	66,50573** (2,9406)	26,93302* (10.25146)	33,5029** (1,85909)			
Woman 85plus	77,45044** (2,75347)	22,93301* (7.89583)	24,04516** (1,41778)	22,62652** (5,72138)	7,17586** (0,52326)	

Handicap	72,39441** (1,09026)	18,55036* (7.13591)	31,05717** (1,24397)	18,51754* (6,00175)	-2,39248** (0,43532)	
Low income	-4,77208** (1,08979)		17,87092** (1,24688)	12,47688* (6,30511)	10,43049** (0,43286)	6,35061** (1.31133)
Informal care						
Cardiovascular- problems	22,22369** (1,25354)	43,27255** (9.19858)				
COPD	16,53743** (1,35118)					
Diabetes	17,92213** (1,11792)		2,67768* (1,26037)	12,54032* (6,36227)		3,98361* (1.06708)
Alzheimer's	26,40851** (1,46666)	17,61129* (7.92948)	16,66494** (1,6766)	20,70666* (5,49718)	-4,84572** (0,57911)	
Parkinson's	50,25458** (2,45639)		30,28476** (30,28476)		-2,09214* (0,98551)	
Hours social care/ population						
Total NH beds/ population						
Year dummy 2009	13,22714** (1,62851)	-40,6908** (8,930 49)	20,47182** (2,00627)	-33.79567** (6.26670)		
Year dummy 2010	10,54033** (1,60398)		17,15722** (1,98018)			
Year dummy 2011	10,09299** (1,58648)		14,26929** (1,96171)			
Year dummy 2012	-3,61884* (1,49523)		7,2712** (1,86526)			



Year dummy 2013	-4,59003* (1,48658)		6,96088* (1,8561)	27.00804* (8.44215)		
Year dummy 2014			6,78866* (1,85029)			
Year dummy 2015			4,03248* (1,83691)			
Year dummy 2016						
Linear trend					-0,37111** (0.10579)	
Logarithmic trend						
Logarithmic trend 2012- 2017						
R-square	0.1038	0.0059	0.0305	0.0089	0.0214	0.0041
N	87,432	11,371	87,432	11,371	62,223	7,039

\*\*  $p < 0.0001$  \*  $p < 0.05$

Table 6 Comparison simulations results for home care (2018-2019) with real data from VAZG

Category of care and type of OLS model	Year	OLS model1	OLS model2	SUM	VAZG/RIZIV	model/RIZIV
Nursing tasks at home -Backward model with year dummies	2018	27 794 312	1 491 835	29 286 147	33 084 568	88.52%
	2019	28 374 601	1 532 145	29 906 745	33 941 117	88.11%
Social care hours at home - Backward model with year dummies	2018	11 587 309	963 999	12 551 308	13 967 046	89.86%
	2019	11 810 211	985 982	12 796 193	14 077 788	90.90%
Logistic help hours at home - Backward model with linear trend	2018	3 701 490	150 401	3 851 891	4 137 748	93.09%
	2019	3 687 738	153 560	3 841 298	4 118 134	93.28%





**Steunpunt Welzijn, Volksgezondheid en Gezin**

**Towards a projection model for the Flemish Social Protection**

### **Part III**

**A first step to projecting future needs, service use, and costs in ambulatory mental health care and psychosocial rehabilitation**

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 Part III: A first step to projecting future needs, service use, and costs in ambulatory mental health care and psychosocial rehabilitation

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Dit rapport kwam tot stand met de steun van de Vlaamse Overheid. In deze tekst komen onderzoeksresultaten van de auteur(s) naar voor en niet die van de Vlaamse Overheid. De Vlaamse Overheid kan niet aansprakelijk gesteld worden voor het gebruik dat kan worden gemaakt van de meegedeelde gegevens.

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## Chapter 1

# Introduction to projecting future needs and costs in mental health care and rehabilitation

The Flemish Government is responsible for a diverse range of ambulatory and residential mental health care facilities and rehabilitation centers in Flanders. In this report (Part III), we want to paint a picture of these facilities, focusing on needs, current use, and costs with the objective of providing building blocks for the projection of future needs and costs.

In the first section of this introductory chapter, we start by giving a brief overview of mental health care and rehabilitation facilities in Flanders, hereby illustrating the complex structure of the care landscape. The second section elaborates on the limitations of available information on needs, use, and costs in the Flemish mental health care and rehabilitation sector and the implications thereof for constructing a projection model for future needs and costs.

The next chapters consecutively focus on specific mental health care facilities (Chapter 2 and 3) and rehabilitation centers (Chapters 4 to 6), with chapters following the structure below when service use data are available.

- First, we describe the target group, the objectives and the organizational structure of the facility.
- Second, we discuss financing and costs, both for the clients and the government.
- Third, we introduce the available data with respect to service use and associated costs.
- Finally, we bring together all information in an attempt to project future needs and costs, hereby considering external information such as demographics and prevalence data and with particular emphasis on gaps in the available data.

The last chapter summarizes and combines the information from the previous chapters, with concrete suggestions for data collection aimed at developing an approach to future needs and costs projection, similar to the approach presented in Part II of this research project.

## 1 Mental health care facilities and rehabilitation centers in Flanders

In addition to psychiatric hospitals and psychiatric care homes, mental health care and rehabilitation facilities under the responsibility of the Flemish Agency for Care and Health (Agentschap Zorg en Gezondheid) include the ambulatory Centers for Mental Health Care, Sheltered Living Initiatives, and various care centers with Rehabilitation Agreements. Along with these facilities, the Agency for Care and Health finances the Flemish Mental Health Care Concertation Platform, which was established in 2019 through the fusion of five Flemish provincial concertation platforms and is aimed at further improving cooperation between the different actors in the mental health care sector.

### 1.1 Centers for Mental Health Care

The Centers for Mental Health Care (Centra voor geestelijke gezondheidszorg or CGG) offer ambulatory psychiatric or psychotherapeutic care to people with significant mental health problems. The Agency for Care and Health is currently responsible for 18 CGG in Flanders (after the recent merge of two centers in

East Flanders) and one in Brussels. The modalities for recognition, financing, and personnel are set out in the Flemish Government Decision of 17 December 1999 to implement the Decree of 18 May 1999 regarding mental health care (Vlaamse overheid, 1999). Flemish Government financing predominantly consists of a predetermined envelope and client fees for non-medical consultations and therapeutic sessions are fixed. In the Centers for Mental Health Care all care activities are registered in an electronic patient file (EPD).

In Chapter 2, we describe the Centers for Mental Health Care in more detail.

## **1.2 Sheltered Living Initiatives**

Between 1990 and 2000 the Sheltered Living Initiatives (Initiatieven beschut wonen or IBW) were created as an alternative to classic psychiatric hospitalization, following a wave of change from mental health care in psychiatric hospitals to care in the community. The Sheltered Living Initiatives offer long-term care to adult or elderly clients with long-lasting psychiatric problems. The sector was taken over from the Federal Government by the Agency for Care and Health, following the Flemish Government Decision of 7 December 2018 to implement the Decree of 6 July 2018 concerning the acquisition of the sectors of psychiatric care homes, sheltered living initiatives, rehabilitation agreements, rehabilitation hospitals and multidisciplinary counselling teams for palliative care (Vlaamse overheid, 2018).

Seeing that service use data were not available for the Sheltered Living Initiatives for this research project, we limit our description to a short overview of target group, organizational structure, and service use in Chapter 3.

## **1.3 Centers with rehabilitation agreements**

The centers with rehabilitation agreements provide services aimed at physical as well as psychosocial rehabilitation. The sector was also taken over from the Federal Government following the Flemish Government Decision of 7 December 2018 to implement the Decree of 6 July 2018 (Vlaamse overheid, 2018).

In general, the objective of all facilities with rehabilitation agreements is to help clients overcome or recover from physical and psychological disorders, functional limitations, addictions, and other vulnerabilities in order to regain autonomy. This objective is translated into a therapeutic care plan per client with specific rehabilitation goals specified. As a rule, the duration of rehabilitation is limited and consists of specialized treatment, individually or in group. Most centers offer ambulatory care, but relatively short-term residential care may be available as well (e.g. in rehabilitation for addicts).

The Agency for Care and Health of the Flemish Government finances the rehabilitation services billed to the health insurance funds of the clients. Specific modalities with respect to objectives, target group, rehabilitation activities, financing, personnel, administration and registration, etc. are described in separate rehabilitation agreements per center (in most cases) or per facility type (e.g. in the case of the Centers for Ambulatory Rehabilitation). All rehabilitation agreements can be consulted on the website of the Flemish Agency for Care and Health (<https://www.zorg-en-gezondheid.be/revalidatieovereenkomsten>).

The facilities with rehabilitation agreements include:

- Centers for Ambulatory Rehabilitation (Centra voor Ambulante Revalidatie/CAR), predominately aimed at children and adolescents with autism, ADHD, or other conditions in need of multidisciplinary diagnosis or treatment



- Rehabilitation Centers for Addiction (Revalidatiecentra voor verslaving)
- Psychosocial Rehabilitation Centers for Adults (Psychosociale revalidatiecentra voor volwassenen)
- Psychosocial Rehabilitation Centers for Children and Adolescents (Psychosociale revalidatiecentra voor kinderen en jongeren)
- Autism Reference Centers (Referentiecentra voor Autisme/RCA)
- Rehabilitation Units for Disturbances in Early Parent-Child Interactions (Revalidatie-eenheden voor vroegtijdige stoornissen in de interactie ouders-kinderen)
- Centers for Locomotor and Neurological Rehabilitation (Revalidatievoorzieningen locomotorische en neurologische revalidatie)
- Rehabilitation Centers for Children with Respiratory and Neurological Disorders (Revalidatie voor kinderen met respiratoire en neurologische aandoeningen)
- Centers for Visual Rehabilitation (Voorzieningen voor visuele revalidatie)
- Respite Care Units (Respijteenheden)

In Chapters 4 and 5 we describe the Centers for Ambulatory Rehabilitation and the Rehabilitation Centers for Addiction in more detail. For the other psychosocial and physical rehabilitation centers the description will be limited to a short overview in Chapter 6.

## **2 Data-availability and other constraints to projecting future needs, use, and costs**

To get a complete idea of future needs and costs in mental health care and rehabilitation, an ideal dataset could be described as follows:

- Rows would correspond to specific needs groups, with grouping based on an optimal differentiation from a mental health or rehabilitation policy point of view.
- Columns would correspond to different mental health care and rehabilitation services
- Data table entries would contain the number of individuals in needs group  $i$  treated by service  $j$ .

Such a dataset would not only give a picture of the differentiated ways in which a given needs group is treated (per row), but also of the differentiated client groups a particular service provides care to (per column). Ideally, there should also be a 'no treatment' column to account for unsatisfied needs as well.

Contrary to this ideal situation, however, we are confronted with scattered data sources containing (at best) piecemeal information, which is far from sufficient to produce a coherent overall picture of service use in the mental health care and rehabilitation sector. Important variables for distinguishing needs groups are lacking or are not consistently registered in a standardized way and time series are too short to give a reliable idea of changes and developments over time.

The remainder of this chapter briefly introduces available data sources and limitations to using service use data in projecting future trends. In the final chapter of this report, we will suggest concrete steps to start constructing the ideal dataset described above.

### **2.1 Available mental health care and rehabilitation service use data.**

At present, the most comprehensive database containing information on health care service use and costs is the health insurance database managed by the Inter-Mutualistic Agency (IMA/AIM), of which a representative longitudinal panel is selected as a permanent sample, the EPS. Since we already described the EPS database in great detail in Part II, we limit the description here to a short summary of its strengths and limitations with respect to mental health care and rehabilitation service use.

The EPS offers information in panel form, making it possible to track individuals over time. In this report, we concentrate on data from 2009 onwards, as there was a break in most series in the year before that. Although the EPS contains detailed information on use and costs of certain services and facilities, based on various nomenclature codes, this is not the case for all services and facilities. In some cases, nomenclature codes are few and rather general with little detail about the actual care activities they refer to. Moreover, data in the EPS are restricted to services and facilities that were covered by the health insurance funds as part of the federal health insurance system at the time of starting the permanent sample. Therefore, the database does not contain information on services that were already under the responsibility of the Flemish Government at that point, such as the Centers for Mental Health Care.

Apart from a few basic socio-economic variables and indirect morbidity information based on medication use, information about individual client characteristics is limited in the EPS and certainly insufficient to trace population mental health care and rehabilitation needs in detail. In addition, the number of observations relevant to certain specific care services may be extremely small. This is partly due to the sampling procedure, with oversampling for elderly people, but not for younger groups, as was discussed in the second part of the report. However, the main reason for small sample sizes is linked to the services themselves, which may be answering care needs with low prevalence in the population, for instance in the case of childhood respiratory and neurological disorders.

In addition to the EPS database, there are more or less accessible data sources with more or less comprehensive information, directly linked to specific mental health care or rehabilitation services. These data sources will be introduced in more detail when describing the respective services in the following chapters and include:

- The Electronic Patient File registration data (EPD) and personnel data from the Centers for Mental Health Care (see Chapter 2)
- The Treatment Demand Indicator data (TDI) managed by Sciensano and referring to addiction treatment (see Chapter 5)
- Annual report data from the Centers for Ambulatory Rehabilitation (see Chapter 4)

## **2.2 Limitations of mental health care and rehabilitation service use data**

While undoubtedly useful, all of the existing data on mental health care and rehabilitation service use offer only individual building blocks, with more information needed to build a complete picture. In addition, we have to consider the more fundamental question as to what we can learn from observational use data about future mental health care and rehabilitation needs. When supply of services is sufficient and the selection of clients using these services reflects the pattern of needs in society, observational data (e.g. time series of past use and client characteristics) should give a good idea about developing trends. We presented this approach to projecting future needs and associated costs in general terms in Part I of this report and applied it to residential and home care for elderly people in Part II.

A similar approach in the mental health care and rehabilitation sector is not straightforward though. For most services, capacity is fixed by the regulator and insufficient to cover care needs. In addition, specific historical circumstances have led to a regional spread of facilities that does not necessarily match the geographical distribution of needs. With service use thus partly driven by admission policies, supply restrictions, and regional availability, different clients with similar care needs may end up in various services and facilities, not all of them equally suited to their needs. To some extent, waiting lists can be informative of this problem. However, waiting list data are likely to be incomplete as well, as long waiting lists may

discourage individuals from applying. Ultimately, potential clients may not appear in the data at all when actual care needs are not perceived as a problem that can and should be treated, and are not transformed into demand due to lacking or limited supply of suitable services. In this context, service use data are hardly informative of needs, and future projections solely based on observations about past use, may be very misleading as an indicator of coming trends.

It is thus necessary to expand our method to projecting future needs from current use data and incorporate external data, which may be illuminating of mental health care or rehabilitation needs. In paragraph 2.3, we suggest some possible approaches.

### **2.3 External data regarding mental health care or rehabilitation needs**

The most obvious data informative of population needs are population prevalence data. An important data source in this regard is the Belgian national Health Interview Survey (HIS, <https://hisia.wiv-isp.be/>), which is embedded in the European Health Interview Survey project (EHIS) (<https://ec.europa.eu/eurostat/web/microdata/european-health-interview-survey>) and provides a series of repeated cross-sectional datasets. The purpose of the HIS is to assess the general and mental health status of the Belgian population and to follow up relevant health indicators. Data are collected every four to five years and contain information on subjective health, specific (mental) health conditions, long-term limitations, psychosocial problems in children and adolescents, health determinants, environmental factors, socio-economical background, etc. Questions on service use are included as well, but do not extend to the services described in this report.

In Appendix 1, we summarize relevant prevalence information from international literature and the Belgian HIS database to shed some light on mental health care and rehabilitation needs in Flanders. From this summary, it is clear that Flemish prevalence data are insufficient at present. With four to five-year gaps and operationalizations changing in between measurements in the Belgian Health Interview Survey, complete time series for the Flemish population are not available. For some problems or conditions, yearly time series are available from neighboring or similar countries, but evolutions in these countries do not necessarily correspond to the Flemish population and prevalence percentages may differ greatly between countries (e.g. for substance abuse). Regional prevalence percentages within Flanders are sometimes obtainable from the HIS prevalence data, but are considered unrepresentative, as sample sizes per province are mostly too small.



## Chapter 2

### The Centers for Mental Health Care

The Centers for Mental Health Care (Centra voor geestelijke gezondheidszorg or CGG) offer ambulatory psychiatric or psychotherapeutic care to vulnerable persons with moderate or severe mental health problems with a significant risk of chronicity. As such, they are positioned as secondary care services in the mental health care landscape. The Agency for Care and Health of the Flemish Government is responsible for 18 CGG in Flanders and one in Brussels. The modalities for recognition, financing, and personnel are set out in the Flemish Government Decision 17 December 1999 to implement the Decree of 18 May 1999 regarding mental health care (Vlaamse overheid, 1999). Client fees for non-medical consultations and therapeutic sessions are fixed. Fees for medical and certain para-medical consultations are determined by the National Institute for Health and Disability Insurance (NIHDI) and reimbursed by the health insurance funds. In the CGG care activities are registered in an electronic patient file (EPD).

In this chapter we describe target group, objectives and organizational structure of the Centers for Mental Health Care (section 1), financing and costs (section 2), data sources containing information on current use and costs pertaining to the activities of the CGG (section 3), and the projection of future needs and costs based on the available information presented in previous sections (section 4).

#### **1 Target group, objectives, and organizational structure**

Ambulatory mental health care in the Centers for Mental Health Care is aimed at three main target groups: children and adolescents, adults, and elderly people with significant mental health problems. Most CGG consist of multiple multidisciplinary teams at different locations, with every team including at least one or more psychiatrists, psychologists, and social workers.

We discuss CGG target groups, objectives and organizational structure in more detail in the next paragraphs, based on information of the Flemish Agency for Care and Health.

##### **1.1 Target group and objectives**

The main target groups of the Centers for Mental Health Care are children and adolescents (0-17 years), adults (18-59 years), and elderly people (60 years or more) with mental health problems of a serious nature or with a significant risk of following a chronic course. According to the CGG reference frame, clients should be taken in when a multidisciplinary approach is indicated and ambulatory treatment is feasible. In the adult target group, special attention is given to clients with enhanced reimbursement status (e.g. due to low income) or without health insurance status (e.g. asylum seekers, undocumented migrants).

In most cases, clients are referred to the Centers for Mental Health Care, e.g. by primary care general practitioners, psychiatric hospitals, Centers for Student Guidance (CLB), Centers for General Welfare Work (CAW), the Belgian justice department, etc. However, a considerable number of clients come without referral.

Generally, a care period in the Centers for Mental Health Care consists of three stages: Intake and diagnosis, drawing up of a treatment plan, and the actual treatment or counselling stage.

The main purpose of the intake procedure is to decide as quickly as possible whether the client belongs in the CGG or needs care elsewhere. Therefore, the first session with the client should take place within one month for 75% of clients and within two months for all clients. The intake procedure is a multidisciplinary process of problem clarification and diagnosis, leading to a treatment plan within the center or referral to other care facilities. The decision is made in consultation with the client (system) and is aimed at selecting the least drastic available recovery-oriented treatment with maximal benefit and maximal responsibility and self-reliance of the client. Involvement of the context and close relations is encouraged throughout the process. Considering age, maturity and developmental stage, an assessment of suicide risk is frequently included.

Following intake, a plan for treatment in the center is drawn up in a maximum of four consultations. It contains information about medication use (including psychiatric drugs), somatic problems and complaints, history of psychological problems, relevant socio-economic factors (work, social relations, living conditions, etc.), substance use, the clients' expectations for care, diagnosis and hypotheses, objectives, planned treatment and counselling (actions and interventions), alignment with relevant parallel interventions by other care or service providers, and an evaluation scheme.

Depending on problem and target group, a diverse selection of evidence-based treatment or counselling interventions is available in the Centers for Mental Health Care, such as individual therapy, group therapy, family therapy, medical treatment, crisis intervention, follow-up contract, psycho-education, activation activities, etc. During treatment the treatment plan is used as an interactive clinical work instrument, documenting consultations with the client and important aspects of treatment and counselling. Care periods outlasting six months are discussed in the multidisciplinary team, focusing on objectives, treatment status, and appropriateness of further treatment or counselling. As an equal partner, the client is actively involved in periodical evaluations and adjustments to his or her treatment (plan). Treatment usually takes place in the CGG, but can be home-based as well.

In addition to the core task of every Center for Mental Health Care, specific types of interventions can be provided (approximately one fourth of all care periods). These include forensic care, addiction treatment, VDIP (Early Detection and Intervention Psychosis), and other forms of specific care, such as tobacco, alcohol and drug prevention (TAD), suicide prevention (SP), care for people with disabilities and additional mental health problems, etc. The majority of clients in these specific care programs are adults.

Finally, the CGG regularly engage in joint projects with other partners, focused on distinct target groups or themes (e.g. psychiatric care at home, domestic violence and child abuse, alternative judicial measures, care at work, etc.) and offer advice and support to other care organizations, such as Special Youth Care, nursing homes, CAW, prisons, etc.

## **1.2 Organizational structure**

There are 19 Centers for Mental Health Care in Flanders and Brussels, four of which are based in each of the provinces Antwerp, East-Flanders, and West-Flanders, three in Flemish-Brabant and Limburg, and one in Brussels. Each CGG consists of multiple teams at a total of 94 different locations throughout Flanders. This spread should guarantee sufficient accessibility in all Flemish regions. A maximum of two CGG can be officially recognized per catchment area of adjoining municipalities with a minimum of 400.000 inhabitants. There are no predetermined criteria with respect to staffing in function of target groups or population size of the catchment area. An up-to-date version of all locations can be found on the joint CGG-website,

managed by the healthcare umbrella organization Zorgnet-Icuro (<https://www.centrageestelijkegezondheidszorg.be>).

The Centers for Mental Health Care work with multidisciplinary teams, including at least one or more psychiatrists, psychologists, and social workers, supplemented with reception or administrative staff. Depending on the project or target group, the basic team can further consist of occupational therapists, speech therapists, (remedial) educationalists or educators, psychological assistants, sociologists, criminologists, medical staff (general practitioners, specialists or nurses), etc.

Waiting lists in the Centers for Mental Health Care can be long and increased gradually in recent years. As a result of over demand and long waiting lists, some CGG enter into cooperation agreements with independent psychologists.

In Section 3 of this chapter we provide more detailed information on the characteristics of target clients and the use of services in the Centers for Mental Health Care, based on available data sources.

## **2 Financing and costs**

The Centers for Mental Health Care are mainly subsidized by the Flemish Government, but also receive specific third-party funding from federal and local governments and non-governmental organizations. Other financial resources include health insurance and client contributions and financial and exceptional revenues booked by the CGG, the latter of which are for the most part financially insignificant. According to an analysis of the Belgian Court of Audit (2011), Flemish Government subsidies, third-party funding, health insurance and client contributions accounted for approximately 80%, 10%, 4%, and 2% of financing, respectively between 2008 and 2011.

The Flemish Government financing predominantly consists of a fixed envelope, which is largely based on historical personnel data. Envelopes are raised as a result of indexation, seniority coefficients, and in the context of Flemish Intersectoral Agreements. In general, the envelope system is not adapted to care needs in the catchment area or costs of delivered performances.

Between 2008 and 2012, personnel costs accounted for at least 80% of total costs in every Center for Mental Health Care (Departement Welzijn, Volksgezondheid en Gezin, 2012). From 2011 to 2017 approximately 80% of personnel costs (in terms of full-time equivalents or FTE) were financed through the envelope. In 2018 and 2019 the proportion of alternative financing sources increased slightly, resulting in 74% envelope financing (Agentschap Zorg en Gezondheid, personnel data, n.d.). The management agreements between the different CGG and the Flemish Government state 70% as the minimum percentage of the envelope to be spent on personnel costs (in 2007-2009 and 2010-2012). The CGG can transfer up to 20% of yearly funds to build up a cumulated reserve, which may not exceed 50% of the yearly envelope since 2018.

Besides the fixed envelope, the Flemish Government provides additional funding to projects and assignments focused on specific target groups, problem areas, regional needs, or acute crisis situations. This additional financing is awarded in the context of a covenant with the Flemish Government or ad hoc and can be divided into project subsidies and supplements. The latter are generally included into the envelope in the year following its first occurrence and are aimed at specific target groups in most cases. For example, in 2008, a supplement for forensic care was added. More recently, financing for the target groups of children and adolescents (2011) and elderly people (2012) was raised, following an increase in new intakes in 2010 for the first group and leading to more new intakes between 2013 and 2017 for the latter.

Usually, the distribution of supplemental means across the Centers for Mental Health Care is based on the number of inhabitants in the catchment area, rather than objective care need parameters.

Diverse projects are subsidized by the Flemish Government, including implementation of primary care psychological function, psychiatric care at home, care for domestic violence and child abuse victims, alternative judicial measures, care at work, buddy projects, etc. In most cases, distribution of funding proceeds stepwise or indirectly. In stepwise project funding, one center receives all means, dividing them further to other CGG, functioning as project partners. Indirect funding runs through project coordinating organizations like Care Net Flanders (Zorgnet Vlaanderen) and the Federation of Mental Health Care Services (Federatie Diensten Geestelijke Gezondheidszorg or FDGG). According to the 2011 investigation of the Belgian Court of Audit, up till then, the only project with funding based on an environmental analysis of care needs was the project 'Early detection, diagnosis, guidance, and treatment of young adults with schizophrenic psychosis'. Means for this project were determined to supply treatment for 20% of all occurring psychosis in the catchment area, hereby considering the presence of other care services, population characteristics, and epidemiological data.

Finally, Flemish Government financing also includes specific minor subsidies, such as the VIPA-investment subsidies, designated to construction projects or infrastructure improvements.

The federal and local governmental and non-governmental third-party financing consists of a diverse range of subsidies and payments. Almost half of these means are employment subsidies aimed at enhancing employment in the social profit sector. The other half are specific project subsidies

Client and health insurance contributions for non-medical and medical performances constitute a rather limited financing source for the Centers for Mental Health Care. Since 2013 client contributions for non-medical consultations and therapeutic sessions in the CGG are fixed (Flemish Government Decision 5 October 2012 regarding client contributions in the Centers for Mental Health Care). The standard fee is 11 Euro. Urgent care and the first consultation are not charged. Clients with enhanced reimbursement status or in budget guidance pay a reduced fee of 4 Euro per consultation. Clients without health insurance status, detainees, and 'persons in a situation worthy of consideration' are exempted from paying fees. Clients with enhanced reimbursement or no health insurance status are probably overrepresented in the CGG. According to NIHDI statistics (RIZIV, 2021), approximately 15% of the Flemish population belong to the first group and less than 1% belong to the second group.

Fees for psychiatrists, other medical consultations, and certain therapeutic activities in the context of specific conventions (e.g. chronic fatigue, rehabilitation, palliative care, etc.) are determined by the National Institute for Health and Disability Insurance (NIHDI) and reimbursed by the health insurance funds.

In Section 3 of this chapter, we give more information on financing and costs in the Centers for Mental Health Care, based on available data sources.



### 3 Data on service use and costs in the Centers for Mental Health Care

In the first paragraph of this section, we present the available data sources containing information on the activities of the Centers for Mental Health Care. In the next two paragraphs, we describe current use (3.2) and costs (3.3) based on these data sources.

#### 3.1 Data sources

As most services offered by the Centers for Mental Health Care are not reimbursed by the health insurance funds, there are no data referring to these services available in the Inter-Mutualistic Agency database. Moreover, the medical and para-medical services provided within the CGG-context by psychiatrists, speech therapists, etc. that are reimbursable by the health insurance funds, cannot be distinguished in the IMA-database from services provided by the same health care professions outside the CGG-context.

Therefore, the description of use and costs in the Centers for Mental Health Care presented in this section is exclusively based on data obtained from the Flemish Agency for Care and Health. First, clients and care activities in the CGG are registered in an electronic patient file (EPD) per center, replacing the former so-called Arcade registration per location or antenna since 2007 (3.1.1). Second, personnel data are available as part of yearly progress reports, starting from 2011 (3.1.2).

##### 3.1.1 Electronic patient file (EPD)

The EPD or electronic patient file is a registration and filing system with client files linked to treatment plans and a calendar shared by caregivers from the same team. As a result, registration of activities, treatment sessions, and client attendance is very detailed and reliable, whereas information that is not actively addressed during treatment sessions may be less complete.

In the EPD, a number of variables are registered mandatory by each Center for Mental Health Care, following an agreement with the Flemish Government. Twice a year, these data are anonymized and exported to the Agency for Care and Health. Although registration of the national insurance number of clients is possible in the EPD, it is mandatory only for clients with addiction problems as part of the TDI-registration (Treatment Demand Indicator, see Chapter 6). For the export to the Agency for Care and Health, a specific client code is used, making clients uniquely identifiable across care periods within the same CGG, but not across different centers.

The set of mandatory variables mainly contains information on user characteristics (i.e. client characteristics and treatment antecedents, such as gender, age, residence, health insurance status, intake problem, diagnosis, referral from) and service characteristics (e.g. waiting time, number of face-to-face contacts, duration, type of treatment or care activity, referral to). The database consists of individual records, with information registered per care period, per client, or per activity. The total number of care periods per registration year is always higher than the total number of clients, as some clients have more than one care period per year, e.g. when treated for two distinct problems (by two different caregiver teams) or when treated twice in the same year with a pause between both treatment periods. For example, in 2018, a total of 55.613 care periods were registered in the CGG, involving 54.601 different clients.

In Table 2.1 registered variables in the EPD database are summarized briefly. Information on different registration levels (client, care period, activity, and personnel) can be coupled through the use of common ID codes on all levels.

Table 2.1 Brief overview of registered variables in the Electronic Patient File database

Registration level	Variables
Client	Client ID; Residence; Nationality; Year of birth; Gender; Health Insurance Status; Client contribution; Contribution type; Presence; ...
Care period	<ul style="list-style-type: none"> <li>• Referrer; Referrer detailed</li> <li>• Intake problem; Intake problem detailed</li> <li>• Status (Intake, FTF1 planned, FTF1, FTF2 (treatment), Ended)</li> <li>• Target group (forensic, addiction care, suicide risk, etc.)</li> <li>• Referral; Referral detail</li> <li>• Closure</li> <li>• Living situation (at beginning/end of care period)</li> <li>• Marital status (at beginning/end of care period)</li> <li>• Profession (at beginning/end of care period)</li> <li>• Income (at beginning/end of care period)</li> <li>• Education (at beginning/end of care period)</li> <li>• Client type (main/secondary)</li> <li>• DSM-5 diagnosis (since 2018)</li> <li>• Drug use variables (for Treatment Demand Indicator)</li> <li>• Legal status, forensic target group variables</li> <li>• Child abuse variables</li> <li>• Suicide risk variables</li> <li>• Treatment evaluation</li> <li>• Previous care, external help</li> <li>• Application date, diagnosis date, closure date, FTF1, FTF2, last FTF</li> </ul>
Activity	Type of activity; Location; Location type; Care type; Duration (in minutes); Occurrence; ...
Personnel	Personnel ID, Function, Location

The Flemish Agency for Care and Health merges the EPD-registration data of all CGG in several databases and regularly publishes key figures and interactive reports on their website. In paragraph 3.2 of this section, we give a description of CGG service use, based on aggregated data per center, derived from the EPD databases that were constructed by the Flemish Agency for Care and Health. Although data ranged from 2008 to 2019, we limited our description to the period from 2010 to 2019, as some variables were not registered yet in previous years and there seemed to be generally more inconsistencies in the earlier data.

### 3.1.2 Personnel data

Personnel data are summarized in yearly electronic reports by the Flemish Agency for Care and Health, covering the period between 2011 and 2019 (with the exception of 2017). The personnel database contains information on the number of FTE (Full-Time Equivalents) by financing source, age category, function (category), and client target group. Descriptions of CGG-personnel data in the remainder of this section are exclusively based on the electronic reports published on the website of the [Agency for Care and Health](#).

### 3.2 Description of service use in the Centers for Mental Health Care

In this paragraph we provide an overview of the overall use of services in the Centers for Mental Health Care (3.2.1), with a comparison between target groups and specific care types (3.2.2) and provinces (3.2.3). In addition, we focus on user characteristics (3.2.4), and service characteristics (3.2.5).

#### 3.2.1 Overall use of services in the Centers for Mental Health Care

The total number of care periods registered in the Centers for Mental Health Care gradually increased from 2010 to a maximum of 58.885 care periods in 2016, which amounts to a 10% increase. From then onwards, the number of care periods decreased again with 2 to 4% each year, leading to a total of 53.548 care periods in 2019, a 9% decrease when compared to 2016. As Figure 2.1 below shows, this recent decreasing trend between 2016 and 2019 was especially apparent in new care periods started in the registration year (almost 13% decrease) and in care periods started in the previous year (12% decrease). Contrary to this trend, the number of care periods started earlier than the previous year continued to increase until 2018, with only a slight decrease in 2019.

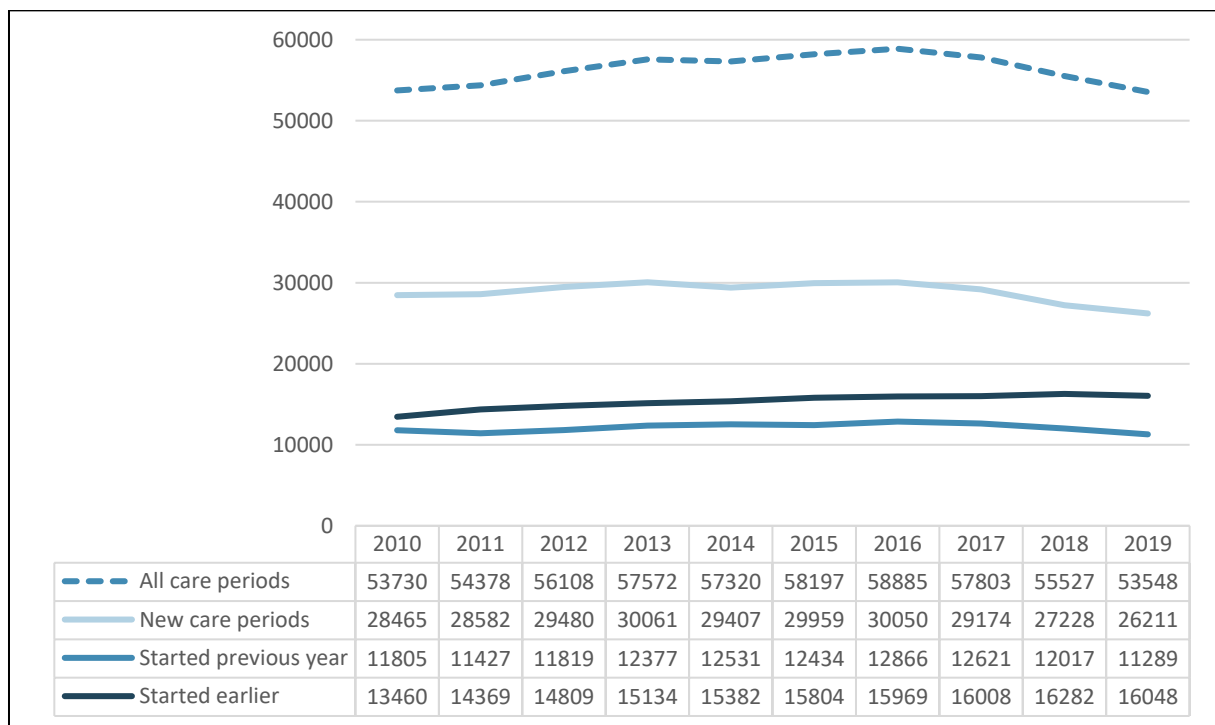


Figure 2.1 Evolution of the number of care periods provided by the Centers for Mental Health Care from 2010 to 2019, by intake year (Agency for Care and Health, EPD aggregated data).

Combining these trends shows a decreasing proportion of new care periods (from 53% in 2008 to 49% in 2019) and an increasing proportion of continuing care periods started earlier than the previous year (from 25% in 2008 to 30% in 2019) in relation to all provided services (see Figure 2.2).

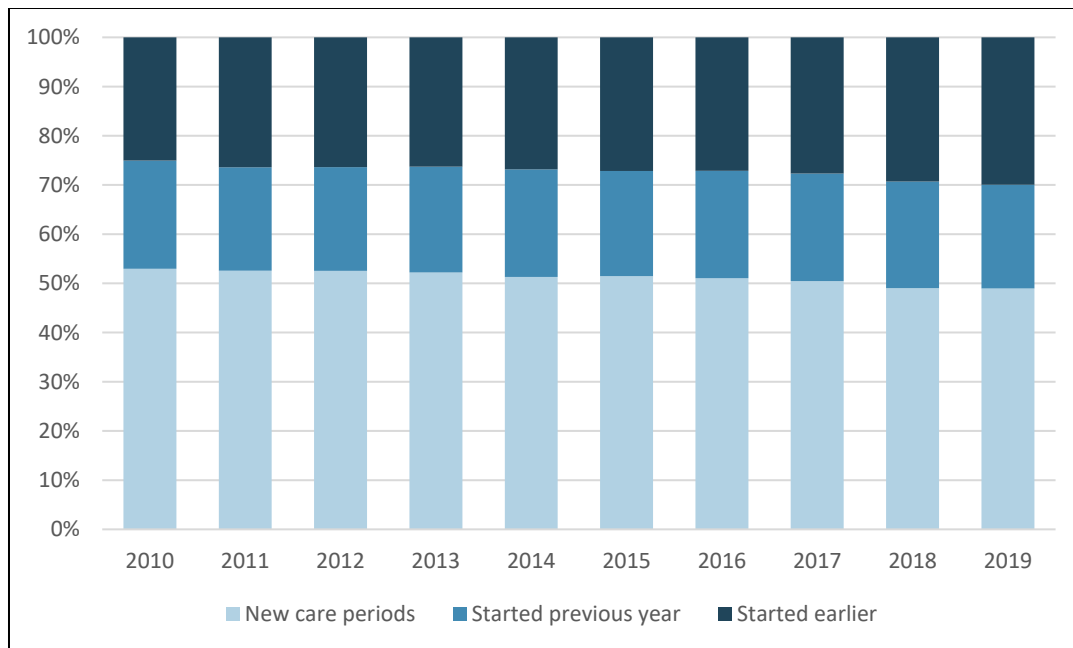


Figure 2.2 Evolution of the proportion of care periods per intake year in the Centers for Mental Health Care from 2010 to 2019 (Agency for Care and Health, EPD aggregated data).

Thus, there seems to be an increase in the duration of treatment offered by the Centers for Mental Health Care in recent years, suggesting an increase in the number of clients with chronic problems in need of long-term treatment. On the one hand, this could reflect a rather positive change in the mental health care landscape towards more community-centered care, leading to people with more serious or chronic problems seeking ambulatory care in the CGG instead of residential psychiatric care. However, it could also be the reflection of more negative trends, including an increase of chronic mental health problems in the Flemish population or insufficient supply in the different mental health care facilities leading to people with relatively less severe or urgent mental disorders ending up at the end of the queue, or ultimately not receiving specialized mental health care at all, with the risk of worsening problems.

In general, the frequency of treatment sessions decreases when the duration of treatment increases, as frequent sessions may become counterproductively, e.g. by creating dependence. Figure 2.3 and 2.4 show the evolution in the number of sessions, using the 'face-to-face contacts (FTF) in the last two years of treatment' variable. For this variable, we limit the presentation of results to the period between 2012 and 2019 due to irregularities in earlier data.

The trend in the total number of care periods shown in Figure 2.1 above is reflected by a similar trend in the total number of face-to-face contacts (FTF) in the last two years of treatment for all care periods registered in the registration year (Figure 2.3).

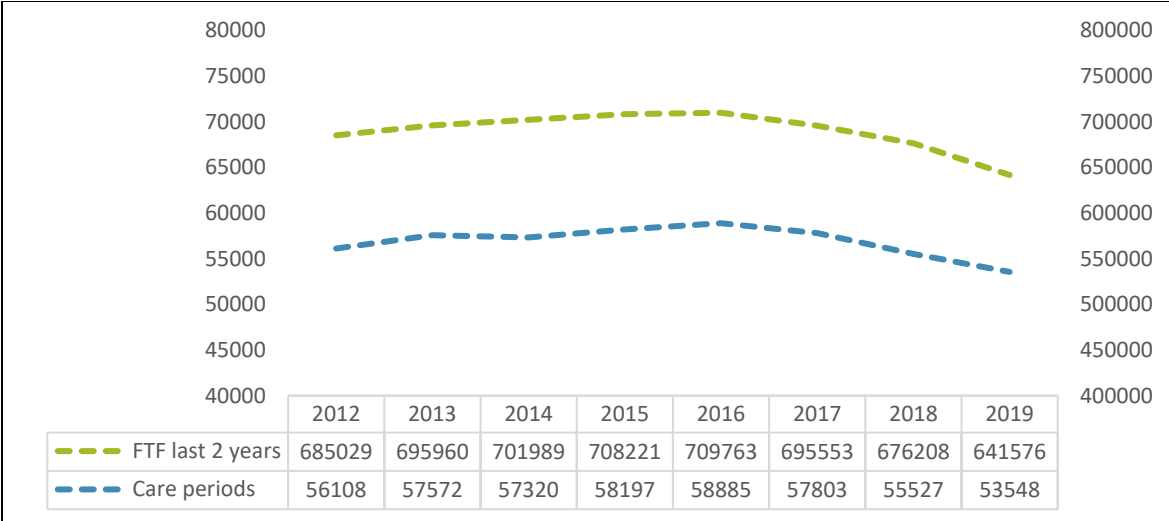


Figure 2.3 Comparison of the number of care periods and the number of face-to-face contacts in the last 2 years of treatment in the Centers for Mental Health Care from 2012 to 2019 (Agency for Care and Health, EPD aggregated data).

When looking more closely at the different intake years (Figure 2.4), recently started care periods (new or started in the previous year) show a similar downward trend in the number of face-to-face contacts and the number of care periods. However, in care periods started earlier than the previous year, the number of FTF-contacts remained constant while the number of care periods increased.

As a result, the ratio between the number of care periods and the number of face-to-face contacts only slightly diminished for care periods started in more recent years, whereas the number of face-to-face contacts per care period went down from almost 25 in 2012 to less than 23 in 2019 in care periods started earlier (see figure 2.5).

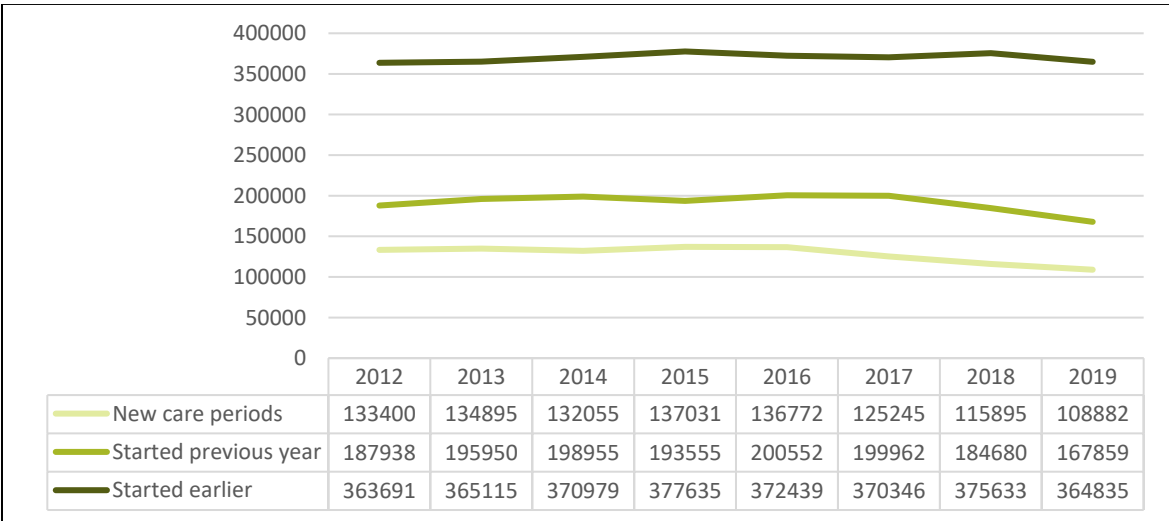


Figure 2.4 Evolution of the number of face-to-face contacts in the last 2 years of treatment by intake year in the Centers for Mental Health Care between 2012 and 2019 (Agency for Care and Health, EPD aggregated data).

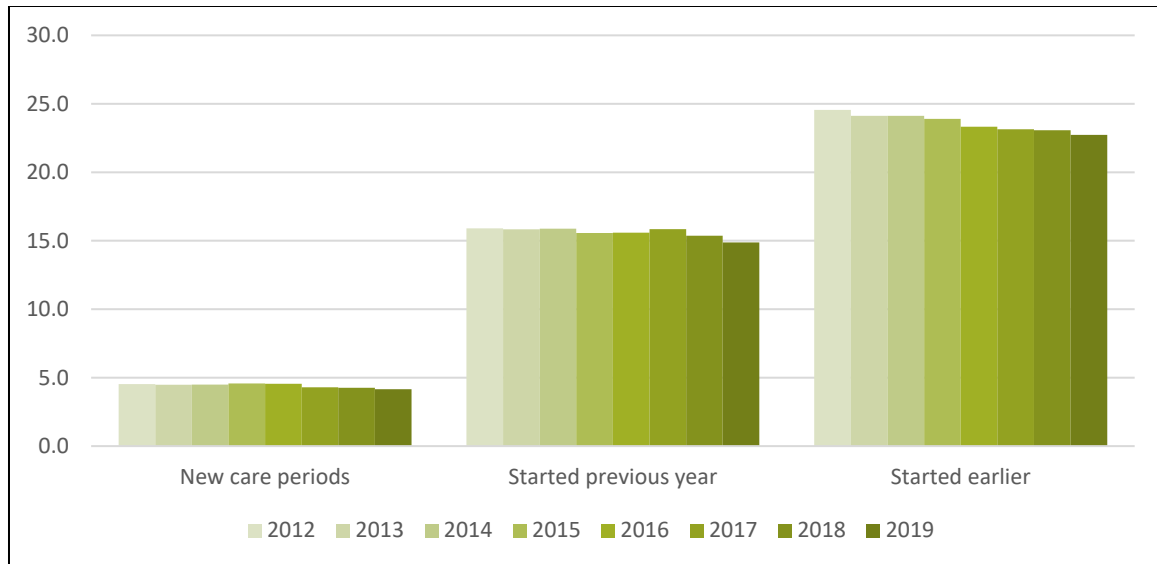


Figure 2.5 Evolution of the number of face-to-face contacts in the last two years of treatment per care period in the Centers for Mental Health Care from 2012 to 2019 (Agency for Care and Health, EPD aggregated data).

In summary, there was not only a decrease in the total number of care periods and the total number of face-to-face contacts registered by the Centers for Mental Health Care, but a decrease in the number of face-to-face contacts per registered care period as well, especially in care periods started earlier and in recent registration years.

At first sight, these results suggest a recent capacity reduction in the Centers for Mental Health Care, which seems to be reflected in the frequency of face-to-face contacts, as well as in the number of services offered. However, there is no indication of a capacity reduction when considering personnel data, as shown in Figure 2.6. The number of Full Time Equivalents (FTE) employed in the CGG for actual client care showed a limited increase of approximately 7% from 2011 to 2018 and 2019. In addition, FTE for prevention activities and other specific activities increased even more.

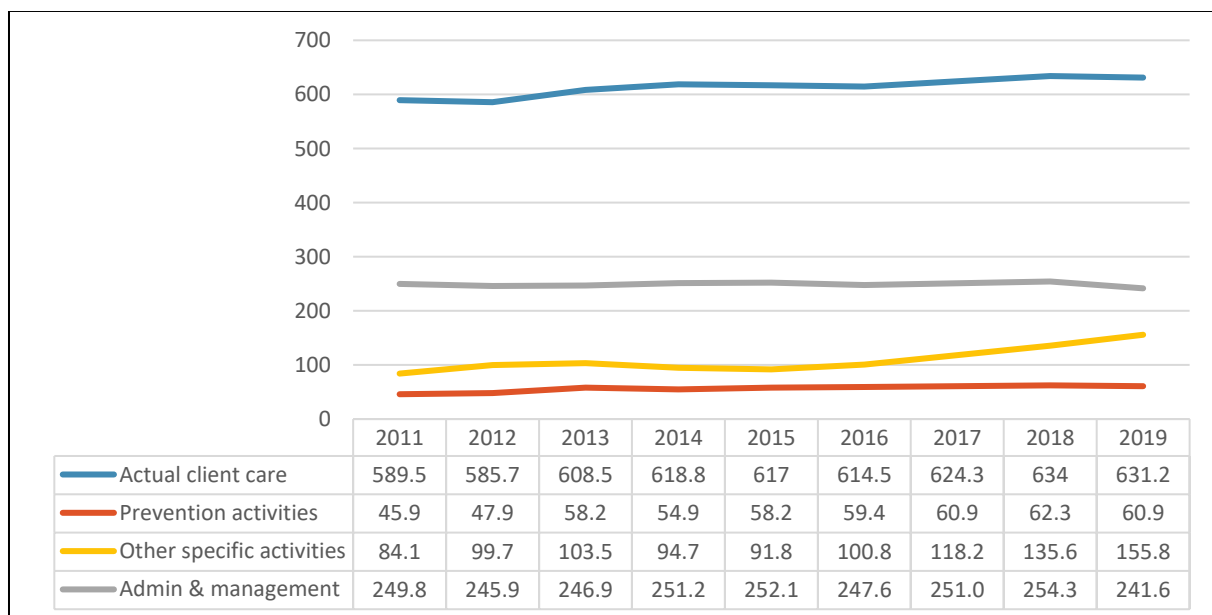


Figure 2.6 Evolution of Full Time Equivalents in the Centers for Mental Health Care between 2011 and 2019 (with interpolated numbers for 2017) (Agency for Care and Health, Personnel web report).

Although the relative decrease in the number of FTF-contacts for the care periods started earlier than the previous year may be expected if the proportion of very long care periods increased, the almost 10% decrease in the total number of FTF-contacts for all registered care periods between 2016 and 2019, together with nearly constant staffing levels for actual client care in the same time period, suggests that additional tasks, not registered in the other categories in Figure 2.6 above, may still take up staffing time previously used for FTF-contacts with clients. Further investigation into the data is necessary to understand this picture.

### 3.2.2 Use of services per target group and care type in the Centers for Mental Health Care

#### Target group

Between 2010 and 2019 the adult target group (18 to 59 years) accounted for approximately two thirds of recent care periods (new or started in the previous years), the children and adolescent target group (under 18) for one fourth, and the elderly target group for less than 10% (Figure 2.7). Long care periods started earlier than the previous year were relatively less common in the youngest target group (2%) and relatively more common in the adult (82%) and elderly group (16%), suggesting longer care periods in the latter two age groups. Within the adult target group, this was even more the case for clients with enhanced reimbursement status, with 38% of care periods started earlier than the previous year, as compared to 30 and 33% in the registration year or the year before.

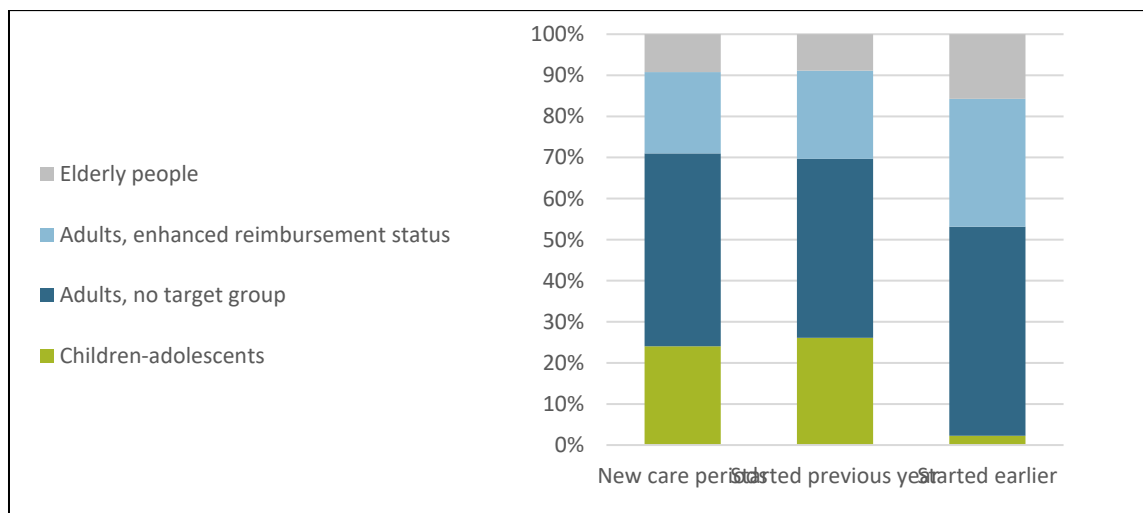


Figure 2.7 Proportion of care periods for target groups per intake year in the Centers for Mental Health Care between 2010 and 2019 (Agency for Care and Health, EPD aggregated data).

As shown in Figure 2.8 and 2.9 below, the proportion of (new) care periods remained rather constant between 2010 and 2019 in the adult target group, whereas total numbers increased from 2010 to 2016 and decreased again since then.

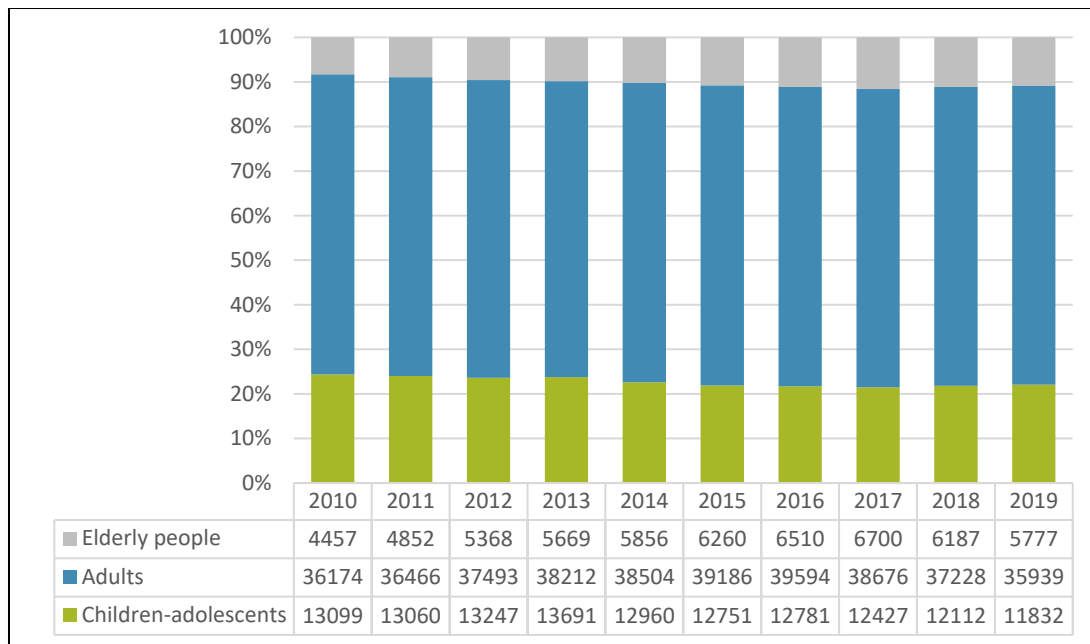


Figure 2.8 Evolution of the proportion and number of all care periods offered to age target groups in the Centers for Mental Health Care from 2010 to 2019 (Agency for Care and Health, EPD aggregated data).

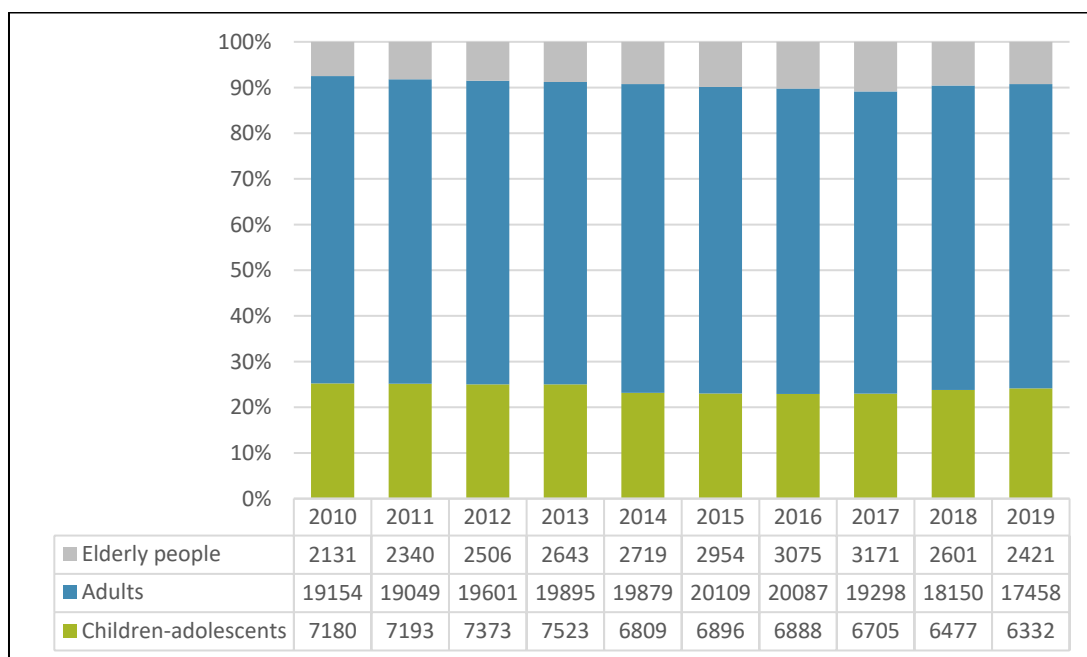


Figure 2.9 Evolution of the proportion and number of new care periods offered to age target groups in the Centers for Mental Health Care from 2010 to 2019 (Agency for Care and Health, EPD aggregated data).

In the target group of elderly people there was a relatively stronger increase until 2017, followed by a decrease in 2018 and 2019. As a consequence, the proportion of (new) care periods offered to elderly clients mounted from an approximate 8% in 2010 to almost 12% in 2017 to end up around 10% in 2019. Contrary to the elderly target group, the youngest group became somewhat less important, with decreasing numbers of (new) care periods involving children and adolescents, resulting in a decreasing proportion from 24% in 2010 to 22% in 2019 for all registered care periods and from 25% to 24% for new care periods.



Figures 2.10 and 2.11 below focus on the adult target group and show a gradual increase between 2010 and 2017 in the number and proportion of all registered care periods and new care periods offered to adult clients with enhanced reimbursement status. This increase was followed by a strong leap in 2018 and 2019, with more than half of the (new) care periods offered to the enhanced reimbursement target group in both years. It is not clear whether this was the result of actual heightened inflow, or could be due to registration particularities (e.g. improved registration of the enhanced reimbursement status or registration errors).

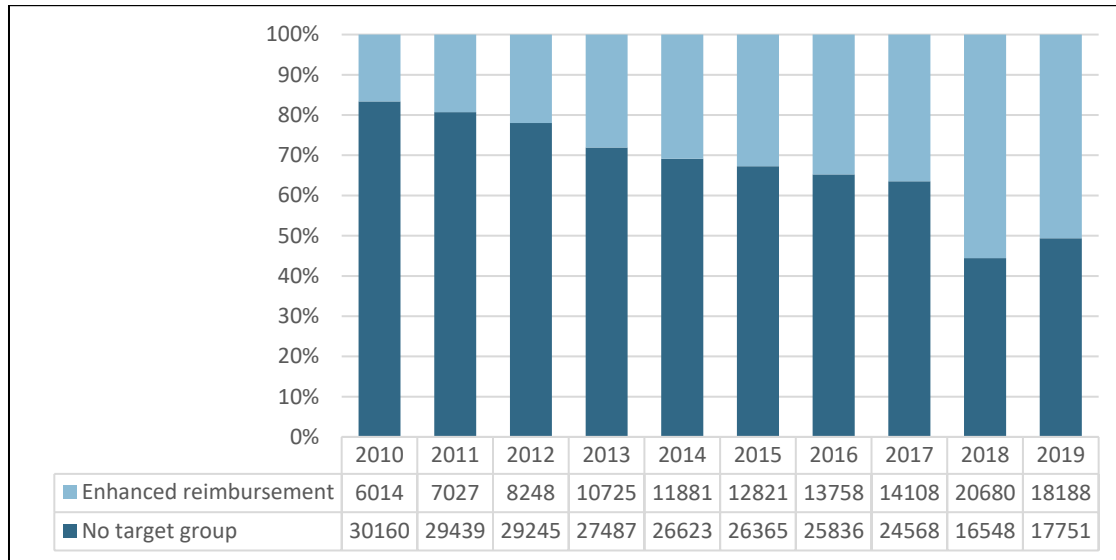


Figure 2.10 Evolution of the proportion and number of all care periods per reimbursement status offered to the adult target group in the Centers for Mental Health Care from 2010 to 2019 (Agency for Care and Health, EPD aggregated data).

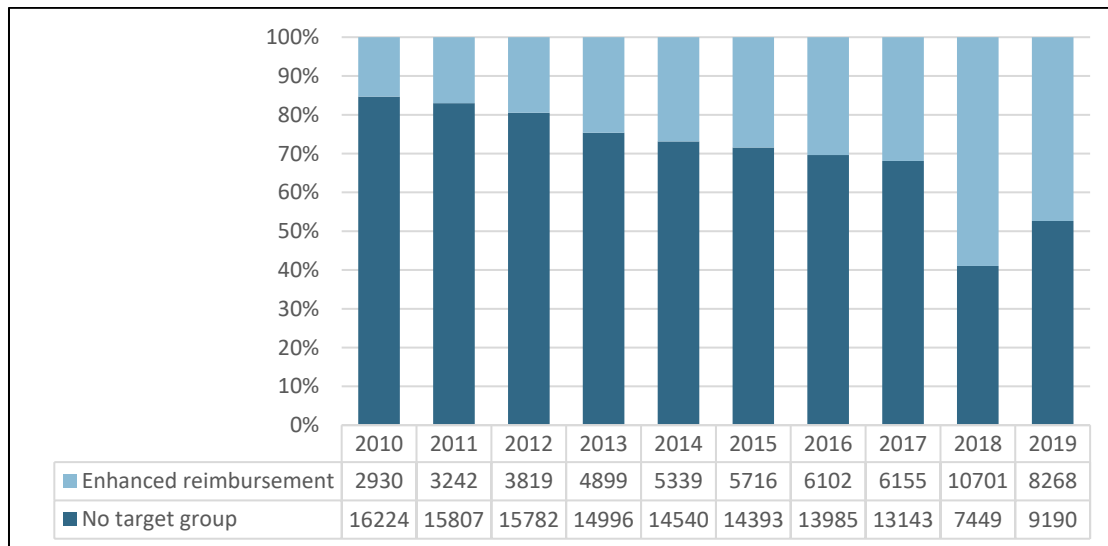


Figure 2.11 Evolution of the proportion and number of new care periods per reimbursement status offered to the adult target group in the Centers for Mental Health Care from 2010 to 2019 (Agency for Care and Health, EPD aggregated data).

Care type

In addition to target group, care in the Centers for Mental Health Care is divided into different care types, referring to the specific caregiver team providing the care activities. The figures below show that specific care types such as addiction care, forensic care, Early Detection and Intervention Programs (EDIP/VDIP), and other specific care types became proportionately more important in recent years. This evolution is somewhat less outspoken for all registered care periods (Figure 2.12) than for new care periods only (Figure 2.13).

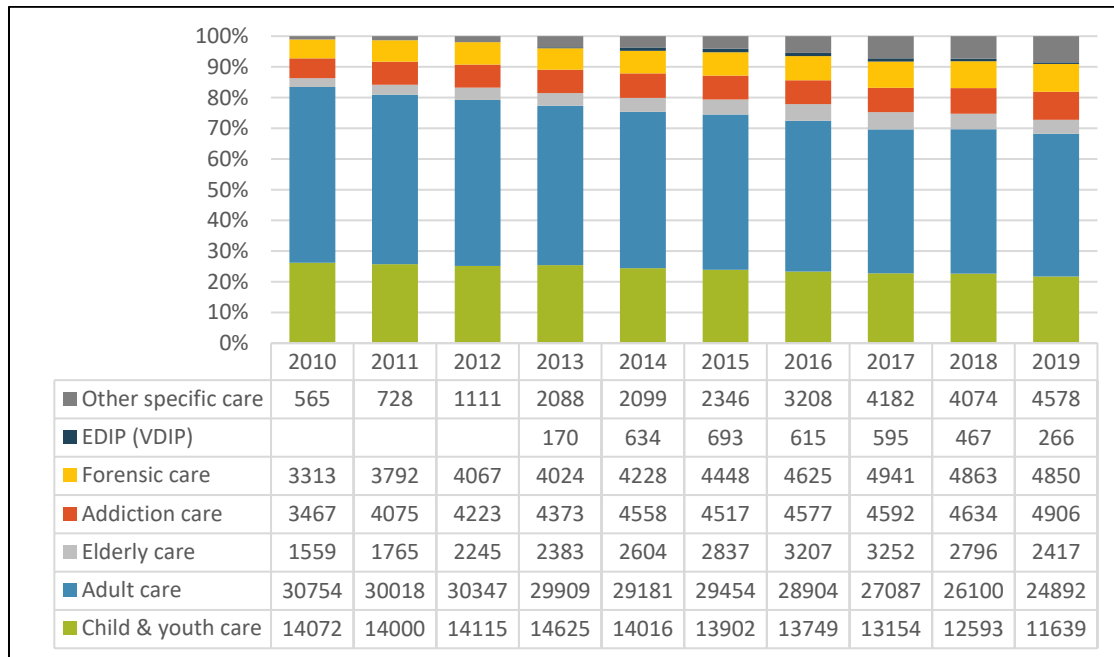


Figure 2.12 Evolution of the proportion and number of all care periods per care type offered in the Centers for Mental Health Care from 2010 to 2019 (Agency for Care and Health, EPD aggregated data).

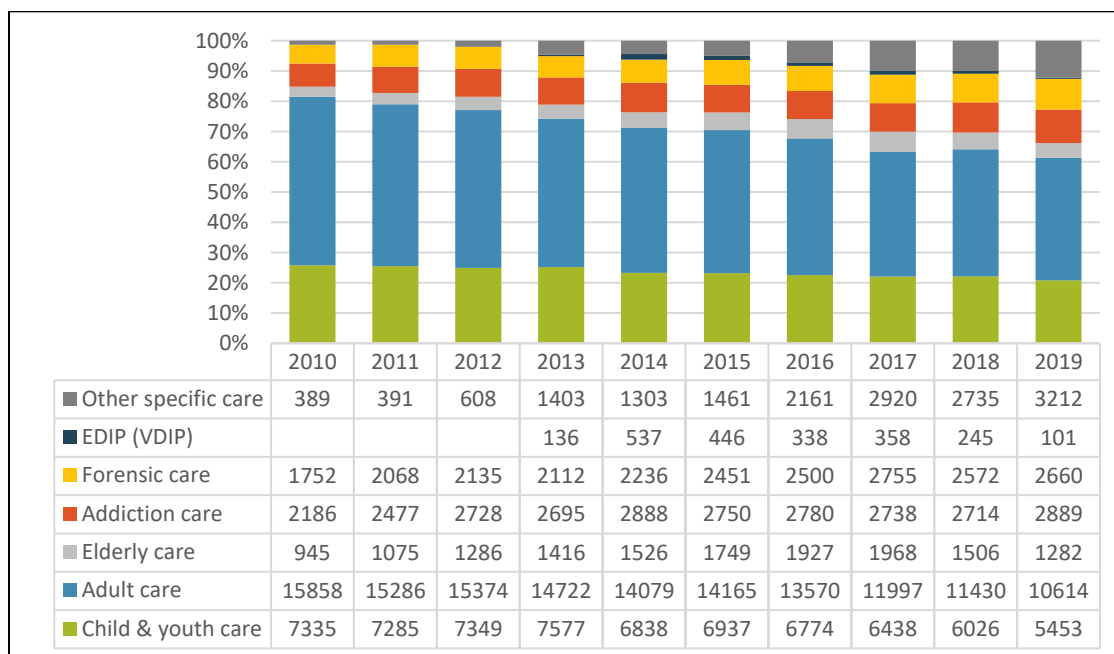


Figure 2.13 Evolution of the proportion and number of new care periods per care type offered in the Centers for Mental Health Care from 2010 to 2019 (Agency for Care and Health, EPD aggregated data).

The proportionate increase of specific care types largely reflects the increasing number of centers offering specific care by designated caregiver teams, with elderly care and other specific care showing the strongest increase in centers registering these care types between 2010 and 2019 (from 12 to 16 CGG and from 7 to 19 CGG, respectively). New forensic care periods were registered in ten to eleven centers and addiction care periods in six or seven centers depending on the registration year. Early detection and intervention programs started in 2013 and were offered in five to eight centers.

As clients are sometimes helped by the same caregiver team in different care periods throughout their life, care type is not always predictable by intake problem, diagnosis or age. This means for example that care periods for clients with various diagnoses may be registered as addiction care or that care periods for adult or elderly clients may be registered as child and youth care. In addition, all care types may include a small number of clients of all ages and with different problems that were first registered as involved in the care for a main client, but then became main clients themselves. The Interpretation of the care type variable is thus not straightforward and requires clarification as to the occurrence of these kind of cases in the registered data.

### 3.2.3 Use of the Centers for Mental Health Care per province

Figures 2.14 and 2.15 show the evolution of all care periods and new care periods in the Centers for Mental Health Care per province. There was a noticeable increase in (new) care periods in Antwerp and a smaller increase in West Flanders. In the other provinces more of a downward trend is observed, especially in Flemish Brabant (including the CGG in Brussels) and Limburg.

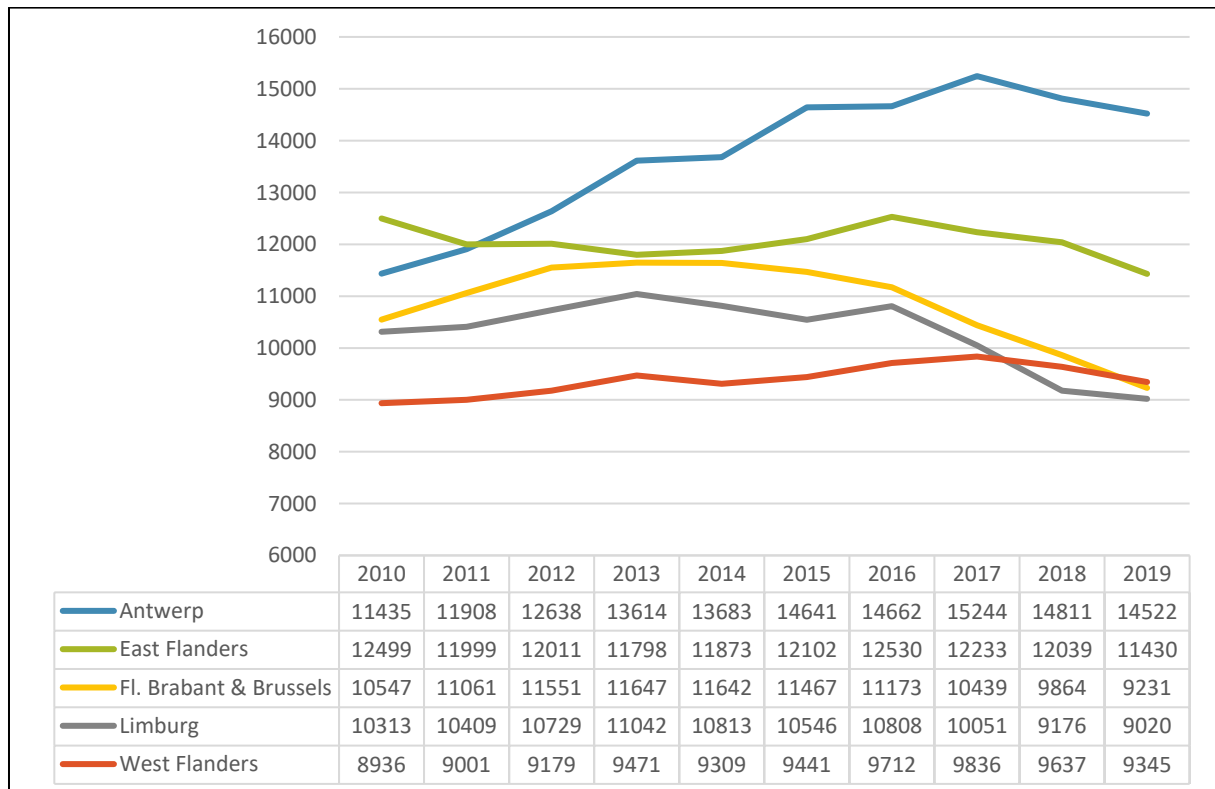


Figure 2.14 Evolution of the total number of care periods per province offered in the Centers for Mental Health Care from 2010 to 2019 (Agency for Care and Health, EPD aggregated data).

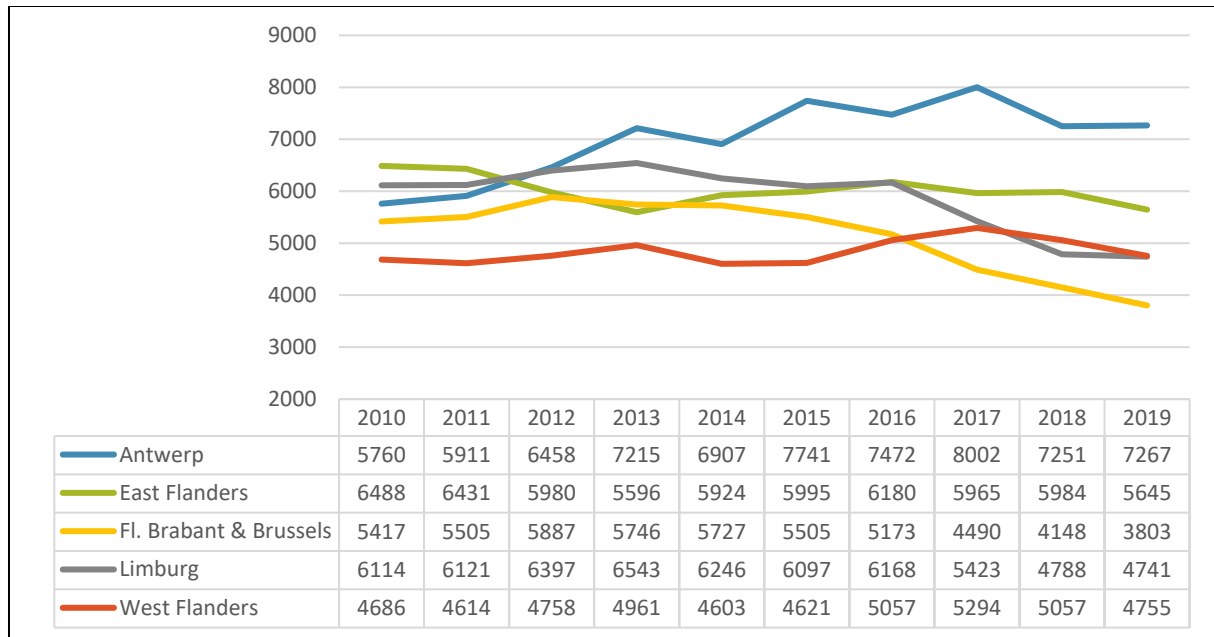


Figure 2.15 Evolution of the number of new care periods per province offered in the Centers for Mental Health Care from 2010 to 2019 (Agency for Care and Health, EPD aggregated data).

In Figures 2.16 and 2.17, the number of care periods offered in the Centers for Mental Health Care are compared to the total population in each Flemish province. The data from the CGG in Brussels were excluded in this comparison.

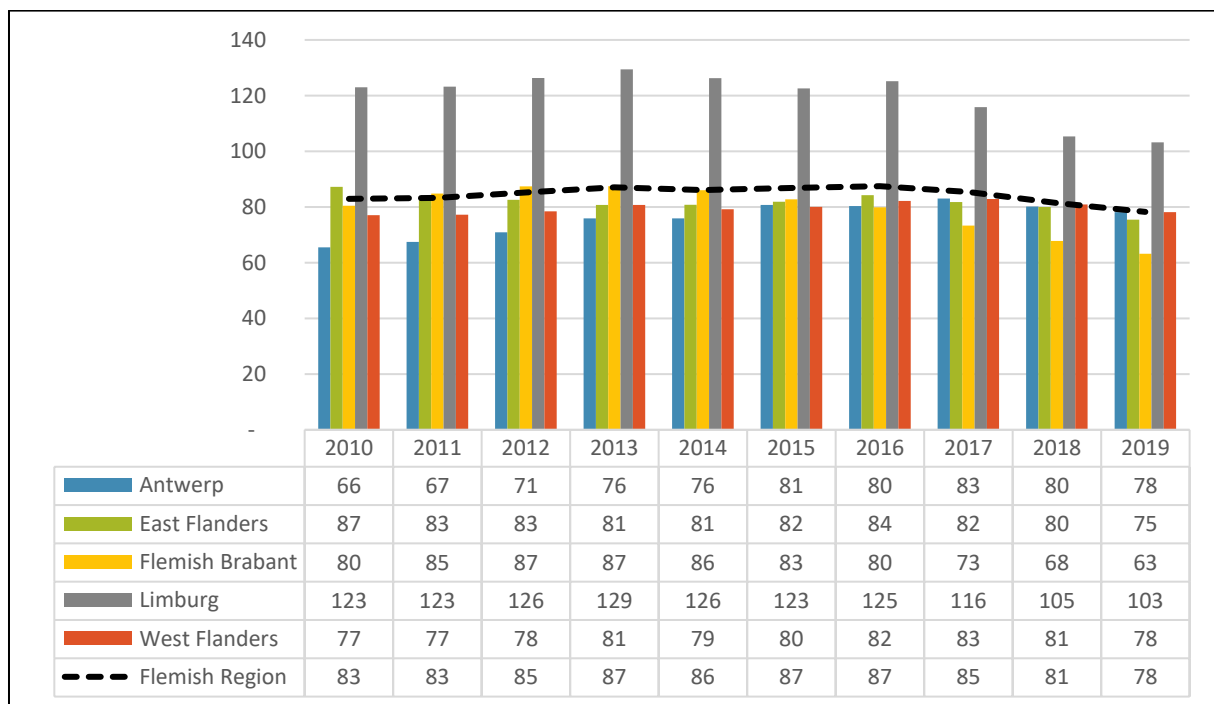


Figure 2.16 Evolution of the number of care periods offered in the Centers for Mental Health Care per 10,000 inhabitants from 2010 to 2019, by province (Agency for Care and Health, EPD aggregated data; Population data: Federaal Planbureau - FOD Economie – Statbel).

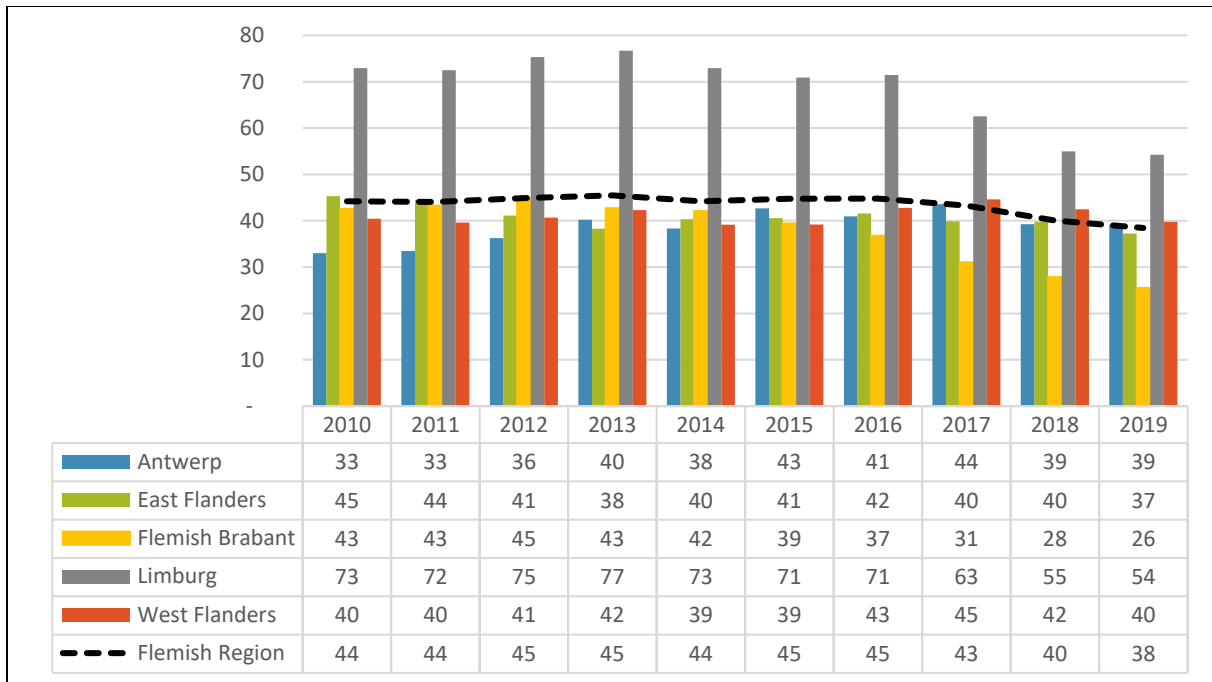


Figure 2.17 Evolution of the number of new care periods offered in the Centers for Mental Health Care per 10.000 inhabitants from 2010 to 2019, by province (Agency for Care and Health, EPD aggregated data; Population data: Federaal Planbureau - FOD Economie – Statbel).

In Flanders as a whole, between 80 and 90 care periods (Figure 2.16) and around 40 new care periods (Figure 2.18) per 10.000 inhabitants per year were registered in the Centers for Mental Health Care. Both ratios were at their lowest point in recent years (2018 and 2019).

With more than 100 care periods and more than 50 new care periods per 10.000 inhabitants in 2019 and an even higher ratio in preceding years, Limburg stands out in both figures. The relatively strong decreasing trend in Limburg was also observed in Flemish Brabant, which led to the lowest ratio of all provinces in recent years. For Antwerp, the reverse was true, with a relatively low ratio in 2010 and 2011, followed by an increasing trend up to 2017. In West Flanders, the ratio remained rather constant and in East Flanders there was a similar downward trend as in Limburg and Flemish Brabant, but to a lesser extent. As there is no reason to assume that the (evolution of the) prevalence for most of the mental disorders treated in the Centers for Mental Health Care significantly differs among provinces, explanations for the observed results are probably found in varying supply factors (e.g. capacity, the availability of alternative supply, etc.) or practice differences (e.g. referral practice, changes in treatment approach or target group, etc.), but could equally be due to registration differences over time or between centers. More information is needed in order to distinguish the potential influence of these factors.

The higher ratio of care periods per 10.000 inhabitants in Limburg as compared to the other Flemish provinces was noticeable in all age target groups, as Figures 2.18 to 2.20 show for new care periods started in the registration year. Although this ratio diminished in recent years, in 2019 there were still 64, 66, and 24 care periods started per 10.000 inhabitants for the children and adolescent, adult and elderly target group respectively, as compared to an average of 47, 48, and 13 care periods in the Flemish Region as a whole.

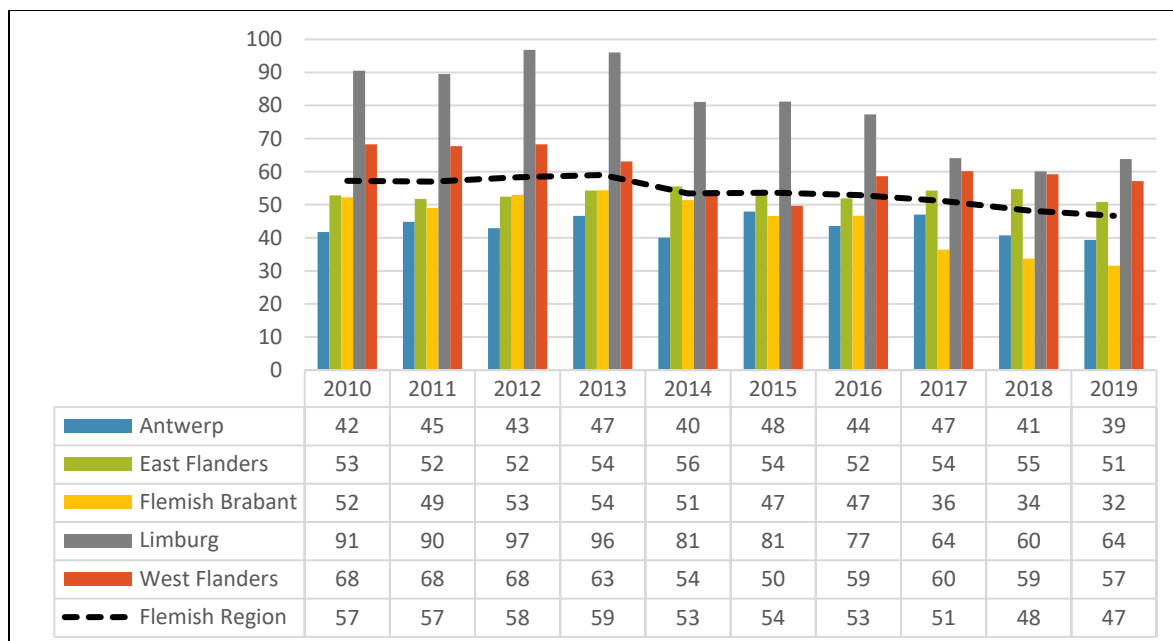


Figure 2.18 Evolution of the number of new care periods offered to children and adolescents in the Centers for Mental Health Care per 10.000 inhabitants under 18 from 2010 to 2019, by province (Agency for Care and Health, EPD aggregated data; Population data: Federaal Planbureau - FOD Economie – Statbel).

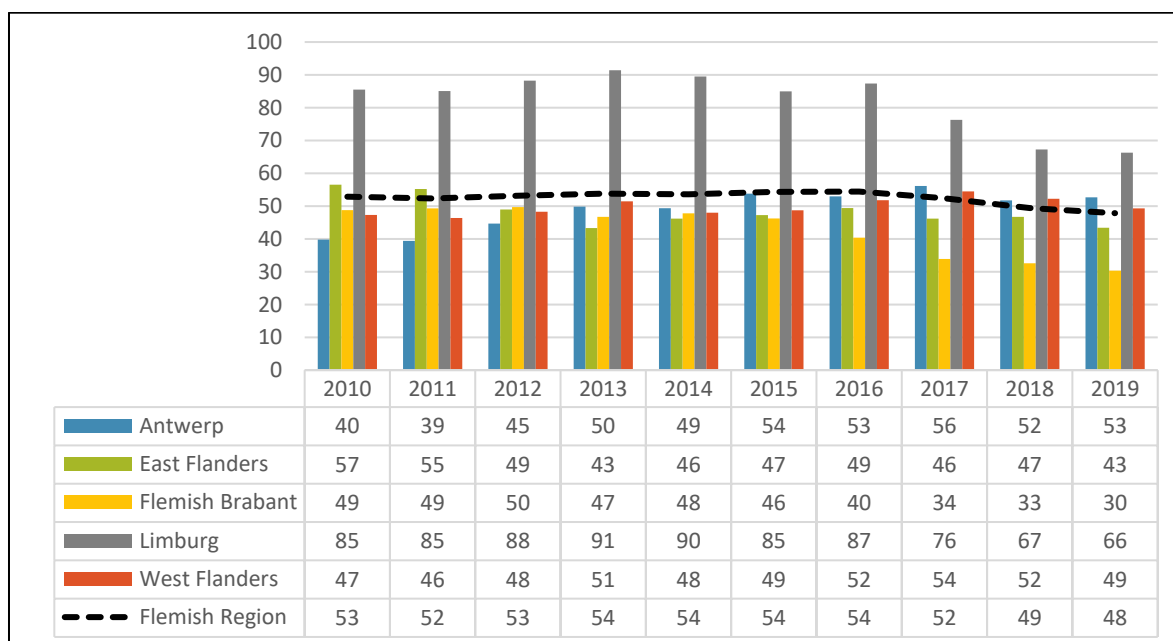


Figure 2.19 Evolution of the number of new care periods offered to adults in the Centers for Mental Health Care per 10.000 inhabitants aged 18 to 59 from 2010 to 2019, by province (Agency for Care and Health, EPD aggregated data; Population data: Federaal Planbureau - FOD Economie – Statbel).

In the children and adolescent and elderly target group the ratio of new care periods per 10.000 inhabitants were lowest in Flemish Brabant and Antwerp, with the former showing a strong decreasing trend over the years, and the latter remaining rather constant. In West Flanders there was a decreasing trend in the children and adolescent target group and an increasing trend in the elderly target group, whereas in East Flanders no clear trend was observed in both target groups. Apart from Limburg, the adult target group showed the highest ratio of new care periods per 10.000 inhabitants in 2019 in Antwerp, followed by West

Flanders. Both of these provinces showed a rather upward trend as compared to a more downward trend in East Flanders and Flemish Brabant, with the latter showing the lowest ratio of 30 new care periods per 10.000 adult inhabitants in 2019.

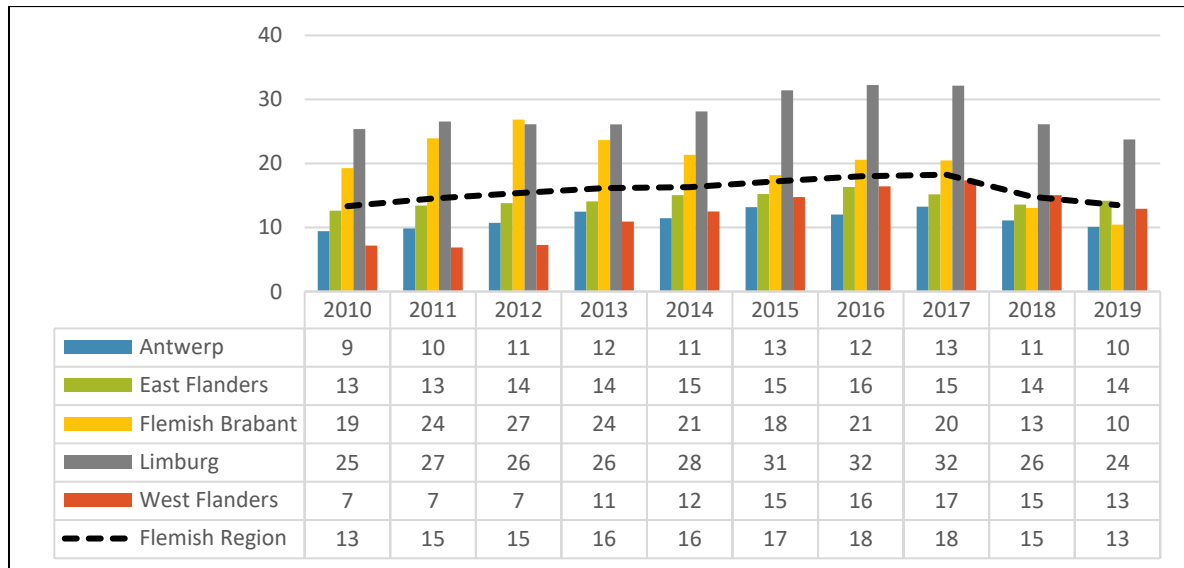


Figure 2.20 Evolution of the number of new care periods offered to elderly people in the Centers for Mental Health Care per 10.000 inhabitants aged 60 or older from 2010 to 2019, by province (Agency for Care and Health, EPD aggregated data; Population data: Federaal Planbureau - FOD Economie – Statbel).

### 3.2.4 Characteristics of service users in the Centers for Mental Health Care

#### *Age and gender*

As shown in Figures 2.7 to 2.9 in paragraph 3.2.2. of this chapter, approximately two thirds of (new) care periods were provided to adult clients between the age of 18 and 59 years, almost one fourth involved children and adolescents and the remaining tenth were elderly people over the age of 60. Although the age of clients is registered in the EPD, the aggregated datasets used for this report, did not allow further refinement in smaller age categories.

In general, female clients are slightly overrepresented in the Centers for Mental Health Care: Approximately 53% of all new care periods between 2010 and 2019 involved female clients. For the target group of elderly people, this percentage amounted to 66% and for the adult target group to 54%. In the target group of children and adolescents, boys outnumbered girls, with 54% and 46% of all new care periods between 2010 and 2019, respectively.

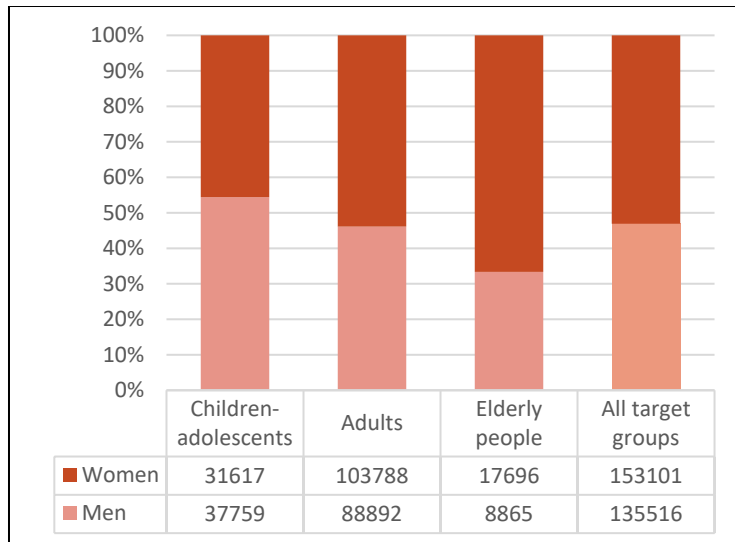


Figure 2.21 Proportion of new care periods offered to men and women per target group in the Centers for Mental Health Care between 2010 to 2019 (Agency for Care and Health, EPD aggregated data).

The total number of care periods offered in the Centers for Mental Health Care showed a stronger increasing trend for female clients than for male clients from 2010 to 2016, with dropping numbers in 2017, and especially 2018 and 2019, for both genders. This resulted in a slightly increased proportion of care periods involving female clients in 2019 as compared to 2010.

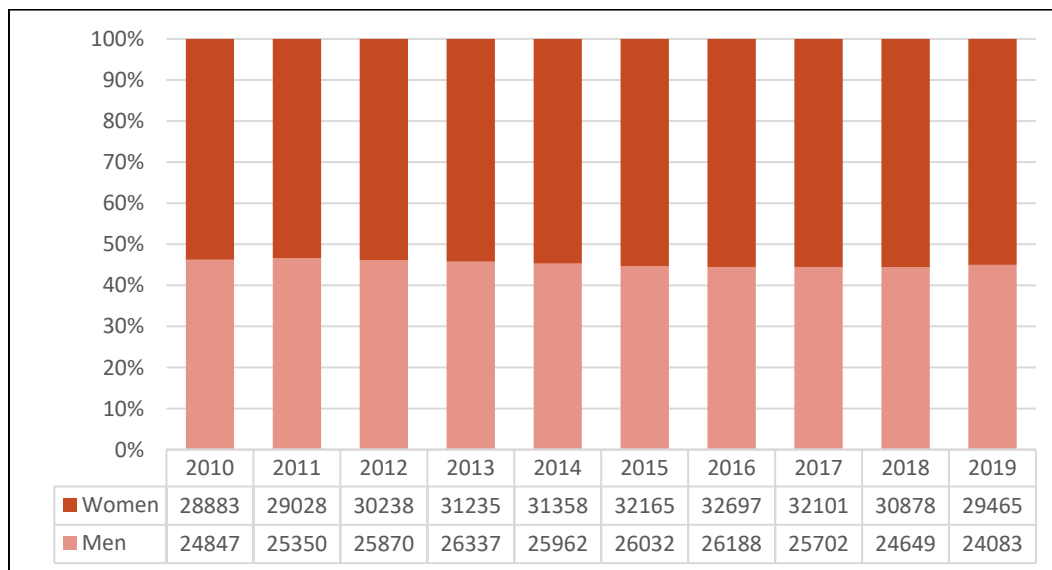


Figure 2.22 Evolution of the proportion and number of all care periods offered to men and women in the Centers for Mental Health Care from 2010 to 2019 (Agency for Care and Health, EPD aggregated data).

The number of new care periods started for male clients augmented slightly from 2010 to 2013, followed by a decreasing trend and a noticeable drop in 2018. New care periods involving female clients showed an increasing trend until 2016 and a relatively strong decrease since then.



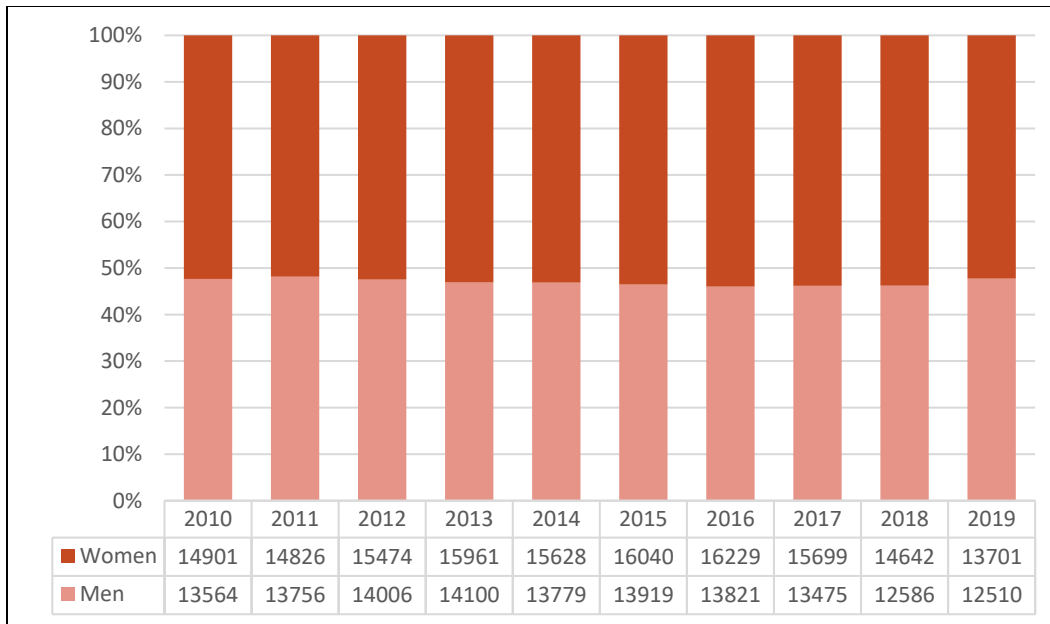


Figure 2.23 Evolution of the proportion and number of new care periods offered to men and women in the Centers for Mental Health Care from 2010 to 2019 (Agency for Care and Health, EPD aggregated data).

*Referrer and intake problem*

As secondary care services, the Centers for Mental Health Care generally take in clients after referral. Between 2010 and 2019, the most important referring instances were general health care services, such as primary care general practitioners (almost 40%), welfare (e.g. Centers for General Welfare Work/CAW or youth welfare services), the education sector (e.g. Centers for Student Guidance, CLB), and justice. Nevertheless, approximately one fourth of new care periods were started for clients without referral, who presented themselves (self-referral) or were advised by family, friends, or others in the clients’ surroundings.

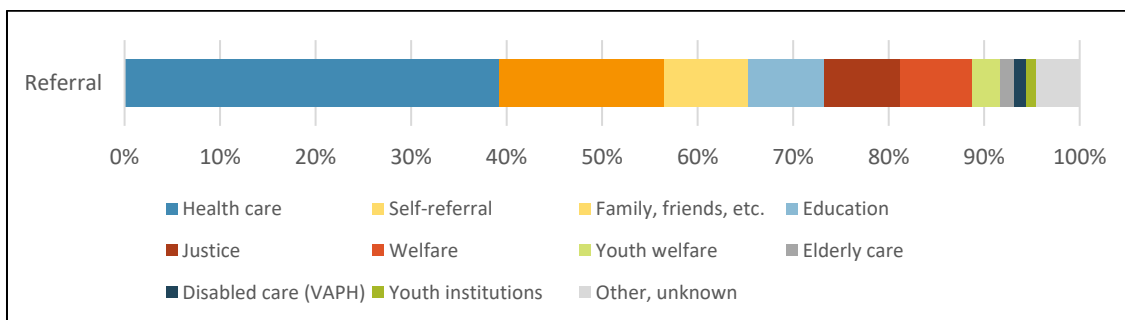


Figure 2.24 Proportion of new care periods by referrer in the Centers of Mental Health Care between 2010 and 2019 (Agency for Care and Health, EPD aggregated data).

The relative importance of different referral instances varied from target group to target group, as shown in Figures 2.25 to 2.28 below. In the children and adolescent target group, 50 to 60% of care periods were started for clients referred by general health care or education services, with the former diminishing somewhat more in recent years than the latter. Referral by youth welfare services, increased until 2018 up to 12% of new care periods, but decreased again in 2019. Care periods started for clients without referral (self-referral or family and friends) showed a downward trend.

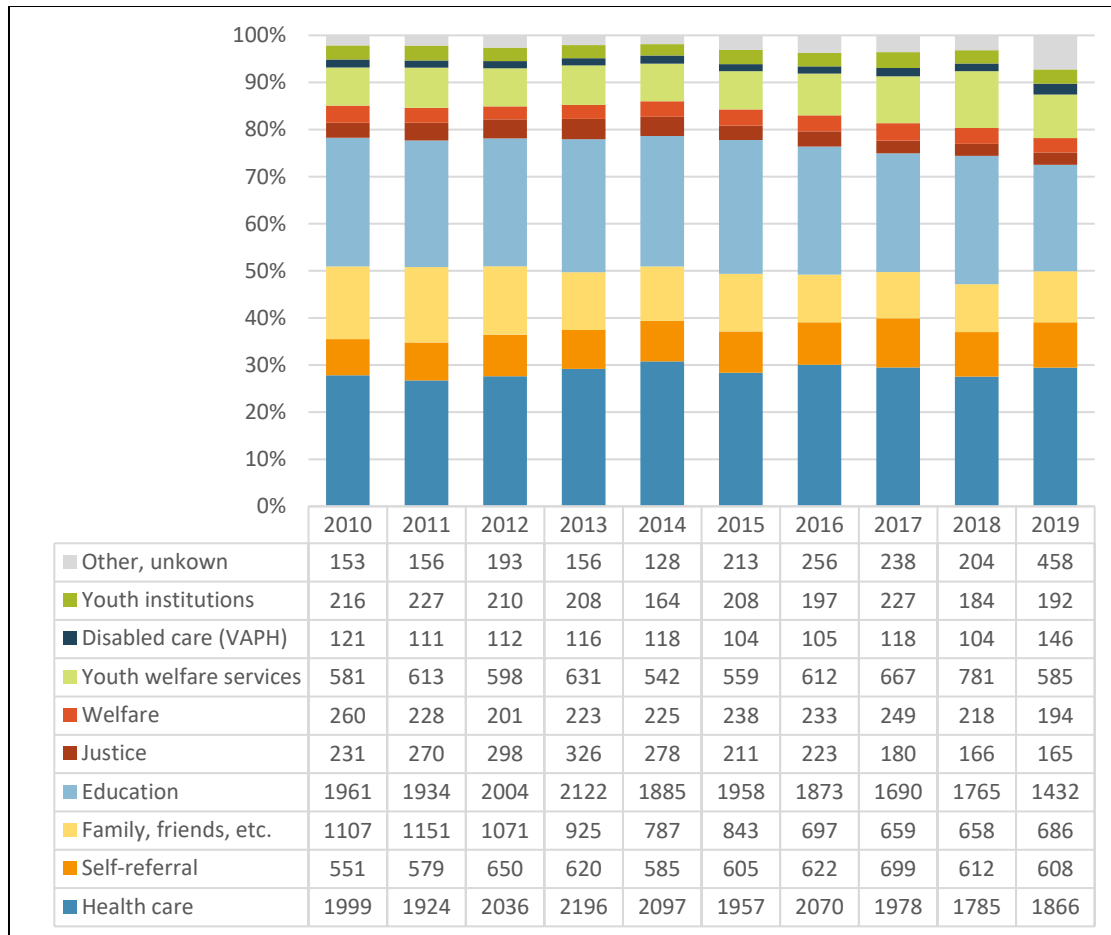


Figure 2.25 Evolution of the proportion and number of new care periods by referrer in the children and adolescent target group in the Centers for Mental Health Care from 2010 to 2019 (Agency for Care and Health, EPD aggregated data).

More than 40% of care periods for adult clients were started after referral by general health care practitioners, followed by the justice department and welfare services as other important referring instances. Referral from justice remained rather constant between 2010 and 2019, whereas referral from welfare became more frequent. As in the children and adolescent target group, the number and proportion of care periods for clients without referral decreased.

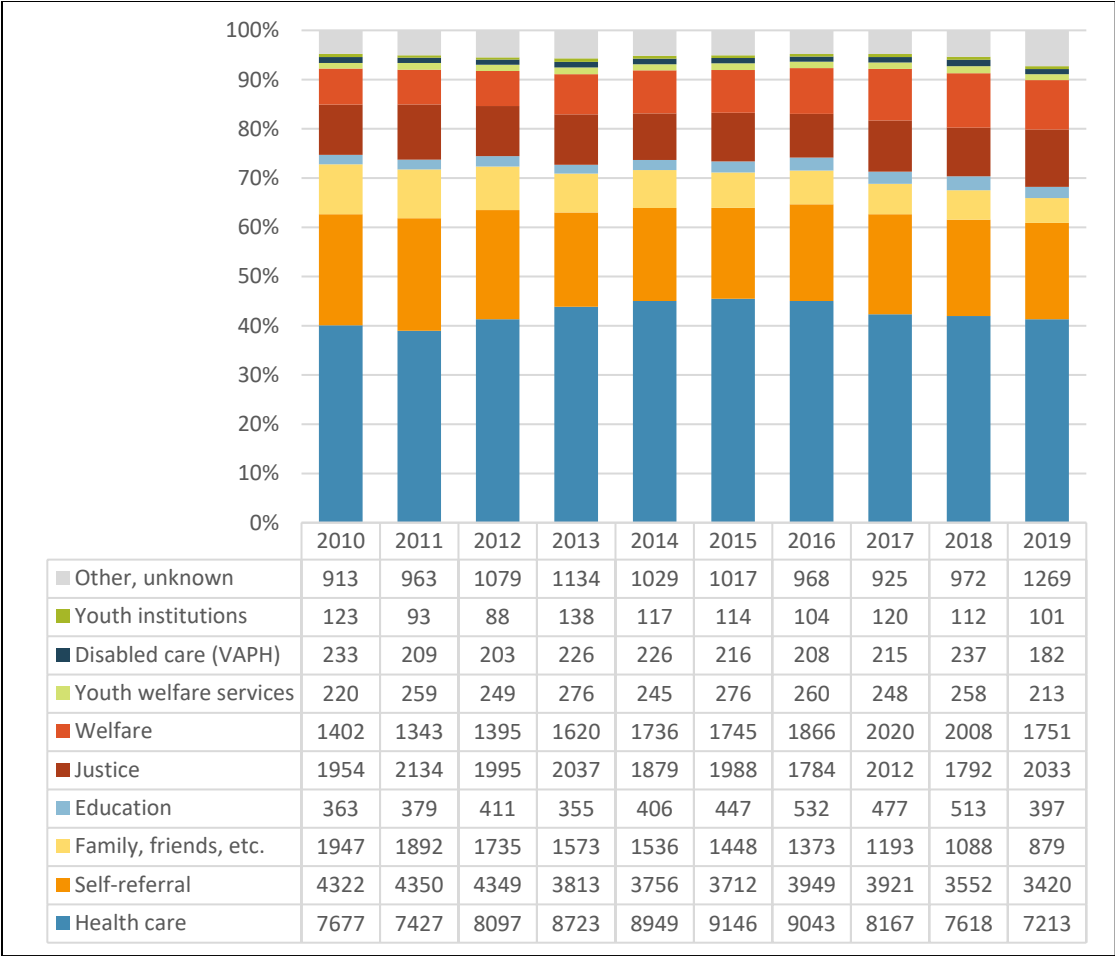


Figure 2.26 Evolution of the proportion and number of new care periods by referrer in the adult target group in the Centers for Mental Health Care from 2010 to 2019 (Agency for Care and Health, EPD aggregated data).

The increasing importance of welfare services as referring instance could be related to the increasing number of care periods offered to adult clients with enhanced reimbursement status. For these clients, 14% of new care periods were started after referral by (youth) welfare services, as compared to 9% for other adult clients, who came more often without referral (Figure 2.27).

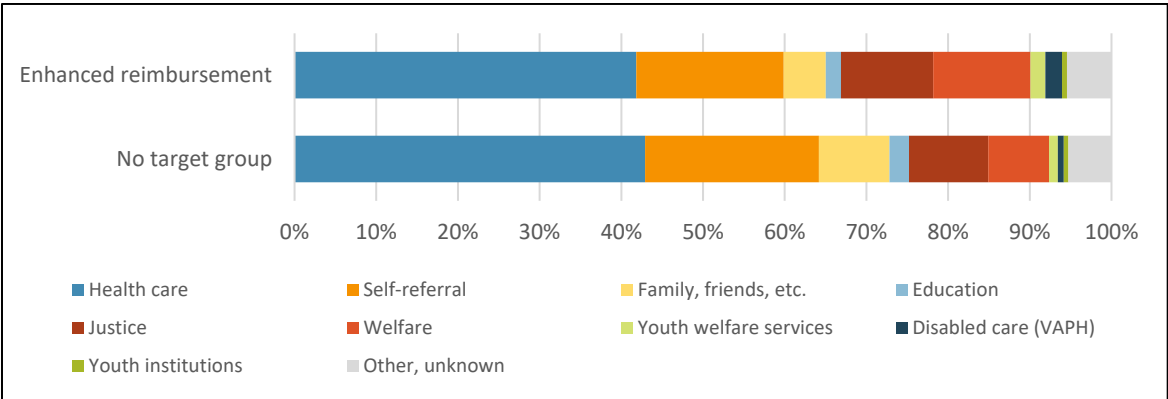


Figure 2.27 Proportion of new care periods by referrer for adult clients with or without enhanced reimbursement in the Centers of Mental Health Care between 2010 and 2019 (Agency for Care and Health, EPD aggregated data).

In the elderly target group, referral from general health care increased significantly from 36% of new care periods in 2010 to 46% in 2019. Referral from elderly care services showed the opposite trend, starting from 20% of new care periods in 2010 to 11% in 2019, which amounted to a comparable proportion as referral from welfare services in that year.

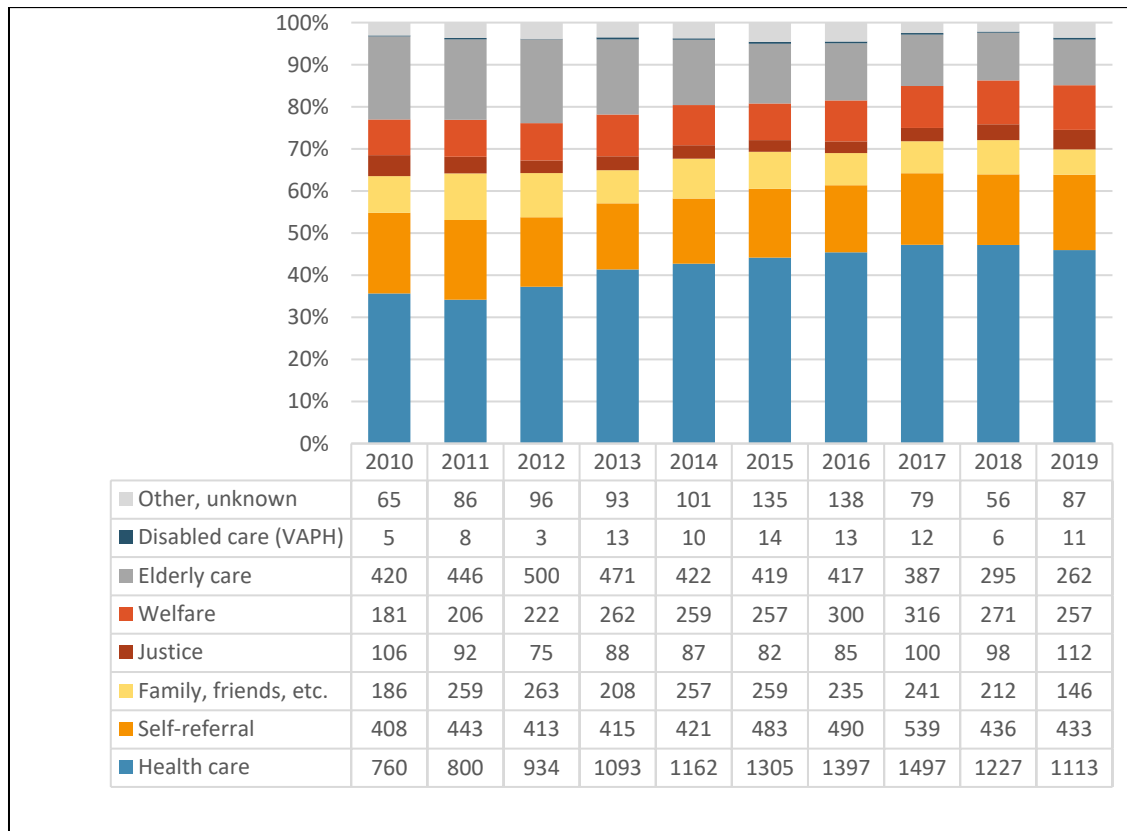


Figure 2.28 Evolution of the proportion and number of new care periods by referrer in the elderly target group in the Centers for Mental Health Care from 2010 to 2019 (Agency for Care and Health, EPD aggregated data).

Nearly eight out of ten new care periods in the Centers for Mental Health Care were started for clients presenting with psychological problems (37%), addiction, coping, interaction, or behavioral problems (each around 10%).

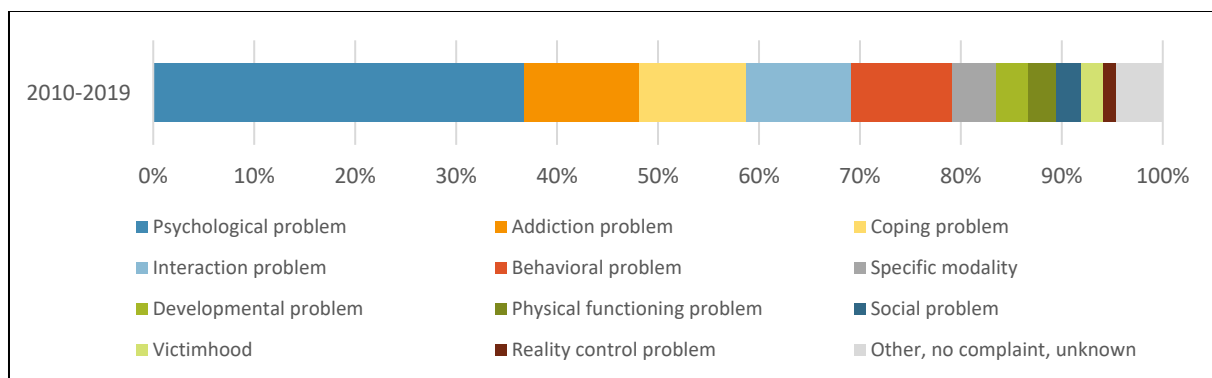


Figure 2.29 Proportion of new care periods per intake problem in the Centers for Mental Health Care between 2010 and 2019 (Agency for Care and Health, EPD aggregated data).

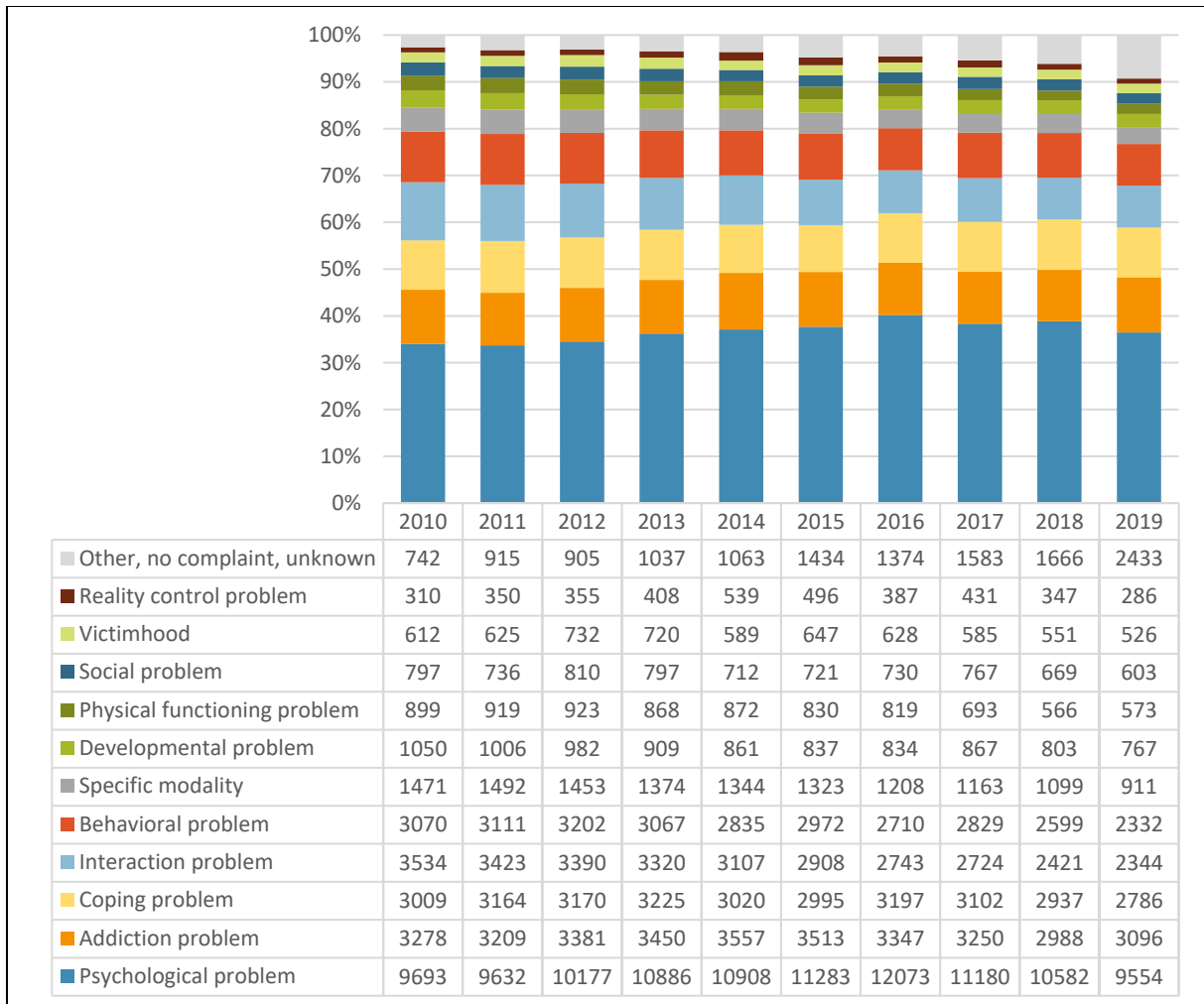


Figure 2.30 Evolution of the number and proportion of new care periods offered per intake problem in the Centers for Mental Health Care from 2010 to 2019 (Agency for Care and Health, EPD aggregated data).

The proportion of new care periods registered for psychological problems increased from 34% in 2010 to 40% in 2016 and decreased again to 36% in 2019. Approximately half of psychological intake problems were depressive mood problems, with the other half including anxiety, stress problems, mood swings, suicide thoughts, etc. (Cloots & Roelandt, 2018).

For most other intake problems, the proportion remained relatively stable, apart from a slight decrease between 2010 and 2019 for interaction problems (12 to 9%), behavioral problems (11 to 9%), and specific modalities (5 to 3%). The latter category consists of requests for diagnosis or advice, psychiatric after care or home care, care in the context of judicious measures, etc. (Cloots & Roelandt, 2018).

For all registered intake problems, the number of care periods was lower in 2019 than in 2010, which may be explained by the lowering total number of care periods on the one hand, and by the increasing proportion of registrations in the category ‘other, no complaint, unknown’ on the other hand.

Figure 2.31 below compares intake problems for new care periods provided to male and female clients in the different age target groups. Between 2010 and 2019, psychological problems were generally the predominant intake problem in all age target groups, varying from 22% in children and adolescents to 41% and 45% in the adult and elderly target groups, respectively. The exception were young boys, with behavioral problems accounting for more new intakes than psychological problems (24% and 17%,

respectively). Other common problems in the children and adolescent target group were interaction and coping problems, which were more frequent in girls, and developmental problems, especially in boys. Half of all new intakes involving adult women were for psychological problems, whereas in adult men, addiction problems were almost as important as psychological problems, together accounting for more than 50% of new care periods. In both the adult and elderly target group, addiction and behavioral problems were more common in men. Adult and elderly women more often presented with coping and interaction problems, the former of which were frequent in elderly men as well.

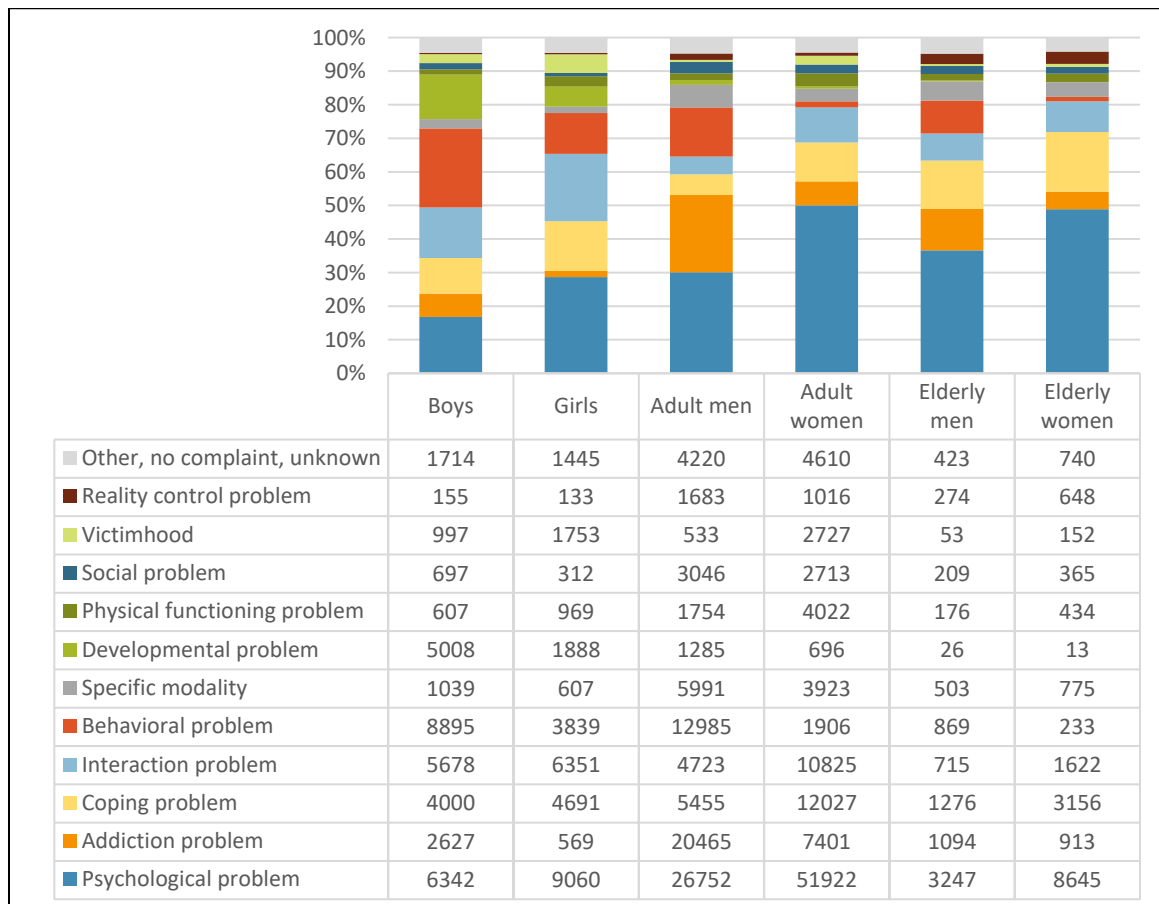


Figure 2.31 Proportion of new care periods per intake problem offered to male and female clients in different age target groups in the Centers for Mental Health Care between 2010 and 2019 (Agency for Care and Health, EPD aggregated data).

### Diagnosis

In the Centers for Mental Health Care, registration of diagnoses was based on DSM-IV diagnostic categories (American Psychiatric Association, 2000) until 2017 and DSM-5 diagnostic categories (APA, 2013) starting from 2018. Because of this change, the years between 2010 and 2017 cannot easily be compared to 2018 and 2019. Therefore, the diagnoses data presented below will be divided into the period from 2010 to 2017 on the one hand and 2018 and 2019 on the other hand.

Figure 2.32 below shows that mood disorders were diagnosed in almost 20% of new care periods started in the Centers for Mental Health Care between 2010 and 2017. Other frequent diagnoses were the category of ‘other conditions with a need for mental health care’, substance-related disorders, adjustment disorders, childhood disorders, and anxiety disorders.

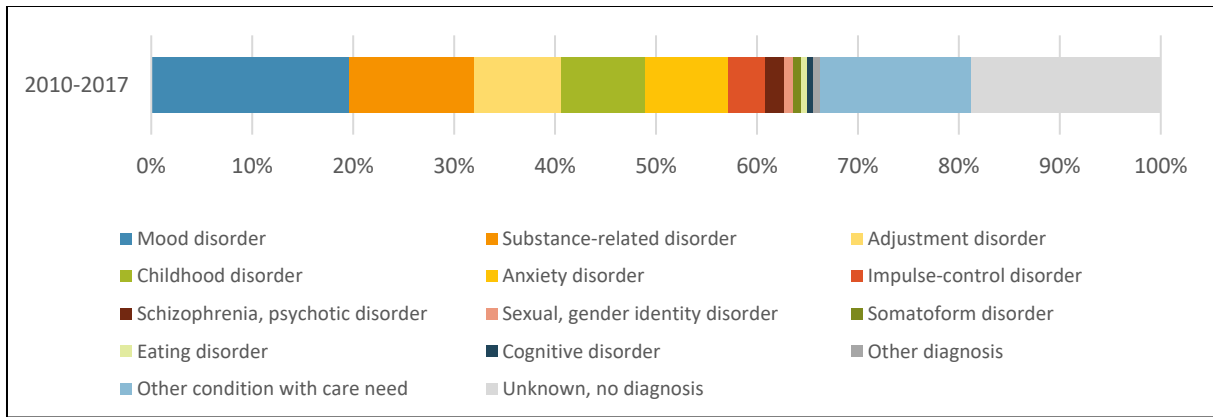


Figure 2.32 Proportion of new care periods per diagnostic category based on DSM-IV in the Centers for Mental Health Care between 2010 and 2017 (Agency for Care and Health, EPD aggregated data).

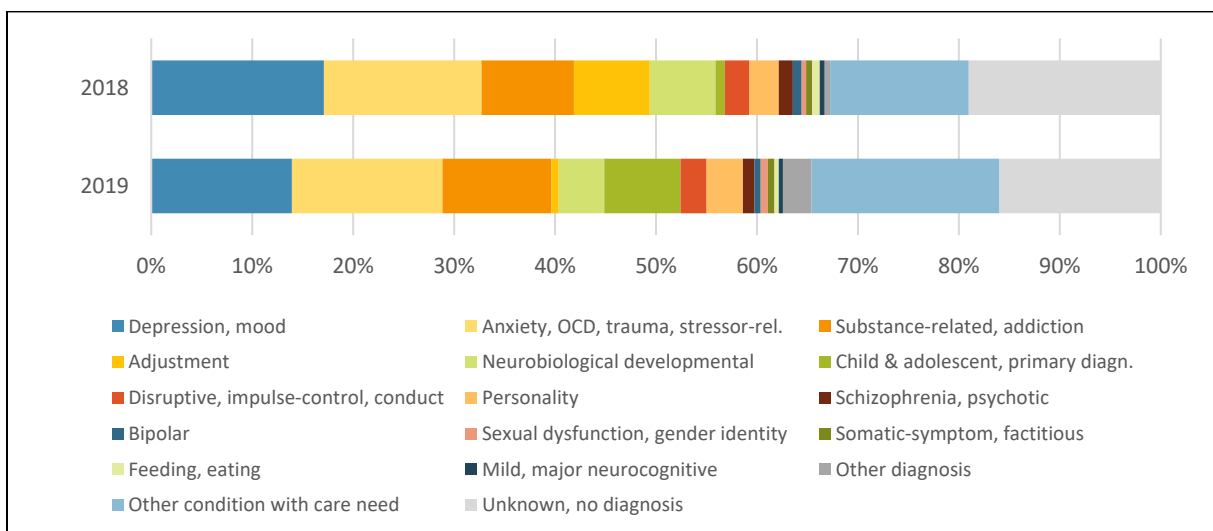


Figure 2.33 Proportion of new care periods per diagnostic category based on DSM-5 in the Centers for Mental Health Care in 2018 and 2019 (Agency for Care and Health, EPD aggregated data).

In 2018 the proportion of new care periods for clients with depressive and other mood disorders was comparable to the proportion of mood disorders in preceding years. In 2019, however, this proportion seemed to become noticeably smaller, whereas other diagnoses, such as child and adolescent disorders (primary diagnosis) and the category ‘other conditions with a need for mental health care’ were registered more often. Anxiety, OCD, and trauma- or stressor-related disorders, which coincide partly with the former DSM-IV category of adjustment disorders in addition to anxiety disorders, were also diagnosed frequently in both 2018 and 2019. However, registration of adjustment disorders themselves was markedly less in 2019 than in 2018. As this and other differences between both years (including the increased number of ‘unknown or no diagnosis’ registrations in 2018) could be due to the changing diagnostics from DSM-IV to DSM-5 in 2018, no further data from that transition year are reported in the remainder of this section.

There were few fluctuations in the numbers and proportion of diagnoses in the Centers for Mental Health Care between 2010 and 2017 (Figure 2.34).

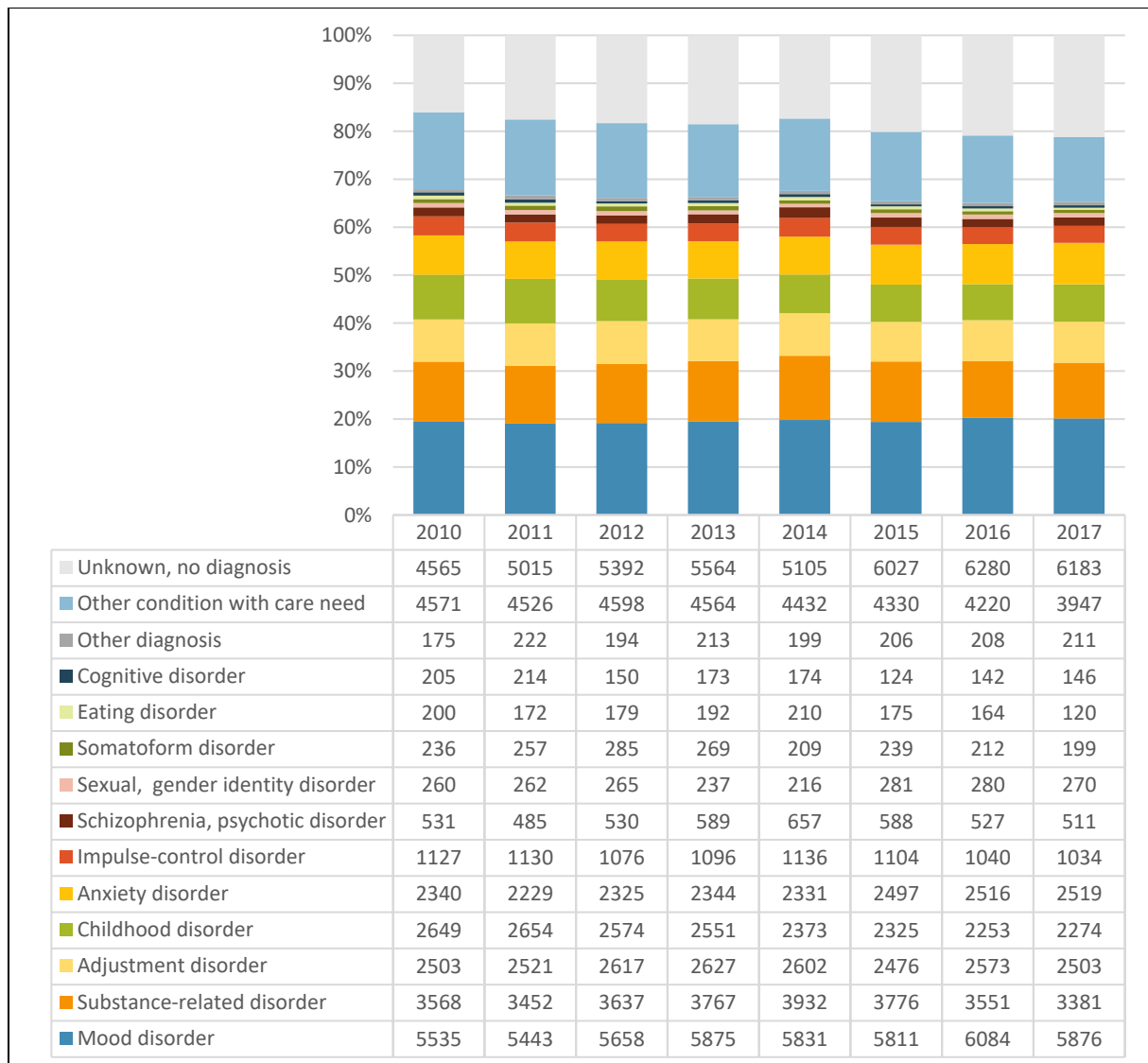


Figure 2.34 Evolution of the number and proportion of new care periods per diagnostic category based on DSM-IV in the Centers for Mental Health Care from 2010 to 2017 (Agency for Care and Health, EPD aggregated data).

Apart from a possible shift between the ‘other conditions with need for mental health care’ to the ‘unknown, no diagnosis’ category, rather stable or limited increasing and decreasing trends were observed. For example, the number and proportion of mood disorders and anxiety disorders mounted somewhat, whereas the number and proportion of other important diagnoses, such as substance-related disorders and childhood disorders went down slightly. When the care periods with ‘unknown or no diagnosis category’ were removed from the analysis, the increasing trends for mood and anxiety disorders became somewhat more outspoken.

Figures 2.35 and 2.36 below show that the frequency of specific diagnoses varied with gender and age target group. Care periods registered in the ‘unknown or no diagnosis’ category, were removed from the analysis, since the proportion of registrations in this category differed substantially between age groups (e.g. from more than 30% in children and adolescents to 12% in elderly women between 2010 and 2017).



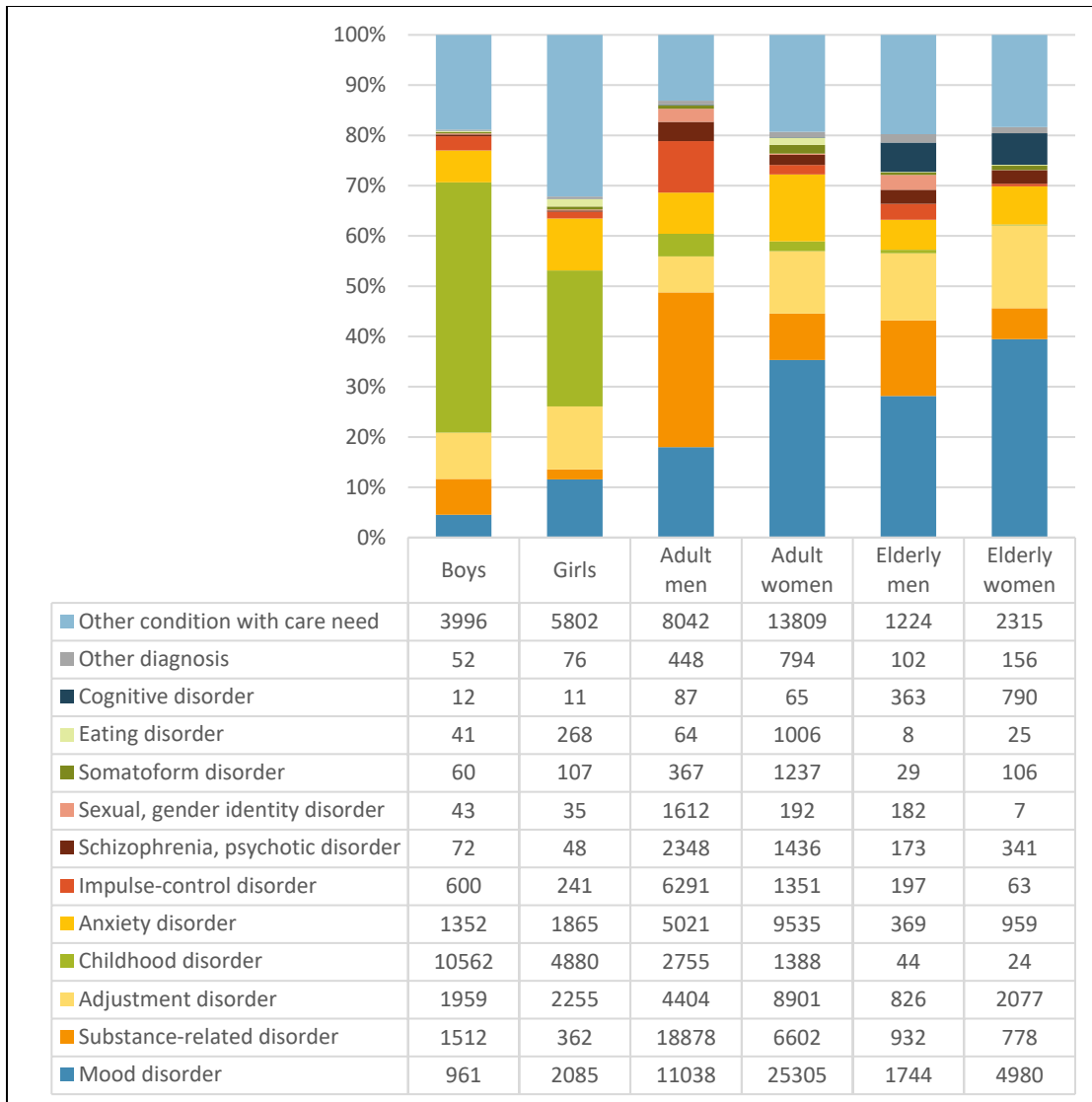


Figure 2.35 Proportion of new care periods per diagnostic category based on DSM-IV offered to male and female clients in different age target groups in the Centers for Mental Health Care between 2010 and 2017 (Agency for Care and Health, EPD aggregated data).

Between 2010 and 2017, mood disorders were much more common in new care periods provided to female than male clients (32% and 15%, respectively), whereas the reverse was true for substance-related disorders (24% male and 8% female clients). In the children and adolescent group, childhood disorders constituted the most important diagnosis, especially for boys, whereas new care periods for girls were more often registered as ‘other conditions with need for mental health care’. In addition to substance-related and mood disorders, impulse-control disorders were relatively frequent in adult men, whereas adult women and elderly people presented more with anxiety and adjustment disorders.

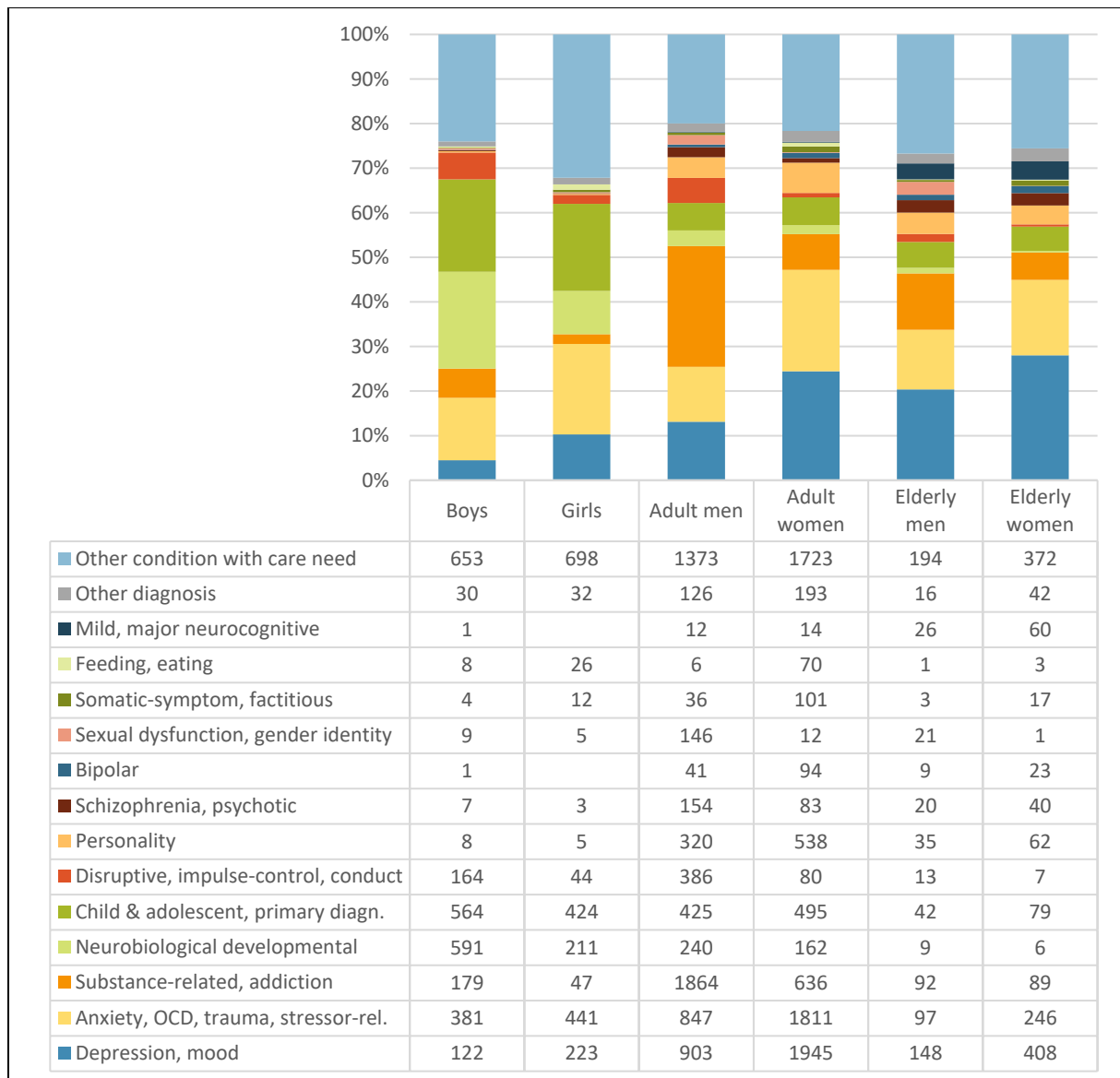


Figure 2.36 Proportion of new care periods per diagnostic category based on DSM-5 offered to male and female clients in different age target groups in the Centers for Mental Health Care in 2019 (Agency for Care and Health, EPD aggregated data).

DSM-5 diagnostics in 2019 led to a comparable picture for the most common diagnoses, such as depressive and other mood disorders, anxiety, OCD, trauma- or stressor-related disorders, and substance-related disorders and addiction. The category of ‘other conditions with need for mental health care’ seemed to be used somewhat more in 2019 than in previous years, and was the largest diagnostic category in both genders in the children and adolescent target group as well as in the group of elderly men.

In both boys and girls, neurobiological developmental disorders were frequently diagnosed in new care periods. The same was true for anxiety, OCD, trauma- or stressor-related disorders and child and adolescent disorders (primary diagnosis), but more so in girls than in boys for the former, and the reverse for the latter. Disruptive, impulse-control, and conduct disorders occurred mostly in new care periods for young boys and adult men, whereas personality disorders were somewhat more frequent in adult women than in adult men and elderly people.

The distribution of diagnoses in the Centers for Mental Health Care also varied from province to province, as shown in Figure 2.37 for the period between 2010 and 2017 and in Figure 2.38 for 2019. Again, the category of ‘unknown or no diagnosis’ was removed from the analysis, as there was a substantial difference in the proportion of registrations in this category between provinces (e.g. 25 to 30% in Antwerp as compared to 10% in Limburg).

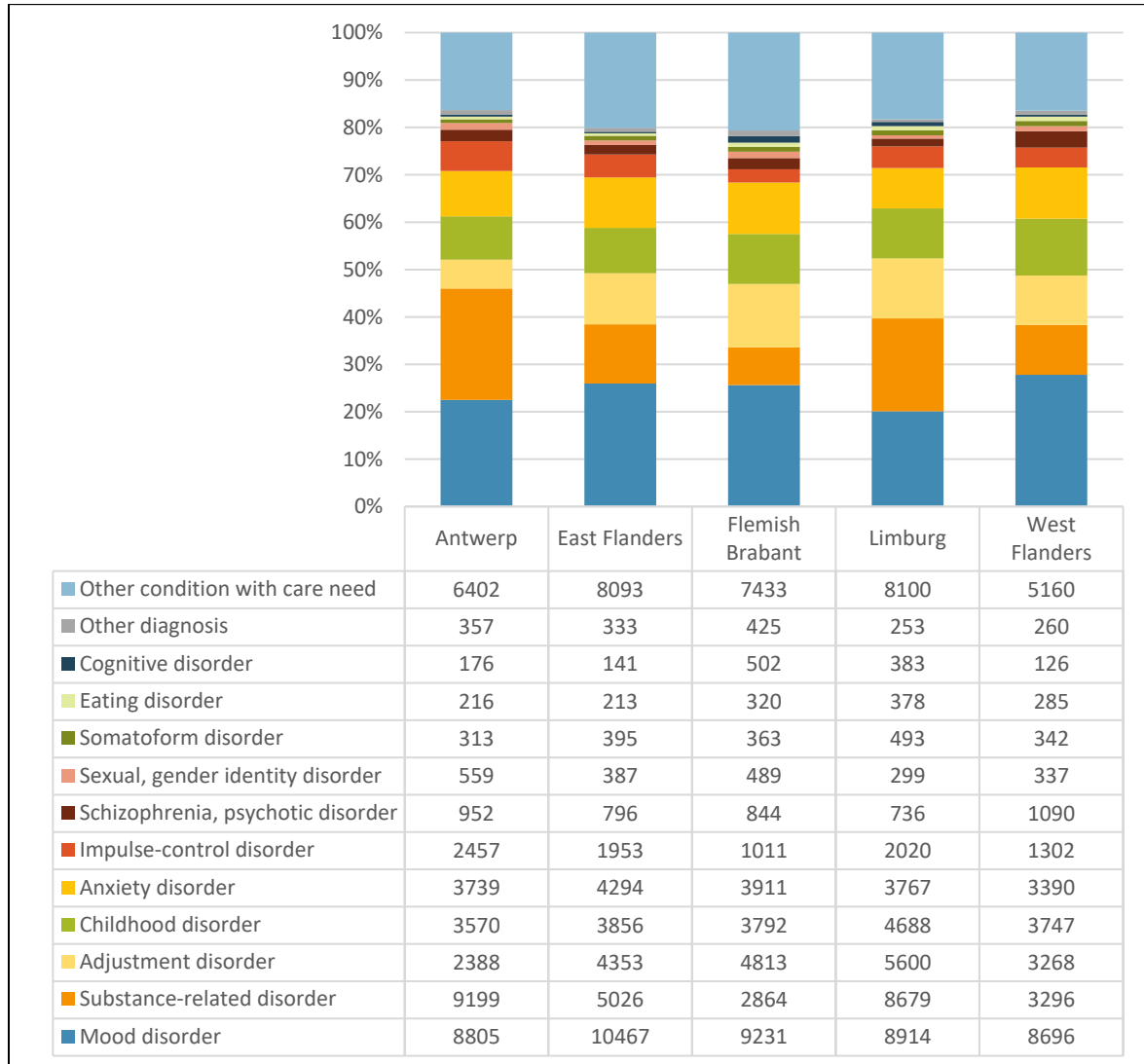


Figure 2.37 Proportion of new care periods per diagnostic category based on DSM-IV in the Centers for Mental Health Care between 2010 and 2017, per province (Agency for Care and Health, EPD aggregated data).

Between 2010 and 2017, substance-related disorders were diagnosed relatively more frequently in Antwerp and Limburg (in 24% and 19% of new care periods, respectively), whereas mood disorders were diagnosed somewhat less frequently in both provinces.

In 2019, the most apparent differences between provinces were in the number of new care periods involving clients with substance-related disorders as well. Proportions varied from 21% in Limburg to 17% in Antwerp, 12% in East Flanders, 8% in West Flanders, and a mere 4% in Flemish Brabant (including Brussels). Differences in the proportion of other diagnoses such as depressive and other mood disorders and anxiety, OCD, trauma- or stressor-related disorders were less outspoken, and ranged for the former

diagnostic category from 14% in Limburg to 21% in East Flanders and for the latter from 14% in Antwerp to 20% in West Flanders and Flemish Brabant.

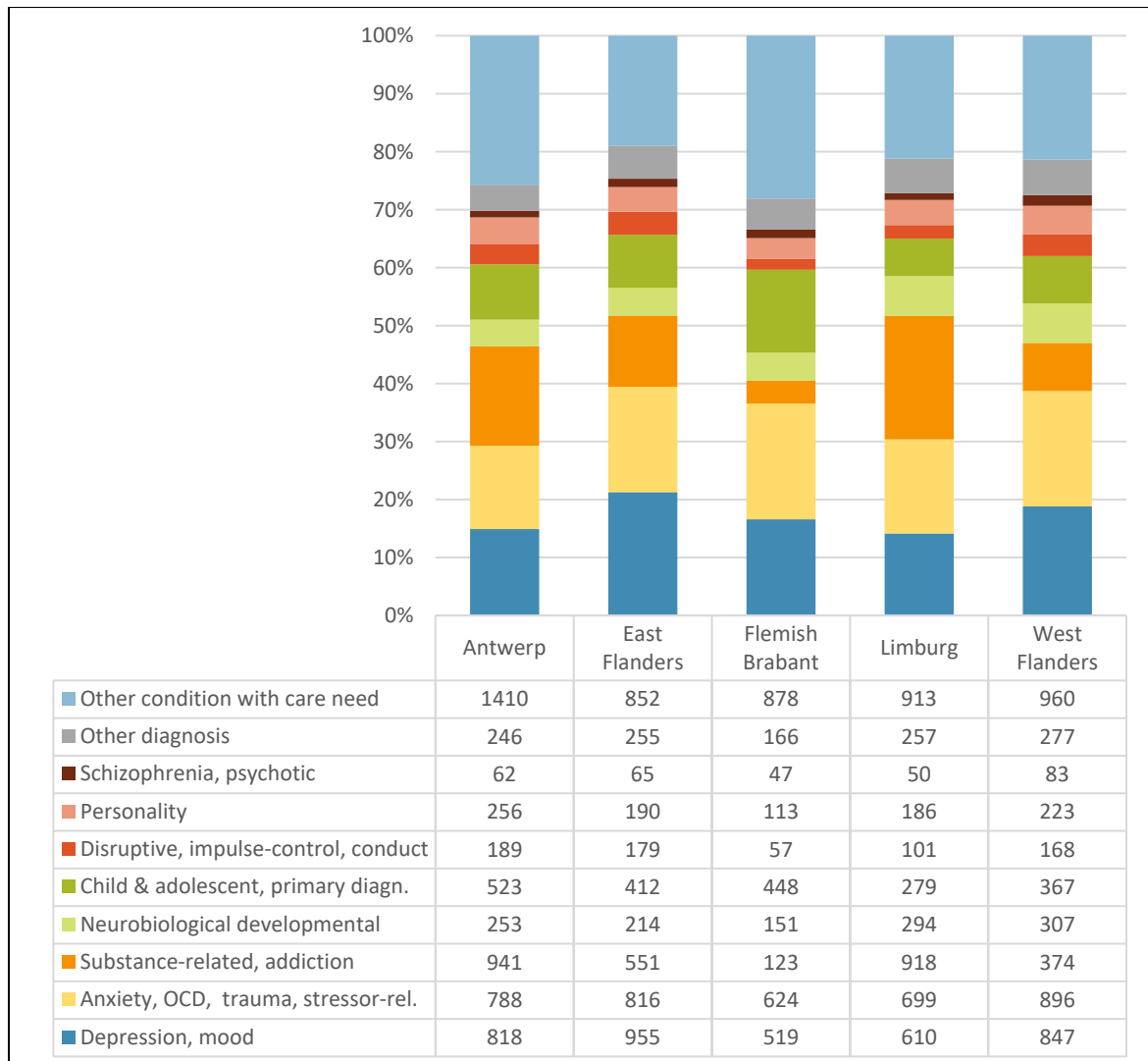


Figure 2.38 Proportion of new care periods per diagnostic category based on DSM-5 in the Centers for Mental Health Care in 2019, per province (Agency for Care and Health, EPD aggregated data).

It is noteworthy that in Chapter 5 below describing the Rehabilitation Centers for Addiction, Limburg seems to be one of the provinces with a relatively large number of ambulatory new care periods for addiction relative to the population as well, suggesting that there may be regional differences in the prevalence of substance-related disorders and addiction problems within Flanders in addition to differences in supply.

### 3.2.5 Service characteristics in the Centers for Mental Health Care

#### *Waiting time*

Generally, an intake session is planned as soon as a referrer or client contacts the Center for Mental Health Care. The intake session is registered as the first face-to-face contact and should take place within one month for 75% of clients and within two months for all clients, according to the CGG reference frame (Agentschap Zorg en Gezondheid, n.d.). The waiting time until the first face-to-face contact or intake is shown in Figure 2.39.

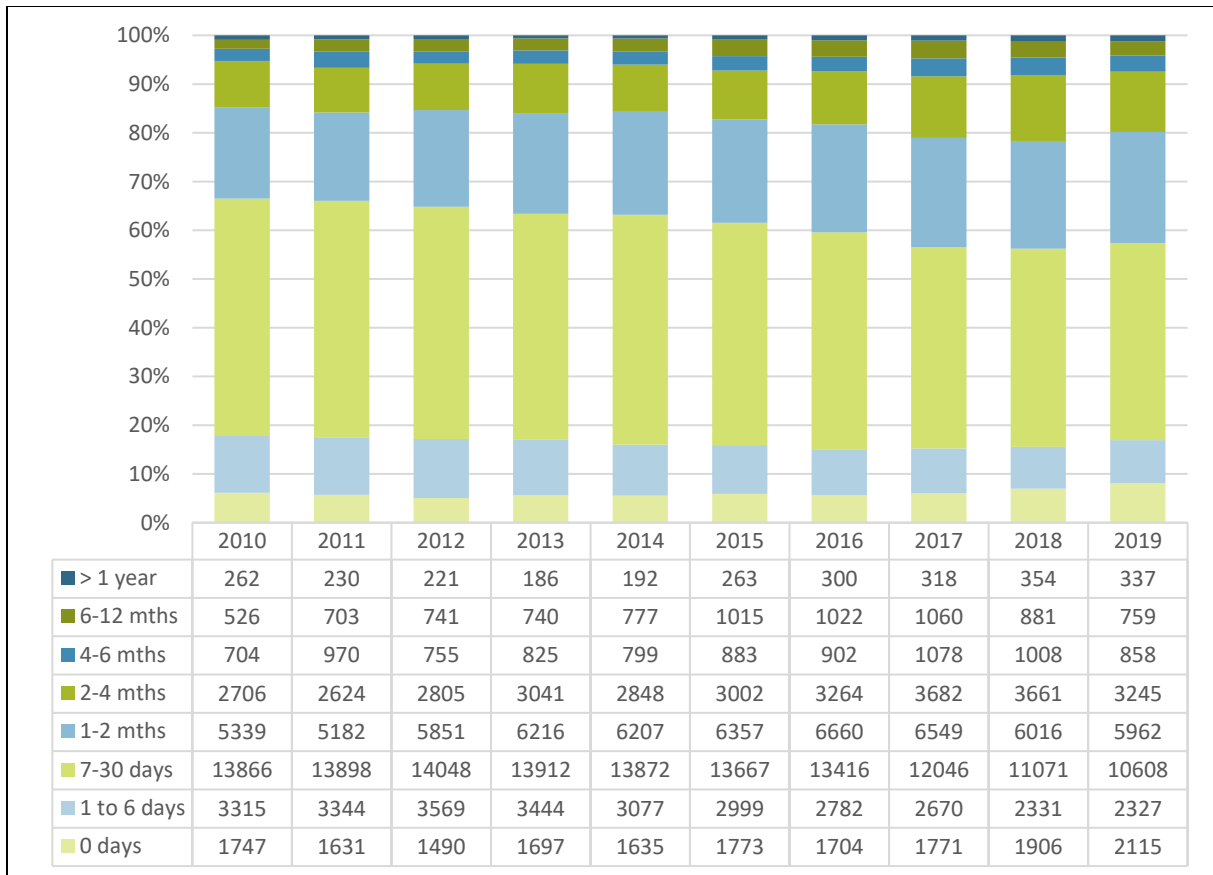


Figure 2.39 Evolution of the waiting time to intake (first face-to-face contact) in the Centers for Mental Health Care from 2010 to 2019 (Agency for Care and Health, EPD aggregated data).

From 2010 to 2018 waiting times increased gradually, with 66% of intake sessions started within one month and 85% within two months in 2010 to a mere 56% and 78% in 2018. In 2019, these percentages ameliorated again slightly to 57% within one month and 80% within two months. It is clear though that the predefined standard of 75% and 100% was not met in the ten years presented in Figure 2.39 above.

In all three age target groups, waiting times to intake increased over the years, as shown by the comparison in Figure 2.40. Shorter waiting times up to one month were relatively more frequently registered for care periods starting between 2010 and 2014 than for care periods starting between 2015 and 2019. For children and adolescents these percentages mounted to 56% in the earliest years and 52% in the latest years, for adults to 66% and 58%, and for elderly people to 78% and 72%. Overall, waiting times for children and adolescents were the longest (54% within one month and 75% within two months) and waiting times for elderly people were the shortest (75% and 91%), with waiting times for adult clients falling in between (62% and 84%).

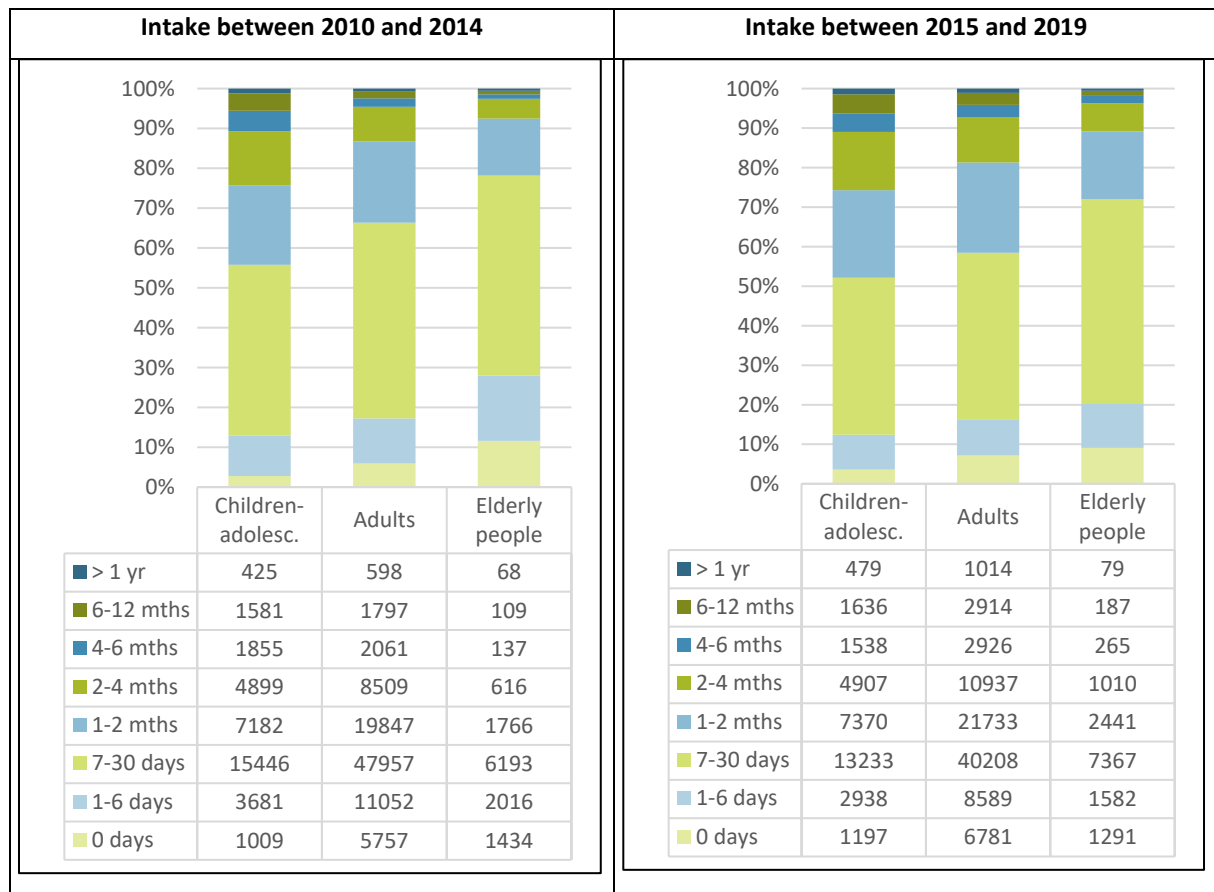


Figure 2.40 Waiting times to intake (first face-to-face contact) by target age group in the Centers for Mental Health Care between 2010 and 2014 and between 2015 and 2019 (Agency for Care and Health, EPD aggregated data).

Between 2010 and 2019, waiting times to the first face-to-face contact varied with the clients' complaint, as shown in Figure 2.41 for a selection of frequently registered intake problems. In general, the shortest waiting times were observed for reality control and addiction problems, with less than 13% of intake sessions taking place after a waiting time of two months or more. For behavioral and developmental problems on the other side of the figure, the proportion of intake sessions with waiting times over two months amounted to 23% and 29%, respectively. This is not surprising, given the fact that these problems are mostly occurring in the target group of children and adolescents, where waiting times are the longest.



Figure 2.41 Waiting times to intake (first face-to-face contact) for frequently registered intake problems in the Centers for Mental Health Care between 2010 and 2019 (Agency for Care and Health, EPD aggregated data).

Figure 2.42 below compares waiting times to intake in the Flemish provinces. In the province of Antwerp, waiting times were highest of all Flemish provinces in 2010, but the proportion of new care periods with shorter waiting times up to one month increased somewhat in the following years. West Flanders showed a mixed picture: The number of care periods with waiting times of (less than) one month was lower in 2019 than in 2010, whereas care periods with waiting times of one to two months increased significantly, which led to a decrease of waiting times over two months. All other provinces ended up with longer waiting times in 2019 than in 2010, with Limburg and Flemish Brabant (excluding Brussels) showing the steepest decrease of care periods with waiting times of one month or less.



Figure 2.42 Evolution per province of the waiting time to intake (first face-to-face contact) in the Centers for Mental Health Care from 2010 to 2019 (Agency for Care and Health, EPD aggregated data).

After the intake session, most clients are again put on a waiting list to start treatment. The first treatment session is registered as the second face-to-face contact. The waiting time from first to second face-to-face contact and the total waiting time to treatment onset can be calculated per care period from the EPD-databases, making it possible to relate mean waiting times to age target group, intake problem, care type, province, and other relevant variables. However, the aggregated output datasets used for presenting the use data in this section, allowed for the calculation of mean waiting times to the first face-to-face contact, but not the calculation of mean waiting times to the second face-to-face contact. Therefore, we limit the description of the waiting time to treatment to the means presented in the interactive report on the website



of the Flemish Agency for Care and Health and compare these to the overall mean waiting time to intake and the mean waiting time to intake per province.

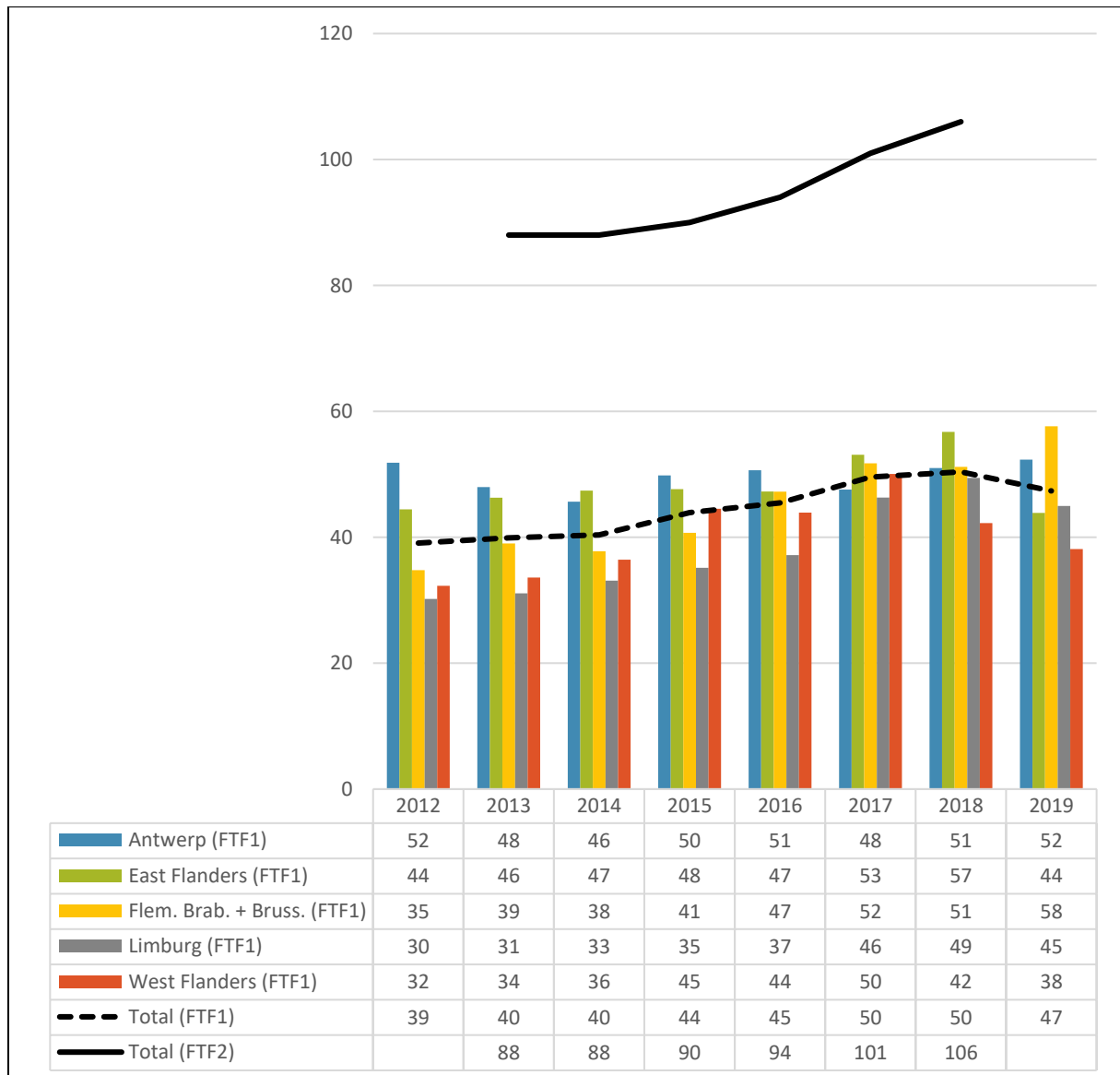


Figure 2.43 Comparison of the evolution of the total mean waiting time to treatment in the Centers for Mental Health Care between 2013 and 2018 with the mean waiting time to intake (total and per province between 2012 and 2019 (Agency for Care and Health, EPD aggregated data - interactive web report).

As expected from Figure 2.43, the evolution of mean waiting times to intake varied in the Flemish provinces, with Antwerp showing constant long waiting times (around 50 days), and other Flemish provinces increasing up to 2017 (West Flanders) or 2018 (East Flanders and Limburg), followed by a decrease that led in 2019 to the lowest mean waiting time in West Flanders (38 days) and somewhat higher numbers in East Flanders (44 days) and Limburg (45 days). In Flemish Brabant (including Brussels), the mean waiting time in 2019 was the highest (58 days) and the result of the strongest increase between 2012 and 2019.

When considering all Flemish provinces, the mean waiting time to intake increased from 40 days in 2013 to 50 days in 2018 and decreased again to 47 days in 2019. The mean waiting time to treatment went from 88 days in 2013 to 106 days in 2018, which means that, in general, the waiting time from first to second face-to-face contact was slightly longer than the waiting time to the first contact and showed a stronger increase.

*Treatment status and treatment duration*

Yearly, approximately 5% of all registered care periods were in the intake phase, 57% were ongoing treatments and 38% ended in the course of the registration year. The number and proportion of care periods in the intake phase increased somewhat between 2010 and 2019, whereas the number and proportion of closed care periods ended up lower in 2019 than in 2010. The number of ongoing care periods mounted until 2016 and came down again since then, but the proportion remained stable around 57%.

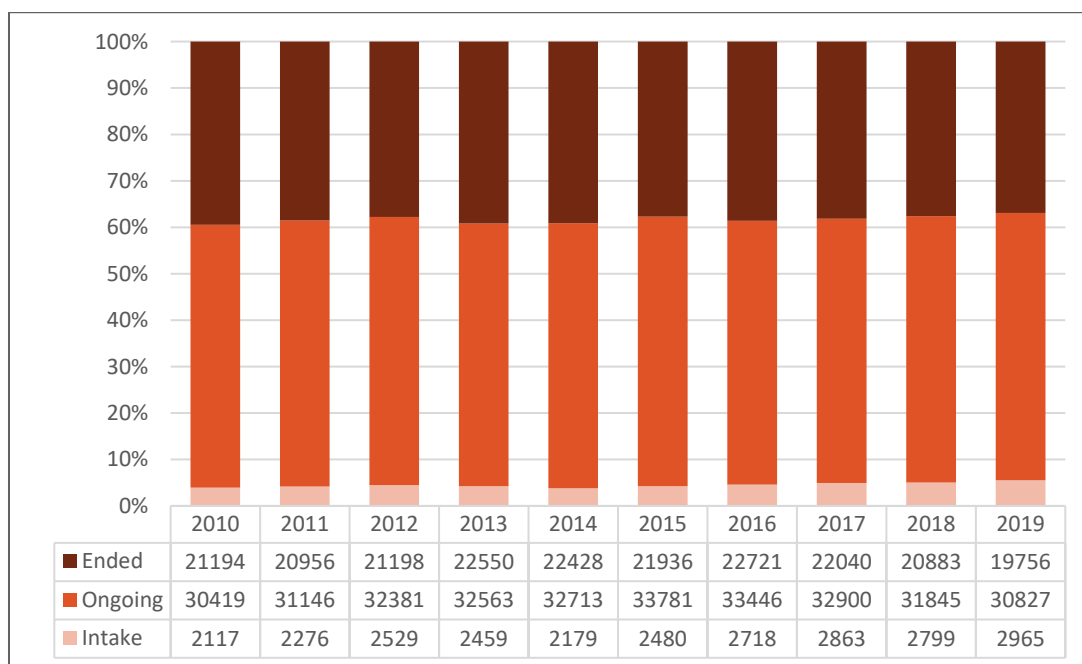


Figure 2.44 Evolution of the proportion of care periods per treatment status in the Centers for Mental Health Care from 2010 to 2019. (Agency for Care and Health, EPD aggregated data).

A relative increase of care periods in the intake phase combined with stable (or decreasing) total capacity, could have a number of reasons. It might reflect the longer duration of the intake phase due to the increased waiting time between intake and treatment on the one hand, or it could be the result of a gradual shortening in treatment duration or a gradual decrease in contact frequency, leaving more capacity for additional clients on the other hand. Although the information in the EPD database allows for the exact calculation of the duration of care periods and the frequency of face-to-face contacts owing to the detailed registration of individual treatment sessions and activities, the aggregated output datasets obtained for this report are limited in that regard. Therefore, two different coarse approaches are used to shed some light on (the evolution of) treatment duration and contact frequency in general and in relation to other variables, such as age target group, intake problem, or diagnosis.

First, we compare the proportion of care periods per intake year, as shown in Figure 2.2 in Paragraph 3.2.1 of this section. This comparison revealed a relative increase of longer care periods started earlier than the previous year and a decrease of new care periods registered in the registration year, which seems to suggest a yearly increase of longer treatments rather than a decrease. When comparing the proportion of ongoing and ended care periods started earlier than the year before registration, there was a slightly stronger increase of ended care periods, indicating that in recent registration years, more relatively longer care periods were closed off than in earlier years (Figure 2.45).

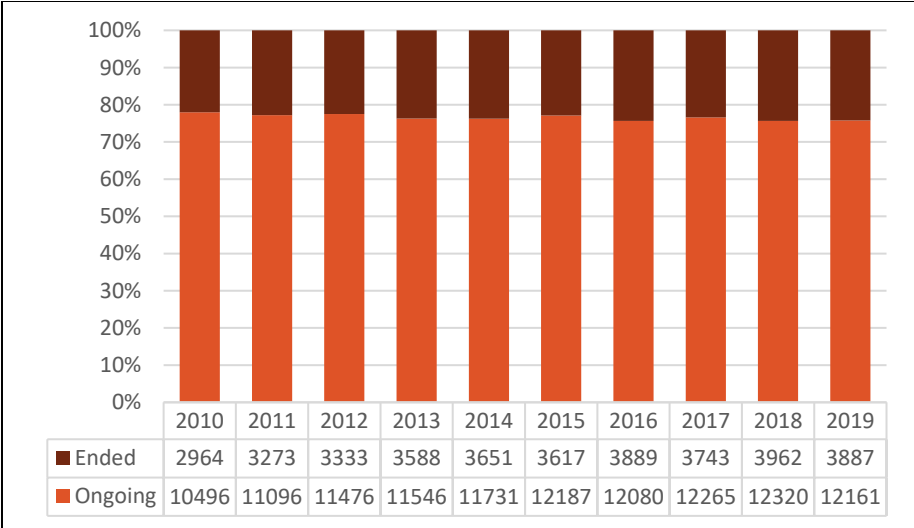


Figure 2.45 Evolution of the proportion of ended and ongoing care periods started earlier than the year before registration in the Centers for Mental Health Care from 2010 to 2019. (Agency for Care and Health, EPD aggregated data).

Longer care periods are not necessarily associated with a total of more face-to-face contacts, as the frequency of contacts generally diminishes in prolonged treatment. The ratio of face-to-face contacts offered in the last two years of treatment per care period was already presented in Figure 2.5 in Paragraph 3.2.1, but is shown again in Figure 2.46 below, with care periods in the intake phase removed from the analysis. Although the ratio amounted to a virtually constant number of 12 face-to-face contacts per care period in every year between 2012 and 2019, the figure shows diminishing ratio’s when intake years were considered separately. In 2019, care periods started earlier than the year before the registration year, were reduced on average with two face-to-face contacts per care period as compared to 2012. Care periods started in the previous year showed a reduction of one face-to-face contact in the same period.

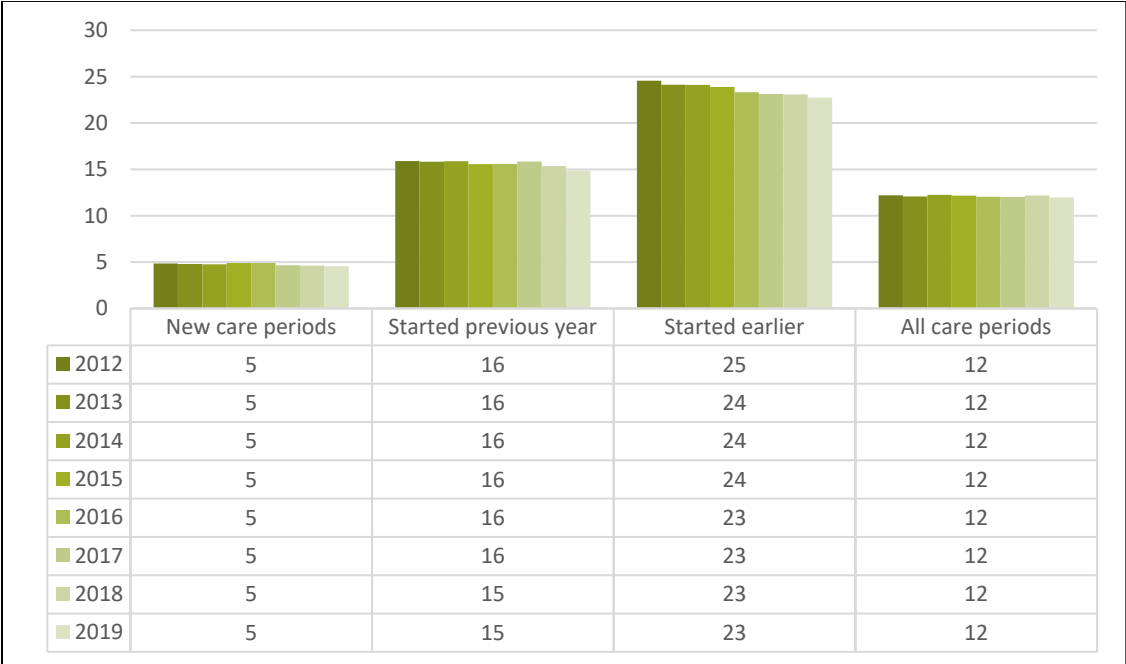


Figure 2.46 Evolution of the number of face-to-face contacts in the last two years of treatment per care period in the Centers for Mental Health Care from 2012 to 2019, with care periods in the intake phase removed (Agency for Care and Health, EPD aggregated data).

The decreasing trend in the number of face-to-face contacts per care period was somewhat stronger for ongoing care periods than for care periods that ended in the registration year, especially in the case of care periods that started before the previous year, with an average reduction of nearly three face-to-face contacts per care period between 2012 and 2019. Ongoing care periods with intake in the previous year showed almost two face-to-face contacts less in 2019 than in 2012 and new ongoing care periods had one less face-to-face contact up to the point of data export.

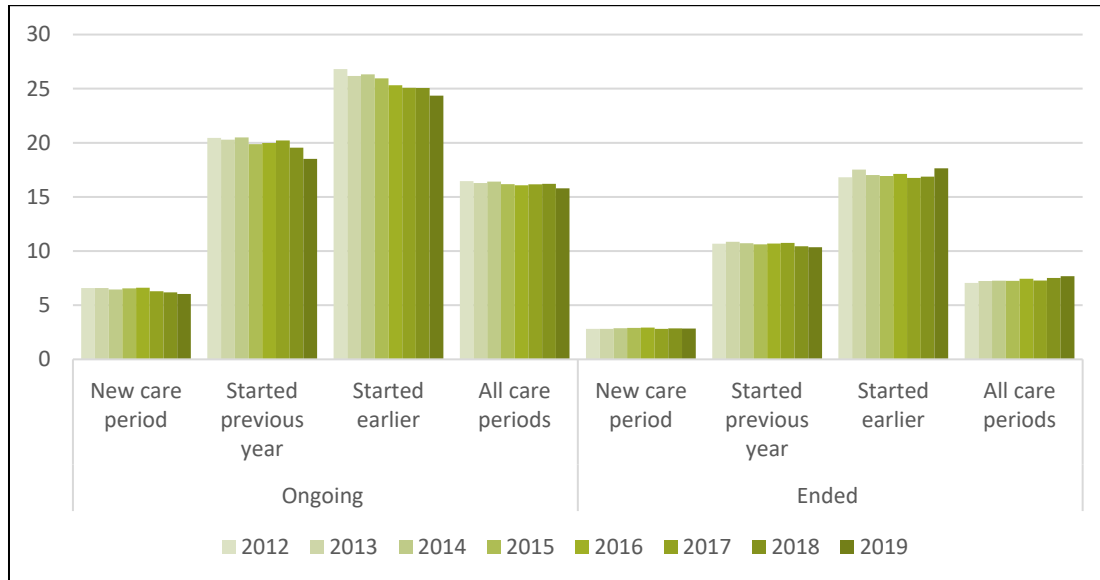


Figure 2.47 Evolution of number of face-to-face contacts in the last two years per care period for ongoing and ended care periods in the Centers for Mental Health Care from 2012 to 2019 (Agency for Care and Health, EPD aggregated data).

As a second measure for treatment duration, we use a categorical variable expressing duration in months (or years) that was constructed for the CGG-data reports published on the website of the Flemish Agency for Care and Health.

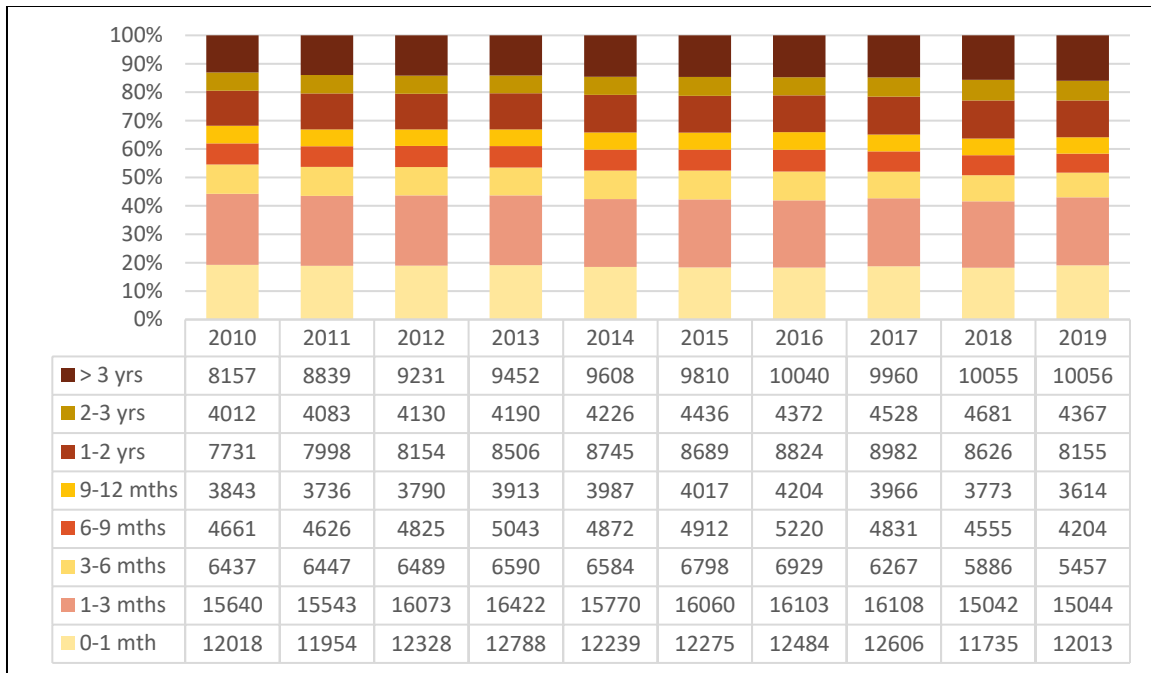


Figure 2.48 Evolution of treatment duration of all care periods registered in the Centers for Mental Health Care between 2010 and 2019 (Agency for Care and Health, EPD aggregated data).

When considering all registered care periods, the largest proportionate increase between 2010 and 2019 was observed for the longest-lasting care periods of more than three years. In general, Figure 2.48 shows that care periods lasting more than a year became relatively more frequent, whereas shorter care periods showed more of a decreasing trend.

Obviously, these trends vary with intake year and treatment status. When comparing the evolution of ongoing and ended care periods with respect to treatment duration, most recently started care periods (in the registration year or the year before) were closed care periods that lasted less than one month (around 20%). The proportion of care periods with a duration of one to two years, ongoing as well as ended, seemed to increase somewhat between 2012 and 2019, as shown in Figure 2.49.

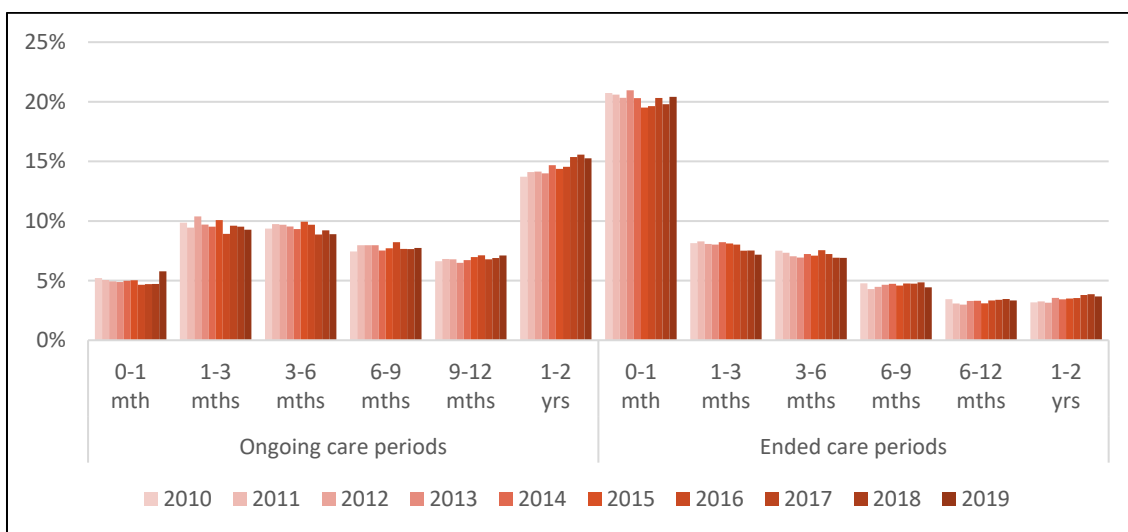


Figure 2.49 Evolution of the proportion of treatment duration categories for ongoing and ended care periods started in the registration year or the year before in the Centers for Mental Health Care (Agency for Care and Health, EPD aggregated data).

In every registration year, at least half of the care periods that started earlier than the previous year (Figure 2.50) were ongoing care periods with a duration of three or more years. In addition, around 9% of all care periods ended in the registration year and fell into the longest duration category as well, with a proportion that increased from 8% in 2010 to 10% in 2019, suggesting that the longest-lasting treatments were closed relatively more often in later years.

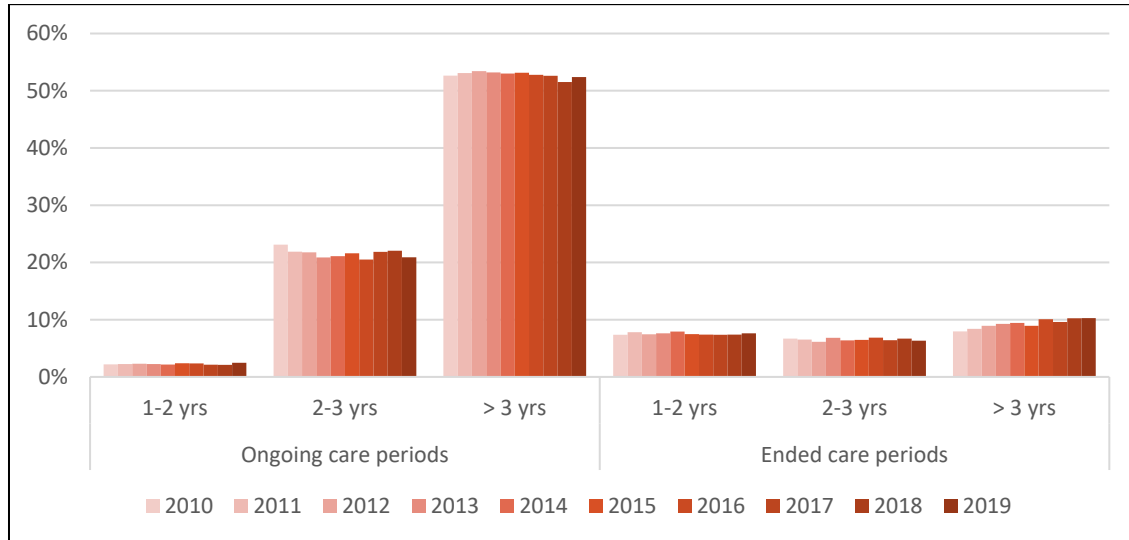


Figure 2.50 Evolution of the proportion of treatment duration for ongoing and ended care periods started earlier than the year before registration in the Centers for Mental Health Care (Agency for Care and Health, EPD aggregated data).

Based on the coarse approaches presented above, conclusions with regard to the evolution in treatment duration and contact frequency in the Centers for Mental Health Care are not straightforward. The proportion of long-lasting care periods that started at least two years before the registration year, increased somewhat as compared to more recently started care periods and consisted of relatively more ongoing care periods with a decreasing number of face-to-face contacts per care period on the one hand, and care periods that were closed off on the other hand, especially when lasting more than three years.

In the remainder of this paragraph age group, intake problem, and diagnosis are related to treatment duration.

In Figure 2.51 the relative occurrence of age groups in longer care periods started earlier than the year before registration is compared with their occurrence in care periods started more recently (also see Paragraph 3.2.2 of this section). While children and adolescents accounted for a much smaller proportion in care periods started earlier than the previous year (2%) than in care periods started in the registration year (24%) or the year before (26%), the reverse was true for the adult (82%, 67%, and 65%, respectively) and elderly target group (16% of earlier care periods and 9% of more recently started care periods), suggesting relatively more long-lasting care periods in the adult and elderly group than in the youngest group.

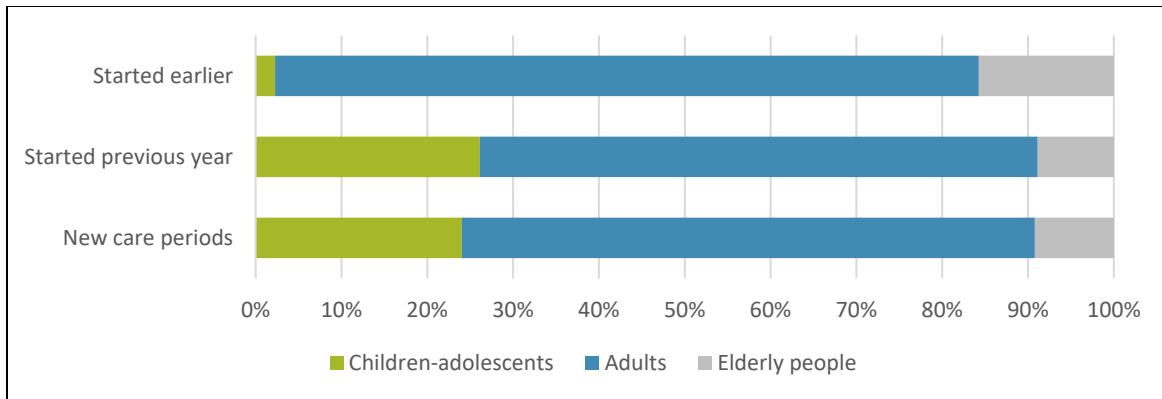


Figure 2.51 Proportion of care periods for age target groups per intake year in the Centers for Mental Health Care between 2010 and 2019 (Agency for Care and Health, EPD aggregated data).

The ratio between the number of face-to-face contacts in the last two years of treatment for ongoing and ended care periods in earlier and more recent intake years, was higher for children and adolescents than for adults, except for ongoing care periods started earlier than the year before registration. In these care periods adults showed the highest ratio, while elderly people showed a markedly lower ratio than the other age groups.

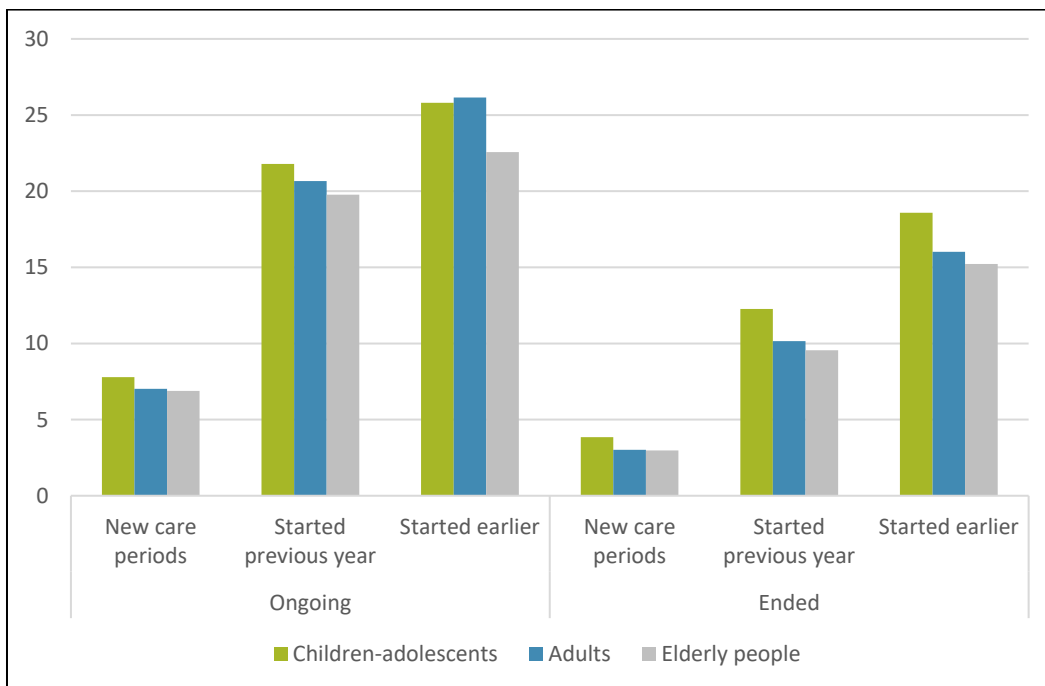


Figure 2.52 The number of face-to-face contacts in the last two years in ongoing and ended care periods per intake year for the age target groups in the Centers for Mental Health Care between 2012 and 2019 (Agency for Care and Health, EPD aggregated data).

In general, the number of face-to-face contacts per care period thus seemed to decrease with age. This trend was not reflected by the length of the care periods in the different age categories (Figure 2.53). The proportion of ongoing as well as ended care periods for children and adolescents lasting more than three years was the lowest, whereas the reverse was true for elderly people, suggesting generally shorter care periods with relatively more face-to-face contacts in the youngest group and generally longer care periods with less face-to-face contacts in the older group. Very short care periods lasting less than one month were markedly more frequent for adult and elderly people than for children and adolescents.

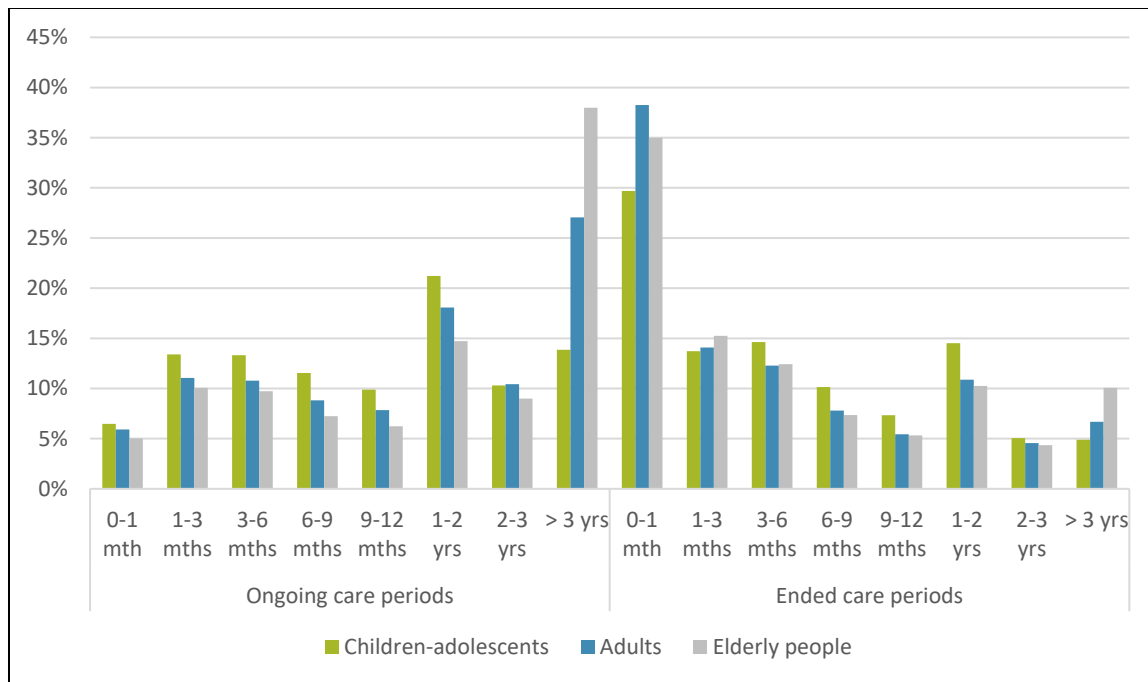


Figure 2.53 Treatment duration of ongoing and ended care periods for the age target groups in the Centers for Mental Health Care between 2010 and 2019 (Agency for Care and Health, EPD aggregated).

When comparing intake years with regard to intake problems, the proportion of care periods for psychological complaints and behavioral problems was somewhat smaller for recently started care periods than for care periods started earlier, suggesting a relatively longer treatment duration than for addiction problems, where the proportion was largest in the registration year.

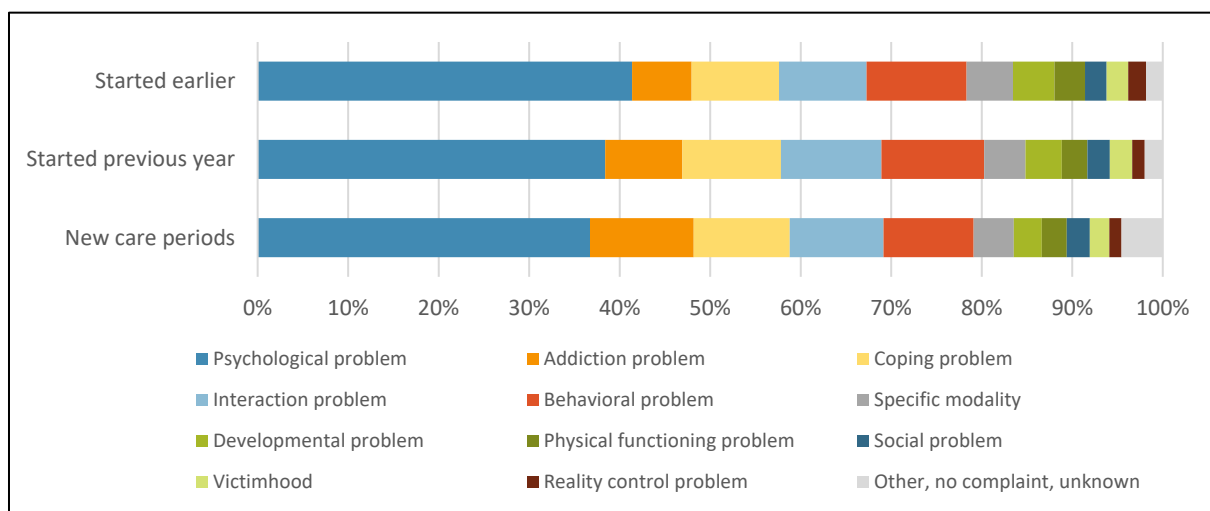


Figure 2.54 Proportion of care periods for intake problems per intake year in the Centers for Mental Health Care between 2010 and 2019 (Agency for Care and Health, EPD aggregated data).

The comparison of the proportion of addiction diagnoses per intake year, led to the same conclusion, with 15% substance-related disorders in the registration year between 2010 and 2017 (Figure 2.55) and 13% in 2019 (Figure 2.56), as compared to 11% and 10% in the previous year and 9% and 8% in the year before that. The occurrence of relatively more shorter than longer care periods, was also observed for anxiety



disorders and impulse-control disorders between 2010 and 2017, for child and adolescent primary diagnoses in 2019, and for other conditions with a need for mental health care in both time periods.

Depression and mood disorders, and especially schizophrenia and other psychotic disorders on the other hand, were relatively more frequent in earlier intake years than in the registration year, suggesting the need for continuing care periods. In 2019, new care periods also showed a smaller proportion of neurobiological developmental disorders, mild and major neurocognitive disorders, and less common diagnoses such as bipolar mood disorders, and sexual dysfunction and gender identity disorders, than care periods registered in the previous year or earlier. The same was true for childhood disorders between 2010 and 2017.

The proportion of the ‘unknown, no diagnosis’ category was removed from both figures below, as it was considerably larger for new care periods (17% between 2010 and 2017 and 16% in 2019) than for care periods started in the previous year (10%) and care periods started earlier (6% and 5%). This may be the result of new care periods still being in the intake phase or early stages of treatment and treatment planning at the time of data delivery to the Agency for Care and Health.

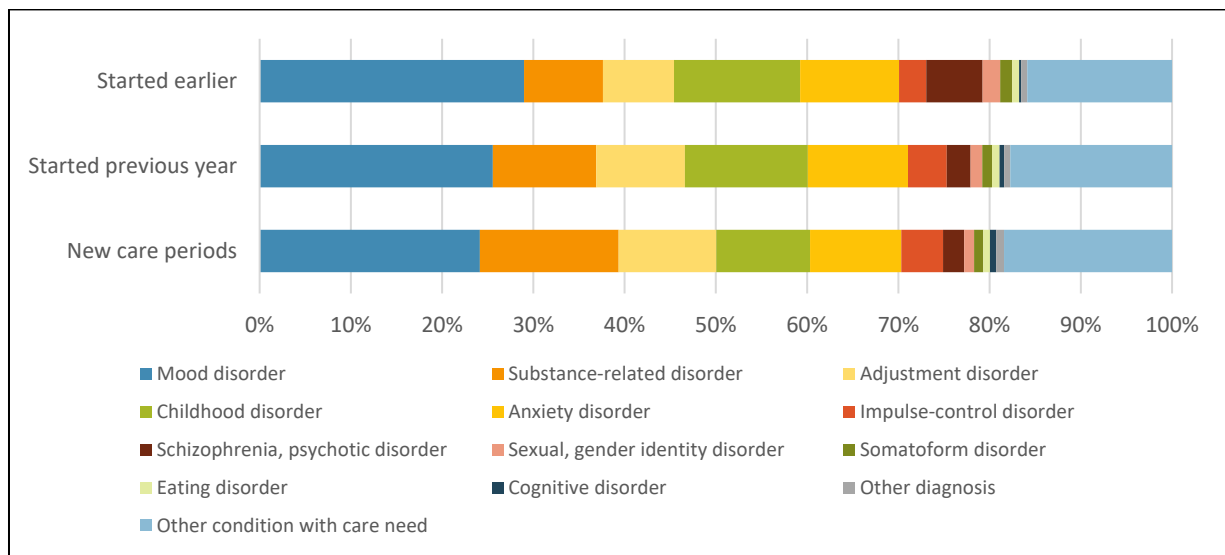


Figure 2.55 Proportion of care periods for diagnoses per intake year in the Centers for Mental Health Care between 2010 and 2017 (Agency for Care and Health, EPD aggregated data).

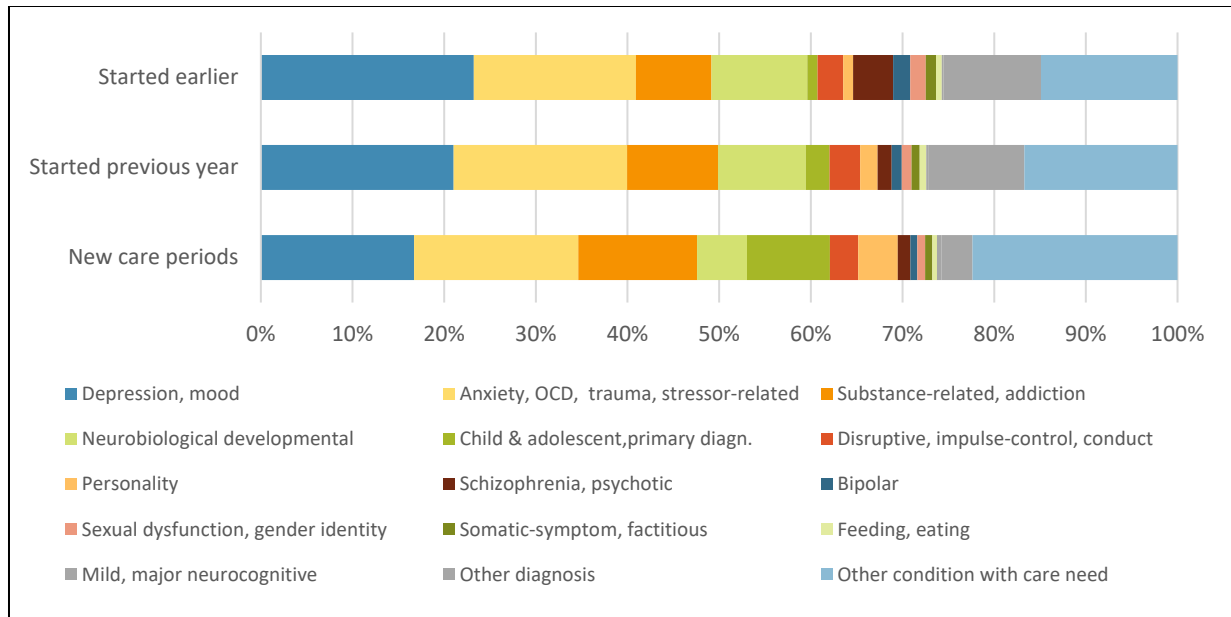


Figure 2.56 Proportion of care periods for diagnoses per intake year in the Centers for Mental Health Care in 2019 (Agency for Care and Health, EPD aggregated data).

### Activities

All care activities offered during care periods in the Centers for Mental Health Care are registered in detail and are divided into five main care activity types: indication-orientation, therapeutic treatment, counselling, activation, and psycho-education. In addition, client presence or (notified) absence is recorded for each planned activity.

The 2017 written report (Cloots & Roelandt, 2018) and the 2018 interactive web report published on the website of the Flemish Agency for Care and Health, show that the total number of registered care activities increased from 2013 to 2016, but decreased again in the two following years. On average, care periods consisted of approximately nine care activities per year, with therapeutic treatment amounting to 57% of all care activities or five treatment activities per care period per year. In general, the proportion of all main care activity types remained rather stable between 2013 and 2018. Care periods for children and adolescents contained relatively more indication and orientation activities, whereas elderly clients received more counselling and activation activities. In at least one out of five planned care activities, the client was absent, with two out of three clients failing to give notice in advance.

### 3.3 Description of costs in the Centers for Mental Health Care

In this paragraph, we present an overview of fragmentary data concerning personnel costs (3.3.1) and client contributions (3.3.2).

#### 3.3.1 Personnel costs

All personnel data reported in this section are taken from the interactive personnel data web report (Agentschap Zorg en Gezondheid, n.d.) published on the website of the Flemish Agency for Care and Health. Figure 2.57 shows the evolution in the number of Full Time Equivalents employed in the Centers for Mental Health Care. Between 2011 and 2019 there was a 12% total increase, with FTE augmenting between 2011 and 2013 and especially since 2018 (or 2017, as data from that year are not available).

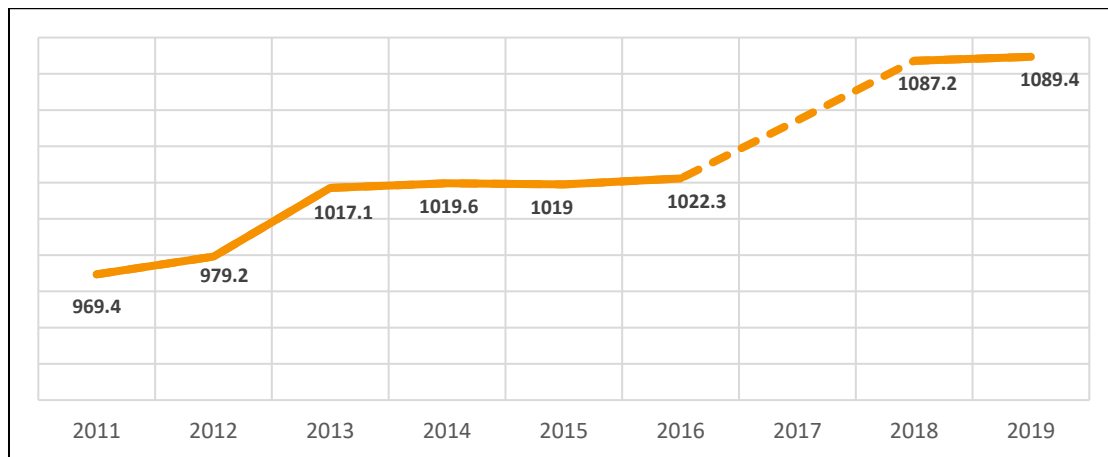


Figure 2.57 Evolution of the number of Full Time Equivalents employed in the Centers for Mental Health Care from 2011 to 2019 (Agency for Care and Health, Personnel web report).

Figure 2.58 below compares financing sources and shows that most of the total FTE increase between 2011 and 2019 was due to a 45% increase of FTE financed by other sources than the fixed Flemish Government envelope, especially since 2018. The number of FTE financed by the envelope itself mounted with a mere 5%, which led to a proportion of 74% envelope financed Full Time Equivalents in 2019 as compared to 79% in 2011. Care givers with an independent working status accounted for 2 to 3% of all FTE.

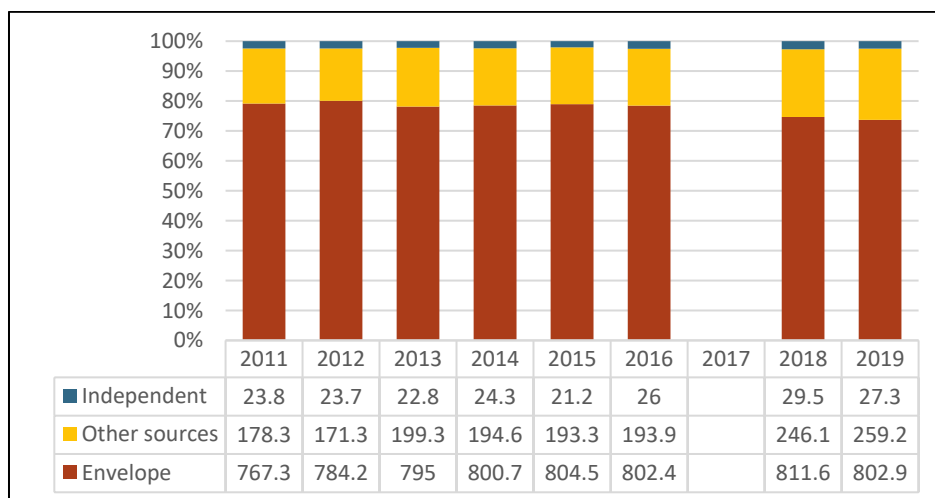


Figure 2.58 Evolution of the number and proportion of Full Time Equivalents by financing source in the Centers for Mental Health Care from 2011 to 2019 (Agency for Care and Health, Personnel web report).

For psychologists, prevention work, and other care functions, the number and proportion of Full Time Equivalents increased between 2011 and 2019, with 38% of FTE in 2011 held by psychologists up to 44% in 2019 (Figure 2.59). The number and proportion of FTE for social work decreased, accounting for 20% in 2011 to 16% in 2019. Full time Equivalents for psychiatrists fluctuated somewhat, but ended up at a comparable number and proportion in 2019 as in 2011. Other functions than care functions (staff, administration, etc.) showed diminishing numbers and proportions, making out 26% of all FTE in 2011 to 23% in 2019.

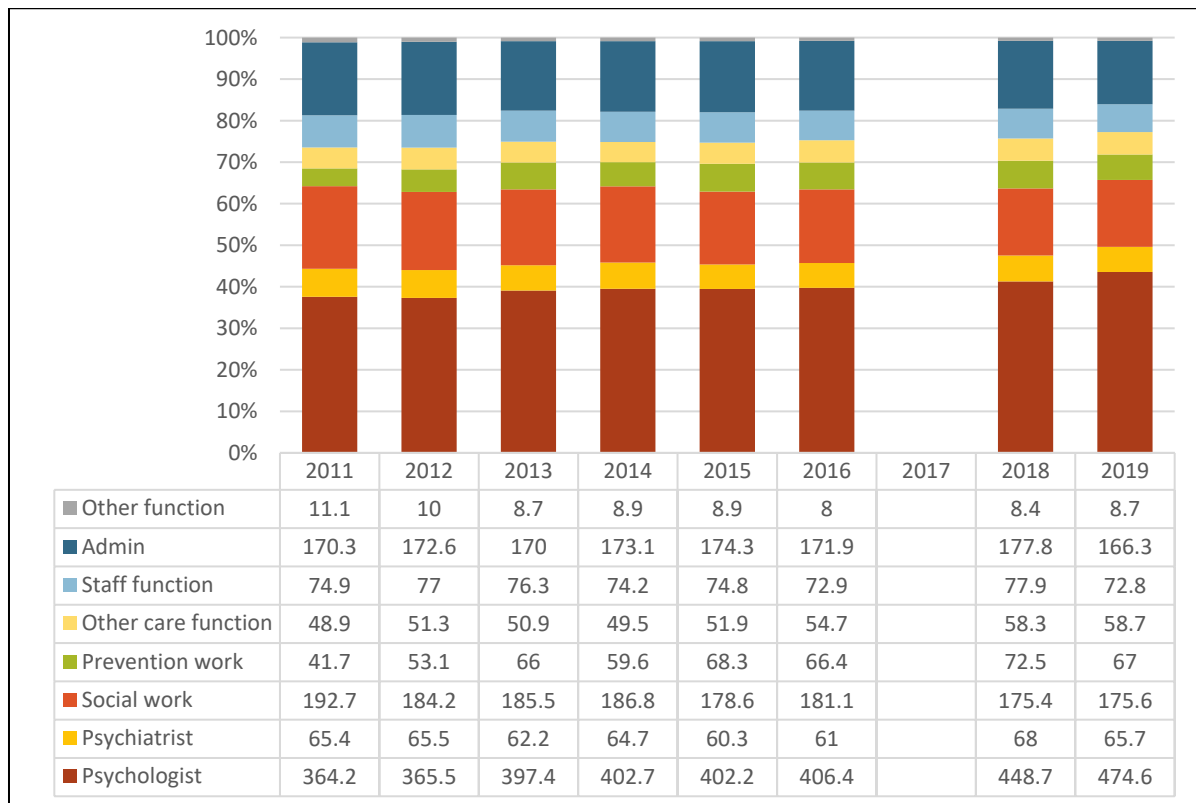


Figure 2.59 Evolution of the number and proportion of Full Time Equivalents by function in the Centers for Mental Health Care from 2011 to 2019 (Agency for Care and Health, Personnel web report).

Envelope financing as well as other financing sources contributed to the increase in Full Time Equivalents for psychologists, with the latter mounting noticeably in 2018 and 2019 to more than an additional 100 FTE, as compared to around 50 FTE in previous years. Full Time Equivalents for social work were financed gradually less by the envelope, with only slight compensation by other financial sources. Care givers with independent working status were mainly psychiatrists. Whereas envelope financing for psychiatrists diminished in number and proportion, psychiatrists with an independent status became more important for the Centers for Mental Health Care, mounting up from 31% of all FTE in 2011 to around 40% from 2016 onwards.

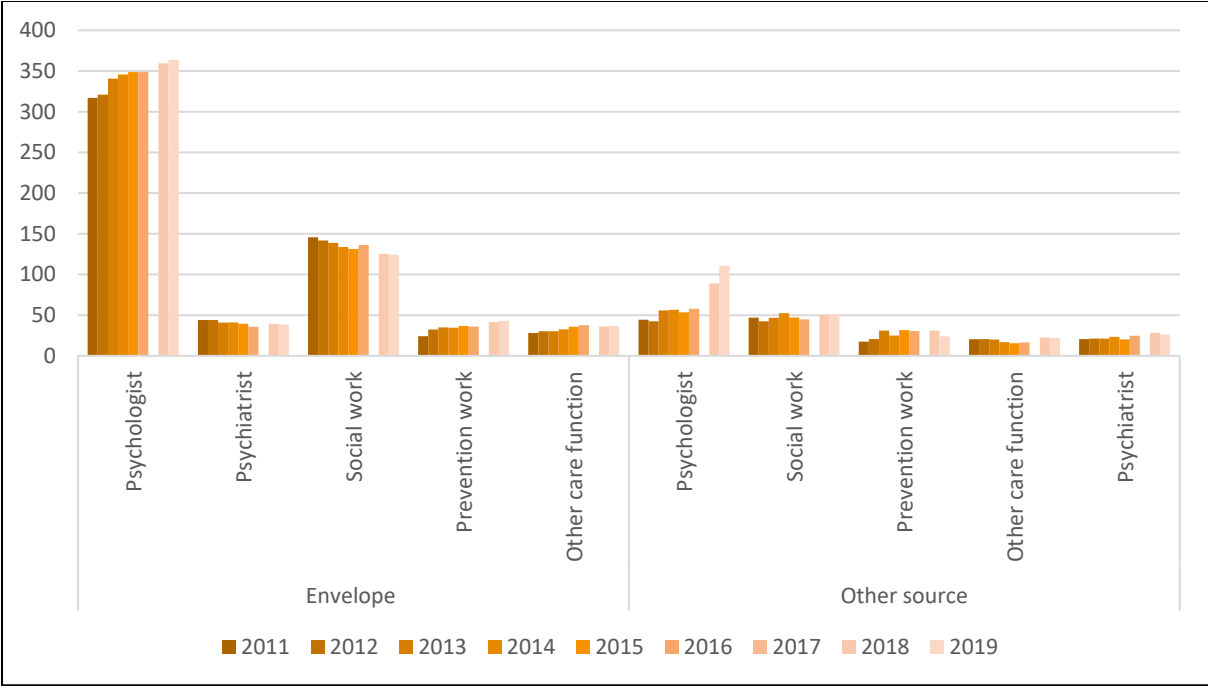


Figure 2.60 Evolution of the number of Full Time Equivalents for care functions by function and financing source in the Centers for Mental Health Care from 2011 to 2019 (Agency for Care and Health, Personnel web report).

For supporting functions, such as staff, administrative, and other non-care functions, the envelope provided the bulk of financing. Notwithstanding this, around one out of four FTE for administration and other non-care functions were financed by other sources, with this proportion increasing somewhat in recent years.

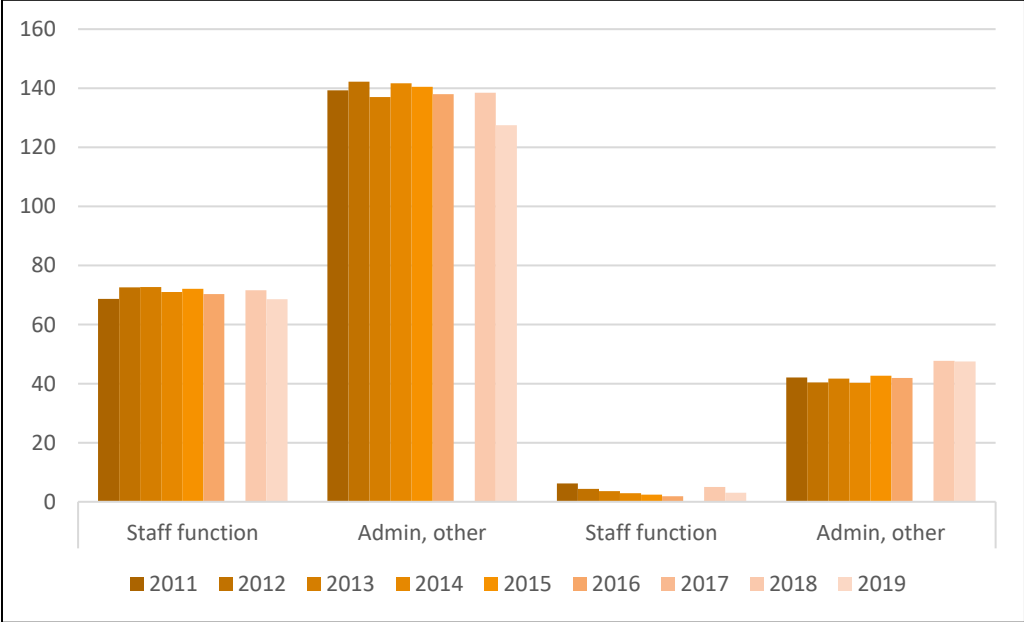


Figure 2.61 Evolution of the number of Full Time Equivalents for supporting functions by function and financing source in the Centers for Mental Health Care from 2011 to 2019 (Agency for Care and Health, Personnel web report).

The apparent discrepancy between the increased FTE and the constant (or even decreasing) number of care periods and face-to-face contacts offered to clients in the two years before registration could be explained

by the fact that most of the additional financing may have been directed to specific care types not necessarily registered as standard treatment sessions. However, more information with respect to registration practices, the EPD-database and the reported personnel data is needed to confirm this hypothesis.

### 3.3.2 Client contributions

Part of the costs in the Centers for Mental Health Care are paid by the clients. Client contributions divide into the regular rate of 11 Euro per session, a reduced rate of 4 Euro per session, and other rates, which may come down to no payment at all or to various rates in the context of projects. Rates are set as a standard at the beginning of a care period, but may be deviated from for certain activities. The actual fee paid by the client can be registered per session or activity, but in 2017 this was done in only 85% of all contacts according to the data report published by the Agency for Care and Health (Cloots & Roelandt, 2018). The standard rate was maintained in approximately 95% of the sessions and activities within the care period, with deviations in most cases limited to the first free face-to-face contact and assertive outreach activities.

Figure 2.62 shows that the number and proportion of care periods with regular standard rates dropped significantly from 58% of all care periods in 2013 to 44% in 2019, whereas the proportion of reduced and other standard rates went up from 27% to 33% and from 15 to 22%, respectively. According to the 2017 data report, no rate care periods accounted for 8% and various other rate care periods for 13% in the other standard rates category in that year (Cloots & Roelandt, 2018).

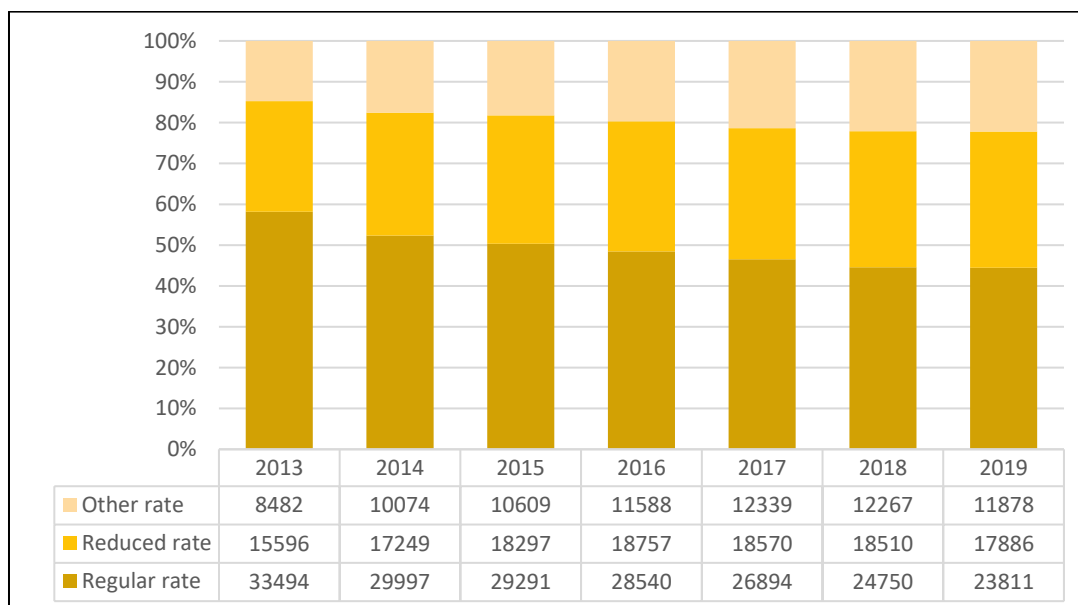


Figure 2.62 Evolution of the proportion of care periods by client contribution in the Centers for Mental Health Care from 2013 to 2019 (Agency for Care and Health, EPD aggregated data).

When comparing standard rates for the different age target groups for the period between 2013 and 2019, results show that regular standard rates were relatively more frequent in care periods involving children and adolescents (60%) than in adults (46%) and elderly people (48%). In almost two thirds of care periods for adults, a reduced rate was paid (32%). This percentage was somewhat lower for children and adolescents (29%) and somewhat higher for elderly people (34%). Other rates were most often applied in

care periods for adults (22%), followed by elderly people (18%), but appeared markedly less frequent in the youngest group (11%).

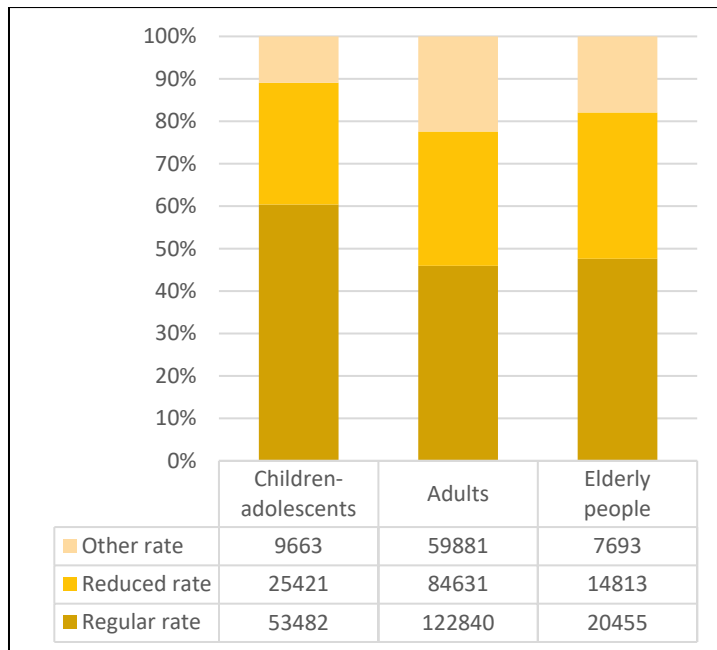


Figure 2.63 Proportion of care periods with regular, reduced, or other rates by age target group in the Centers for Mental Health Care between 2013 and 2019 (Agency for Care and Health, EPD aggregated data).

Normally, clients with enhanced reimbursement status should pay the reduced rate of 4 Euro's. As Figure 2.64 below shows, this was not always the case, with around 10% of reduced rate care periods in the adult no target group and 9% of regular rate care periods in the enhanced reimbursement status target group.

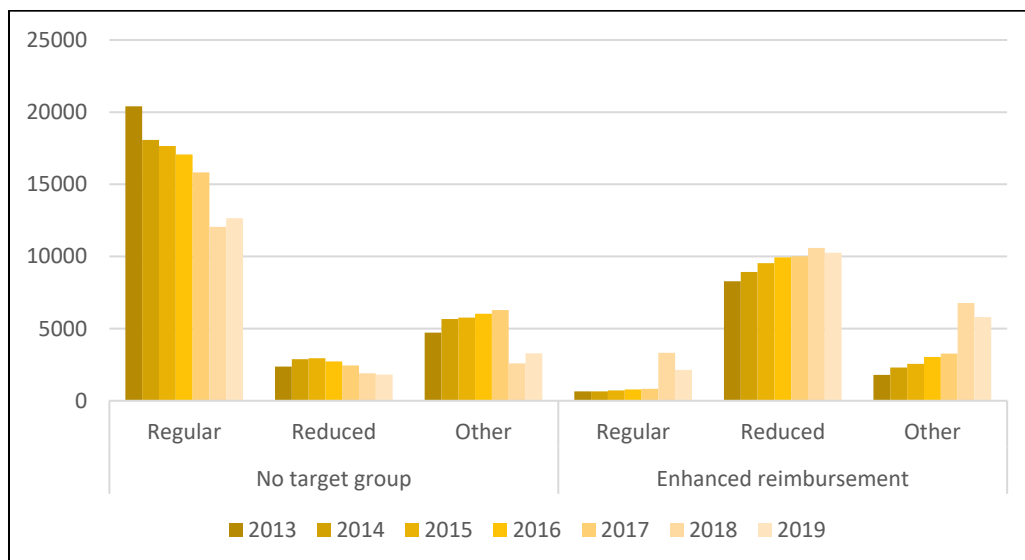


Figure 2.64 Evolution of the number of care periods with regular, reduced, or other rates in the adult target groups in the Centers for Mental Health Care from 2013 to 2019 (Agency for Care and Health, EPD aggregated data).

In 2018 and 2019, there seemed to be a discrepancy between the target group registration and the registration of client contributions, with markedly more regular and other rate care periods in the adult enhanced reimbursement target group than in the previous years, together with markedly less regular and other

rate care periods in the group without enhanced reimbursement status. This shift is possibly related to the noticeable increase in the number and proportion of care periods for clients with enhanced reimbursement status in both years, as previously shown in Figure 2.10 in Section 3.2, Paragraph 3.2.2. Based on the output datasets used for this report, however, it is not possible to distinguish whether it mirrors a meaningful change or could be due to registration changes or data analysis error. Possibly, the 11% missing registrations for the enhanced reimbursement variable according to the 2017 report (Cloots & Roelandt, 2018), may have been registered correctly from 2018 onwards, thereby explaining the sudden rise in clients with that status.

Reduced standard rates were relatively more frequent in care periods for female (35%) than for male clients (27%), whereas the latter had more care periods with other standard rates, many of which involved men with no health insurance status, paying no fee (Cloots & Roelandt, 2018).

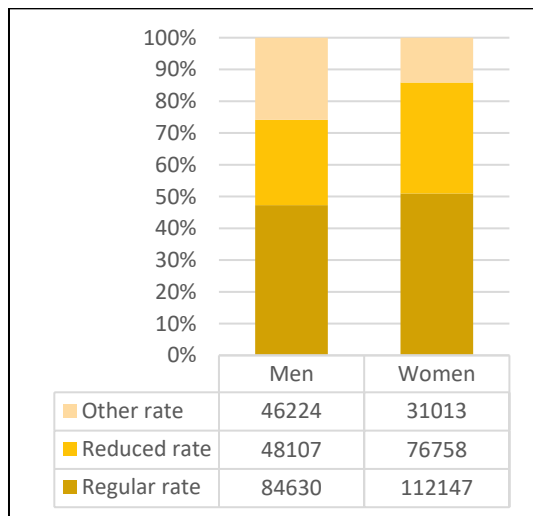


Figure 2.65 Proportion of care periods with regular, reduced, or other rates for male and female clients in the Centers for Mental Health Care between 2013 and 2019 (Agency for Care and Health, EPD aggregated data).

Also, reduced rates were relatively more frequent in care periods started earlier than the year before registration than in more recently started care periods, whereas the reverse was true for care periods with regular or other standard rates, suggesting longer care periods for clients paying reduced rates. This finding corresponds with the data presented in Figure 2.7 in Paragraph 3.2.2 of the previous section, showing relatively more care periods for clients with enhanced reimbursement status in earlier intake years.

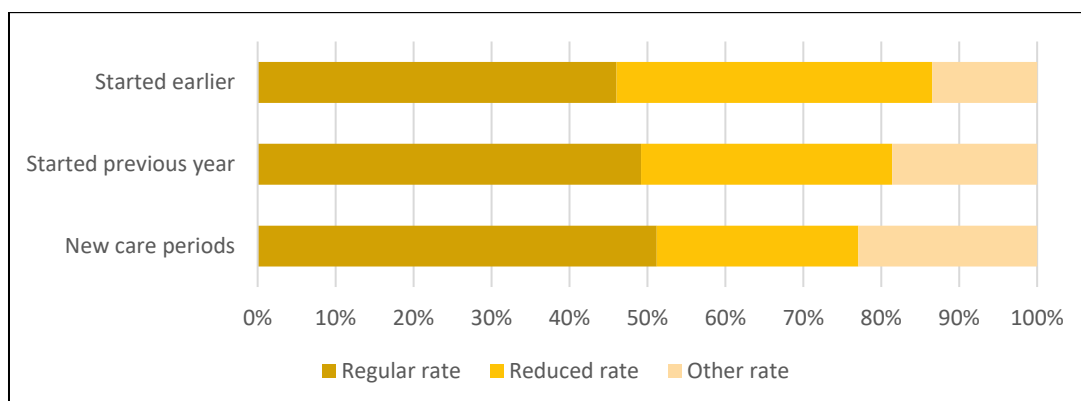


Figure 2.66 Proportion of care periods with regular, reduced, or other rates by intake year in the Centers for Mental Health Care between 2013 and 2019 (Agency for Care and Health, EPD aggregated data).



Figure 2.67 shows varying client contributions per province. The proportion of care periods for clients paying regular rates was largest in Flemish Brabant, followed by East Flanders and West Flanders. In Antwerp and Limburg less than half of the care periods had regular standard rates, with reduced rates mounting up to more than one third of all care periods.

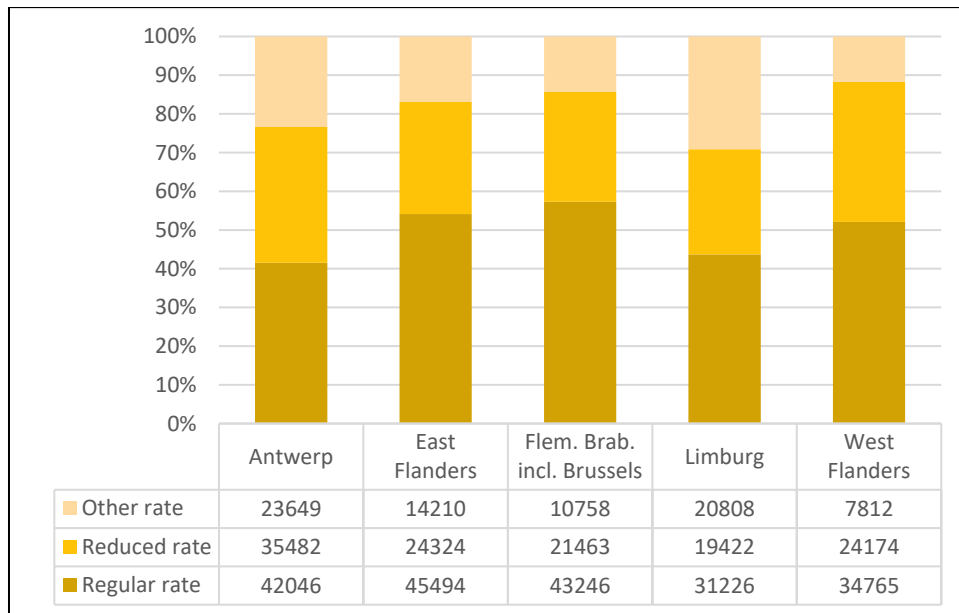


Figure 2.67 Proportion of care periods with regular, reduced, or other rates in the Centers for Mental Health Care between 2013 and 2019, per province (Agency for Care and Health, EPD aggregated data).

#### 4 Projection of future needs, service use, and costs in the Centers for Mental Health Care

For this report, we only obtained a number of separate aggregated datasets derived from the EPD-database, each containing a limited number of variables. Despite the limitations of such data, the description of service use in the Centers for Mental Health Care reported in Section 3 of this chapter illustrates the complexity of predicting future trends, with many interacting factors influencing or associated with (the evolution of) current service use, including gender, age group, province, diagnosis, etc.

The data described above, however, are far from sufficient to predict future care needs, service use, and associated costs in the Centers for Mental Health Care. For the most part, this is due to the reasons discussed in the introductory chapter. Service use can only be informative of care need when supply follows demand and when people seeking care, have access to the appropriate services. As waiting times regularly exceed predefined standards and turn into waiting lists, it is already clear that supply and accessibility are restricted.

In addition to this basic impediment to predicting future trends, limitations to availability of use data impose a second hurdle to constructing well-founded prognosis models. The elaborate EPD registration system used in the Centers for Mental Health Care contains a wealth of relevant information, but there are still some issues to be resolved in order to disclose its full potential. Although, data quality improved significantly with the introduction of the EPD, as compared to the former Arcade registration, standardization is not yet optimal. For instance, most information is registered per care period, but the definition of a care period may vary between centers, making it difficult to compare total numbers between

centers or regions. Also, the reliability of the registrations may vary for different variables, with relatively higher percentages of 'unknown' or 'other' registrations in some variables than in others.

In order to overcome both obstacles mentioned above, many steps need to be taken. As described in the introductory chapter, we already suggested the approach of using prevalence data to assess needs in the context of restricted supply, with waiting lists hindering access to certain services. Appendix 1 summarizes international and Belgian population prevalence data with respect to mental disorders as a means of assessing the potential need for treatment in the Centers for Mental Health Care. Different approaches in applying prevalence percentages to demographic data are described and used for estimating the Flemish population in need of mental health care.

However, the available prevalence data have their limitations as well. Complete yearly time series for the Flemish population are not available, seeing that the Belgian Health Interview Survey, is conducted every four to five years. Moreover, operationalizations for certain disorders changed between measurements, making it difficult to interpret evolutions in the data. Finally, even a clear picture of the prevalence of mental health problems may still be insufficient in predicting service use, as the care offered by the Centers for Mental Health Care may not be appropriate or indicated for all people reporting these problems, e.g. depending on the severity of the condition, comorbidities, or other client characteristics. It is thus necessary to make the connection with service use. However, this is not a simple relationship. Many clients may not find the way to the appropriate service or to any service even when needed. This is a problem not uncommon in a sector where stigma and insufficient knowledge of care offer already hinders access to seeking help, as shown in the ESEMeD/MHEDEA 2000 project (2004), reporting a conservative estimate of 3.1% of the European adult population with unmet needs for mental health care.

In the final chapter of this report, concrete suggestions for improved data are discussed. For now, it was not possible to develop a model that incorporates all relevant variables for predicting service use, as the comprehensive EPD-database with individual client data was not accessible for this report. Therefore, we end this chapter with a few simplified models for the Centers for Mental Health Care, based on a limited number of variables in the aggregated datasets and the estimated Flemish population with mental illness or specific mental health disorders.

#### **4.1 Prediction models for service use in the Centers for Mental Health Care**

In Appendix 2, some simple regression models for predicting the number of care periods and face-to-face contacts in the Centers for Mental Health Care are listed. All regressions are performed on aggregated data per center, which means that the number of cases in the dataset is relatively small. Province dummy variables are included in every model, as a means of controlling the supply factor. However, when predicting totals, observed effects of provinces are difficult to interpret using aggregated datasets per center, given the interaction between the capacity of individual centers, the number of other centers in the province, and possible regional differences in need.

The models in Appendix 2 predict all care periods or face-to-face contacts, care periods and FTF-contacts per age target group, and care periods and FTF-contacts per main diagnosis (mood disorder, anxiety disorder, and substance-related disorder). In a first step, we simply add year dummies to establish time trends. In a second step, estimates of the population in Flanders with any mental illness or specific mental disorders are added. Two approaches are used for these estimates. As a first approach, the prevalence percentages resulting from international meta-analyses (Polanczyk, et al., 2015; Steel et al., 2014) for common mental disorders are applied to the Flemish population data made available by the Belgian Federal

Planning Bureau. Hereby, the constant (gender-)specific percentages are applied to the CGG for children and adolescents on the one hand and both adult and elderly people on the other hand. Consequently, the yearly increase in the resulting estimates per age group and per gender are solely determined by demographic evolutions in the Flemish population. As a second approach, the National Health Interview Survey prevalence percentages for probable mental illness are applied to the Flemish population data from 2008, 2013, and 2018 per age group (adult and elderly) and per gender. In this approach, the increase over time is not only determined by the demographic evolution in the Flemish population, but also by the estimated evolution in the prevalence of probable mental disorder per age group and per gender. All further details with respect to these estimates are described in Appendix 1.

As expected from the description of service use in Section 3 of this chapter, no significant effects were observed for the year dummies in the models using the total number of care periods or face-to-face contacts per center as a dependent variable. In other words, the yearly evolution or variability in these totals is too limited to use as a basis for projecting future trends. The same is true for the regression models per age target group and per main diagnosis, with no significant time effects observed. Nevertheless, the target group of children and adolescents on the one hand and elderly people on the other hand show some sign of evolution, descending for the former group (model 1a in Appendix 2) and ascending until 2017 for the latter (model 1c in Appendix 2).

Given this lack of evolution, it is not surprising that the inclusion of the prevalence-based Flemish population estimates instead of the time dummies has little effect as well. The only significant predictors observed were in the regression models for the elderly target group, with total numbers of care periods significantly predicted by the HIS-prevalence estimate for women with any mental illness (model 5b), and for both men and women with mood (model 5d) and anxiety disorders (model 5f), despite using even a smaller dataset with three observations (years) per center. Meta-analysis-based prevalence estimates for any mental illness in children and adolescents produced marginally significant predictors (models 3a and 4a).

Although the regression analyses presented in Appendix 2 are not very useful for constructing projection models, they clearly illustrate the problem with restricted supply mentioned in the introductory chapter. When hardly any evolution is observed in the past, it is not possible to predict the future, despite prevalence-based estimates clearly showing a rising trend.

In addition to predicting the total number of care periods or face-to-face contacts, a few illustrative regression models were performed on the mean waiting time to intake aggregated data per CGG (Appendix 3). Year dummies produced no significant effects here either, despite the evolutions shown in most provinces in Section 3 of this chapter (Figure 2.44). However, this is probably due to opposite effects in the different age target groups within provinces, as the varying effects of provinces in comparison with the reference province West Flanders in the separate age target group regression models in Appendix 3 show. Again, these models are insufficient to predict evolutions in waiting times, but show that several interacting factors need to be taken into account in any model.



## Chapter 3

### The Sheltered Living Initiatives

The Sheltered Living Initiatives provide housing in the community for people with serious long-term, but stabilized psychological problems. After the Sixth State Reform, the Flemish government became responsible for the programming, recognition, and financing of the Sheltered Living Initiatives.

#### 1 Target group, objectives, and organizational structure

All information regarding the Sheltered Living Initiatives is available on the website of the Agency for Care and Health (<https://www.zorg-en-gezondheid.be/per-domein/geestelijke-gezondheidszorg/initiatieven-beschut-wonen>) and the reference frame for the Sheltered Living Initiatives (Agentschap Zorg en Gezondheid, 2019).

##### 1.1 Target group and objectives

The target group of the Sheltered Living Initiatives are adults and elderly people with serious long-term psychiatric problems who need guidance and support in daily tasks. Through offering this in sheltered houses, the Sheltered Living Initiatives aim at reintegrating clients into society, e.g. by helping them find a job or education opportunities, improving social contact, planning entertainment and free time, etc. They also help clients with administrative tasks, using public transportation, making payments, etc.

The main objectives of the Sheltered Living Initiatives can thus be summarized as follows: (1) strengthening social capacity and self-management of the care user, by offering supervision and guidance with social and administrative skills; (2) supporting the development of clients by helping them with educational or work opportunities, including volunteer work; and (3) guiding clients on how to live independently.

According to the MPG-registration data, the most common diagnoses in the Sheltered Living Initiatives for both men and women are schizophrenia and other psychotic disorders (49% and 40%, respectively in 2014), followed by substance-related disorders in men and mood disorders in women (Agentschap Zorg en Gezondheid, 2014).

At the intake, the supervisor of the Sheltered Living Initiative develops a care plan, together with the client and his/her family. Therapy goals and the clients' objectives are made explicit and areas where help and guidance is needed are identified. Once the client is accepted, the supervisor visits at least once a week, helping the client maintain the house in good condition, doing administrative tasks, planning daily activities, etc. with the objective of helping the client regain autonomy and independent living.

## 1.2 Organizational structure

At the start of 2022, the Flemish government financed 2985 places in 39 Sheltered Living Initiatives in the Flemish Region and 33 places in two initiatives in the Brussels Region. This total of 3018 places consist mostly of group housing, with a capacity of three to ten people per house, but approximately 15% is so-called individual housing, with one or two people receiving care, sometimes in their own home or in a rented house.

In Table 3.1 the number of initiatives and places per province is shown. The table shows that sheltered living places are unequally distributed over Flanders, ranging from approximately 35 places per 100.000 adult inhabitants available in the province of Antwerp to almost three times as much in Limburg.

Table 3.1 The number of Sheltered Living Initiatives, places, and places per 100.000 inhabitants aged 18 or more (Agentschap Zorg en Gezondheid, 2022; Population data: Federal Planning Bureau, Statbel).

	Initiatives	Places	Places / 100.000
Antwerp	6	528	35
East Flanders	10	704	57
Flemish Brabant	7	401	43
<i>Brussels Region</i>	2	33	
Limburg	6	706	99
West Flanders	10	646	66
Total	41	3018	

For personnel in the Sheltered Living Initiatives, a bachelor degree in psychology or social work is required. In addition, all Sheltered Living Initiatives must have a cooperation agreement with a psychiatrist, providing a minimum of three hours of psychiatric consultation per week to the clients in the sheltered house. All in all, there must be at least one full time equivalent for every eight clients (including the psychiatrist).

## 2 Financing and costs

Sheltered Living Initiatives receive funding for each person under their supervision, with most service costs billed under a general basic nomenclature code (762576 until 2019 and 276617 since then). In addition to this main code, three other codes are used for supplemental costs (residence allowance, other costs included in the residence agreement, additional non-included costs).

Costs in the Sheltered Living Initiatives are mostly personnel costs, seeing that other medical costs such as medication or consultation with a physician or psychiatrist are paid by the client and reimbursed by the health insurance funds. Clients also pay a monthly housing fee, with prices varying across different Sheltered Living Initiatives.

### 3 Data on service use and costs in Sheltered Living Initiatives

In the first paragraph of this section, we present the available data sources containing information on the activities of the Sheltered Living Initiatives. In paragraph 3.2 a few figures with respect to service use and costs are shown.

#### 3.1 Data sources

Registration data for the Sheltered Living Initiatives include the Minimal Psychiatric Data (Minimale Psychiatrische Gegevens or MPG) and health insurance data.

The MPG registration is required for all in-patient mental health care Services since 1998 at the beginning and end of each treatment period (Van de Sande, et al., 2006). A web application is provided by the FPS Public Health (FOD Volksgezondheid), but facilities are allowed to use different registration software as well. Registered data include socio-demographic client information, intake problem and diagnostics, and treatment information (Verniest, et al., 2010). MPG registration is completely anonymous, using temporary ID-codes (Coppens, et al. 2018).

For this report, however, we base our description for service use and costs on health insurance data only (3.2.1), seeing that the MPG-data were not obtained.

##### 3.1.1 Health insurance data

Regarding the Sheltered Living Initiatives, aggregated data for the main nomenclature code are available from NIHDI and individual client data are available from the permanent sample (EPS) managed by the Inter-Mutualistic Agency. However, as Table 3.2 shows, the number of registered services and unique clients in the EPS is quite limited. When extrapolating services to the population, using the weights described in Part II of this report, estimations range from 84% to 90% of the actual services registered by NIHDI between 2012 and 2017. Together with the low number of unique clients (after extrapolation leading to an approximate coverage of 85% of the number of places), this means that the EPS sample cannot be considered representative for the total number of people living in sheltered housing.

Table 3.2 The number of unique clients and the total number of services in the Initiatives of Sheltered Living in the EPS-database with a comparison of extrapolated population estimates to the total number of services registered by NIHDI from 2012 to 2017.

<i>Code 762576</i>	<b>2012</b>	<b>2013</b>	<b>2014</b>	<b>2015</b>	<b>2016</b>	<b>2017</b>
EPS unique clients	81	82	86	84	80	77
EPS unique clients extrapolated	2765	2785	2948	2889	2687	2585
EPS services (days)	23736	23635	24527	24363	24541	23960
EPS services extrapolated	803454	811724	841854	827257	821690	814528
NIHDI services (days)	905833	934176	937120	969098	960831	972543
<b>% EPS extrapolated/NIHDI</b>	<b>89%</b>	<b>87%</b>	<b>90%</b>	<b>85%</b>	<b>86%</b>	<b>84%</b>

### 3.2 Description of service use and costs in Sheltered Living Initiatives

Seeing that the EPS sample is not representative for the total number of clients in Sheltered Living Initiatives (Table 3.2) and no other data were available for this project, we limit our description of service use to Figure 3.1, showing the evolution of the mean number of clients per day, calculated by dividing the total number of refunded days by the total number of days in the year. Obviously, the resulting number does not correspond with the total number of unique clients per year, given that not all clients stay the whole year.

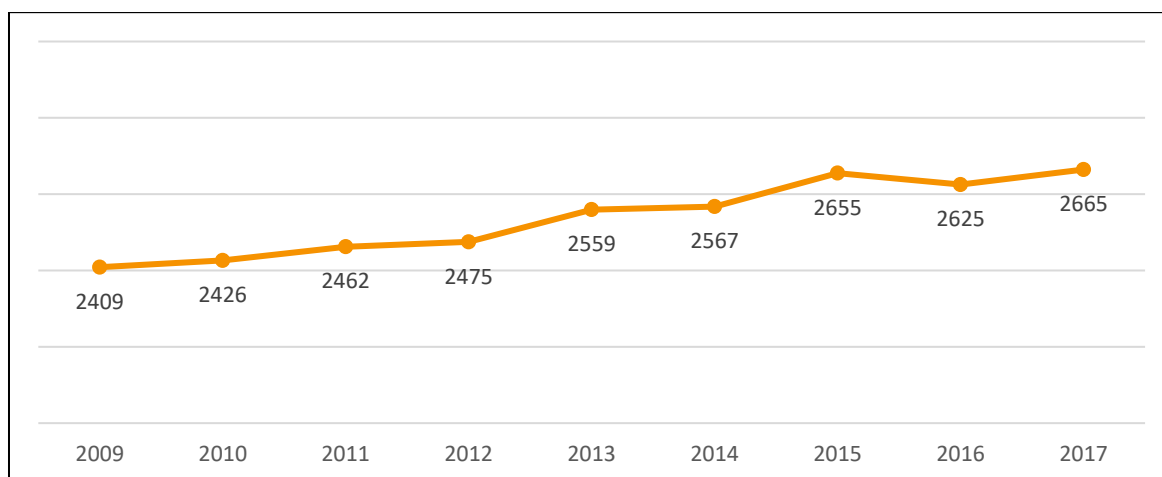


Figure 3.1 Evolution of the mean number of clients per day in the Sheltered Living Initiatives in the Flemish Region from 2009 to 2017 (NIHDI, Health insurance data).

Between 2009 and 2017, the mean number of clients per day in the Sheltered Living Initiatives mounted gradually, resulting in an 11% increase from 2009 to 2017. At the same time, total daily costs billed under the main nomenclature code increased with 28% (see Figure 3.2 below), representing the combined effect of growing service use and a 16% increase in the cost per refunded day (Figure 3.3).

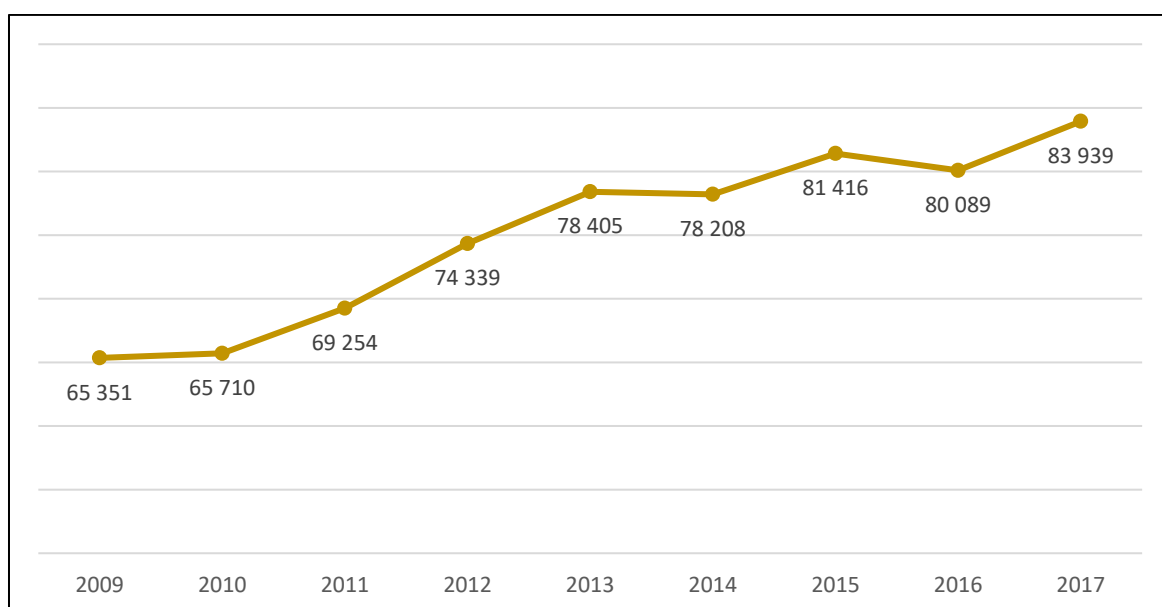


Figure 3.2 Evolution of the total daily cost in the Sheltered Living Initiatives in the Flemish Region from 2009 to 2017 (NIHDI, Health insurance data).



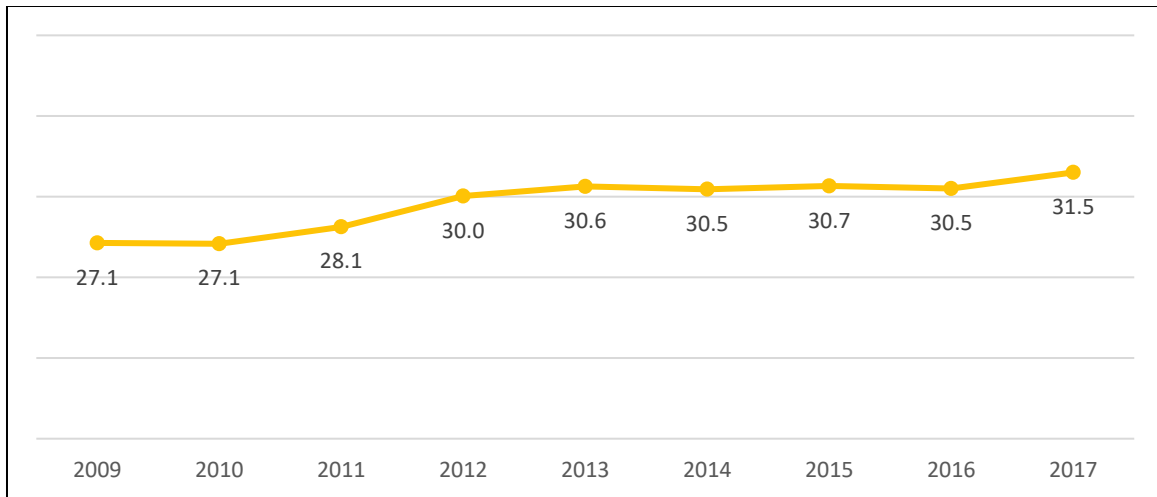


Figure 3.3 Evolution of the cost per day in the Sheltered Living Initiatives in the Flemish Region from 2009 to 2017 (NIHDI, Health insurance data).



## Chapter 4

### The Centers for Ambulatory Rehabilitation

The Centers for Ambulatory Rehabilitation (Centra voor ambulante revalidatie or CAR) offer multidisciplinary diagnostics and psychosocial rehabilitation treatment to children and adolescents with complex developmental disorders and to people of all ages with specific sensory or brain disorders.

Until 2018, services delivered in the Centers for Ambulatory Rehabilitation were financed by the Federal Government through the National Institute for Health and Disability Insurance or NIHDI (Rijksinstituut voor ziekte- en invaliditeitsverzekering or RIZIV) and registered in the IMA-health insurance database managed by the Inter-Mutualistic Agency (IMA). Since January 2019, financing was taken over by the Flemish Government.

In addition to the IMA-database, aggregated statistical data are available in annual reports made up for the Flemish Agency for People with a Disability (Vlaams Agentschap voor Personen met een Handicap or VAPH), with the same reports sent to the Flemish Agency for Care and Health since 2019.

In this chapter we describe target group, objectives, and organizational structure of the Centers for Ambulatory Rehabilitation (section 1), financing and costs (section 2), data sources containing information on current use and costs in the CAR (section 3), and the projection of future needs and costs based on the available information presented in previous sections (section 4).

#### 1 Target group, objectives, and organizational structure

Multidisciplinary care in the Centers for Ambulatory Rehabilitation is mainly aimed at children and adolescents, but people of all ages are treated for certain specific disorders as well. Treatment sessions take place in the rehabilitation center, in the home environment, or at school.

We discuss target groups, objectives and organizational structure in more detail in the next paragraphs, based on information of the [Flemish Agency for Care and Health](#) and the website of the Federation of the Dutch-language Centers for Ambulatory Rehabilitation (<https://revalidatie.be>).

##### 1.1 Target group and objectives

The main target group of the Centers for Ambulatory Rehabilitation are children and adolescents with intellectual disabilities, sensory or brain disorders, and neurobiological developmental disorders like autism, Attention Deficit (Hyperactivity) Disorder (ADHD or ADD), and other complex developmental disorders often manifesting themselves at a young age or in the course of the development of children and adolescents. In addition, behavioral and mood disorders are treated as well, especially when linked to developmental problems. Referral by a physician (e.g. general practitioner, medical specialist, doctor in the Centers for Student Guidance) is necessary.

In many centers, rehabilitation is extended to adults as well for specific sensory or brain disorders, including Acquired Brain Injuries, cerebral palsy, hearing impairment, and stuttering. Most adults are referred by a medical specialist.

Target groups may thus differ somewhat for different Centers for Ambulatory Rehabilitation, mainly as a result of their history, with CAR stemming from two types of centers, the so-called NOK and PSY centers, which were merged into the Centers for Ambulatory Rehabilitation in 2010. Although both centers had a few specific target groups, representing about 16% of all clients in the NOK centers and 7% in the PSY centers (Scheiris et al., 2008), the most common diagnoses were treated by both types of centers.

Generally speaking, the goal of all Centers for Ambulatory Rehabilitation is to help people regain autonomy so that they can play an active role in society, through a process of multidisciplinary diagnosis and treatment and an individualized rehabilitation program. In order to achieve these goals, the CAR offer a program consisting of two main parts:

(1) Examination and the development of a multidisciplinary initial plan: The purpose of the initial plan is to establish or confirm the diagnosis and to determine the direction of the rehabilitation process. This is the initial phase of the program and consists of collecting information of preceding care, assessments, and individual sessions between a therapist and the client and/or family or school. Examination can take up to seven or eight encounters, as different professionals are involved in the diagnostic process, as well as several diagnostic instruments are applied.

(2) Multidisciplinary rehabilitation treatment: The rehabilitation program is discussed and performed in a multidisciplinary way by different professionals within the CAR team. In the case of school-going children, consultations are also held with the school and/or counsellors from the Centers for Student Guidance (CLB) before the start and during the rehabilitation program. Treatment sessions consist of one or more therapists delivering rehabilitation therapy to the client and, if necessary, to the family. Sessions can take place in the rehabilitation facility, in the natural environment or home of the client, or at school. Legislation also requires that at least two contacts take place annually between a medical doctor and the client and/or family.

While these are the general principles, the composition of the CAR-teams may differ, depending on differences in target groups. The rehabilitation agreement with each CAR contains a list of target diagnoses, with medical and therapeutic conditions, as well as specific expert requirements imposed in order to ensure high-quality rehabilitation for each target group.

The CAR target group overlaps to some extent with the target group of the Centers for Mental Health Care (CGG), seeing that both services offer care to children and adolescents with developmental disorders and comorbid mental health problems.

## **1.2 Organizational structure**

At present, there are 43 autonomous Centers for Ambulatory Rehabilitation in 50 locations recognized by the Flemish Agency for Care and Health in Flanders and Brussels. Most autonomous centers are located in the provinces of East Flanders (18 CAR in 21 locations) and West Flanders (12 CAR). In Antwerp there are four CAR in six locations, in Flemish Brabant four in five locations and in Limburg three. Furthermore, one of the centers in Flemish Brabant has a second location in the Brussels Region, and the final two Dutch-language CAR are located in Brussels as well.

In addition to the autonomous CAR, there are three Centers for Ambulatory Rehabilitation linked to university hospitals in Ghent (East Flanders), Antwerp, and Leuven (Flemish Brabant). The university hospital CAR are mainly specialized in ENT (ear-nose-throat) and communication disorders, but in Antwerp, people with other complex developmental disorders are treated as well.

The clearly unequal geographical distribution of the Flemish Centers for Ambulatory Rehabilitation is partly due to the fact that the buildout of these centers was left to individual free initiatives rather than the result of structured planning by the government, guided by rehabilitation needs. Consequently, the sparse availability of these centers in certain areas cause a problem of accessibility and waiting lists, which is further worsened by staff shortages (Kimpe, et al., 2019).

## **2 Financing and costs**

In 1996, the National Institute for Health and Disability Insurance (NIHDI) drew up different conventions for the NOK and PSY centers that later merged into the Centers for Ambulatory Rehabilitation in which target groups, rehabilitation practices, and reimbursement prices were regulated. For each center, NIHDI calculated an individualized budget based upon actual operational costs, covering personnel costs and general costs. In addition to the NIHDI financing, the CAR received maintenance and investment allowances from the Flemish Agency for People with a Disability (Vlaams Agentschap voor Personen met een Handicap/VAPH).

Since the Decree of January 28, 2019 (Vlaamse overheid, 2019) financing is taken over by the Flemish Agency for Care and Health. However, for the time being, the same financing structure has been maintained, with the health insurance funds still responsible for the administrative control and the payment of rehabilitation reimbursement to the care facilities.

Therapy sessions delivered by the CAR are billed under separate target group (i.e. diagnosis) specific nomenclature codes for examination, rehabilitation, and teacher group sessions. CAR nomenclature codes cannot be combined with codes for speech therapy or physiotherapy, which means that, for a person receiving rehabilitation, these therapies have to take place in the CAR by CAR staff members, using the CAR nomenclature codes for billing. There are, however, some exceptions (e.g. for physiotherapy in case of cerebral palsy).

Each CAR receives a fixed budget per year, depending on operational and personnel costs. Budget are reviewed when staffing changes considerably (e.g. higher seniority, new mix of disciplines) or when the CAR receive permission to change target groups or broaden rehabilitation goals.

The client pays a personal fee of 1.80 Euro per rehabilitation session. People with low income status do not have to pay this fee.

## **3 Data on service use and costs in the Centers for Ambulatory Rehabilitation**

In the first paragraph of this section, we present the available data sources containing information on the activities of the Centers for Ambulatory Rehabilitation. In the next two paragraphs, we describe current service use (3.2) and costs (3.3), based on these data sources.

### **3.1 Data sources**

Since 2019, the Centers for Ambulatory Rehabilitation have to send annual reports to the Flemish Agency for Care and Health. Before that, a similar report was already made up yearly for the Flemish Agency for People with a Disability (Vlaams Agentschap voor Personen met een Handicap/VAPH) to receive additional

funding. The client and service use data described in these annual reports sent to the VAPH between 2013 and 2018 were digitalized into a small database (3.2.1). In addition to this self-construed database, health insurance data, available from NIHDI (National Institute for Health and Disability Insurance) and the permanent sample (EPS) from the Inter-Mutualistic Agency are used (3.2.2).

### 3.1.1 Annual report data from the Centers for Ambulatory Rehabilitation to VAPH.

In the annual reports, the Centers for Ambulatory Rehabilitation provide aggregated statistical data relating to clients and service use, based on a common excel-template. Table 4.1 gives an overview of the variables in the annual reports, with relevant variables used for the description of CAR service use in this report marked in grey. These variables were digitalized into a small database, containing aggregated data per CAR location and per year.

Table 4.1 Variables in the CAR annual reports

Variables	Values / clarification
<b>Ongoing rehabilitation on December 31</b>	
Active clients	Number (%) of clients with ongoing rehabilitation on December 31
Active client residence	Number (%) of clients from: <ul style="list-style-type: none"> <li>• Same municipality (core or sub)</li> <li>• Same province (adjacent or non-adjacent municipality)</li> <li>• Different province (adjacent or non-adjacent municipality)</li> <li>• Abroad</li> </ul>
Active client primary diagnosis	Values: ICD-code (International Classification of Diseases) Number (%) of clients per primary diagnosis by: <ul style="list-style-type: none"> <li>• Gender</li> <li>• Age group</li> <li>• Level of education</li> <li>• Employment status</li> <li>• Comorbidities (0 to 3)</li> </ul>
Active client type of care giver	Values: Psychologist, social worker Number (%) of client files per type of care giver by: <ul style="list-style-type: none"> <li>• Stage (intake, specific interventions)</li> </ul>
Active client waiting time examination – rehabilitation	Number (%) of clients in treatment by primary diagnosis and by age <ul style="list-style-type: none"> <li>• Values: 0-2 months, 2-4 months, 4-6 months, 6-9 months, 9-12 months, &gt; 1 year</li> </ul> Mean waiting time for clients in treatment by primary diagnosis and by age
Active client waiting time application – rehabilitation	Number (%) of clients in treatment by primary diagnosis and by age <ul style="list-style-type: none"> <li>• Values: 0-2 months, 2-4 months, 4-6 months, 6-9 months, 9-12 months, &gt; 1 year</li> </ul> Mean waiting time for clients in treatment by primary diagnosis and by age
<b>Current year application</b>	
New applicants	Number (%) of applicants with application in the current year
New applicant application problem	Values: list of application problems (recoded into diagnostic categories*) Number (%) of new applicants per application problem by:

	<ul style="list-style-type: none"> <li>• Referring instance</li> <li>• Gender</li> <li>• Age group</li> <li>• Level of education</li> <li>• Employment status</li> </ul> <p><i>*Note: For the description in Section 3.3 of this report, the listed application problems are recoded into the primary diagnostic categories used for active clients, so as to maximize comparability. Although the application problem is not always confirmed by the final diagnosis, this divergence lessened considerably in recent years due to improved diagnostics by the Centers for Student Guidance (CLB), increased referral by professionals and increased cooperation with hospitals.</i></p>
<b>Current year examination</b>	
Waiting time application – examination	<p>Number (%) of examined applicants by application problem and by age</p> <ul style="list-style-type: none"> <li>• Values: 0-2 months, 2-4 months, 4-6 months, 6-9 months, 9-12 months, &gt; 1 year</li> </ul> <p>Mean waiting time for examined applicants by application problem and by age</p>
<b>Current year completed rehabilitation</b>	
Discharged clients	Number (%) of clients with rehabilitation ended in the current year
Discharged client primary diagnosis	Number (%) of discharged clients per primary diagnosis
Discharged client rehabilitation duration	<p>Values: 0-6 months, 7-12 months, 13-18 months, 19-24 months, 25-36 months, 3 to 4 years, 4 to 5 years, &gt; 5 years</p> <p>Number (%) of discharged clients per primary diagnosis by rehabilitation duration</p> <p>Mean rehabilitation duration for discharged clients per primary diagnosis</p>
<b>Service follow-up variables</b>	
Current year application follow-up	<p>Application follow-up variables: Left before examination, left during examination, examination in current year, waiting for examination on 31/12</p> <p>Number (%) of new applicants per application problem, per application year (current or previous)</p> <p><i>Constructed variable: Current and previous years applicants waiting for examination on 31/12</i></p>
Current year examination follow-up	<p>Examination follow-up variables: No follow-up, referred, ongoing examination on 31/12, waiting for rehabilitation on 31/12, rehabilitation started</p> <p>Number (%) of examined applicants per application problem</p>
Other variables	<p>Current year examination follow-up:</p> <ul style="list-style-type: none"> <li>• No follow-up detail and referral detail by application problem</li> <li>• Relationship application problem – primary diagnosis</li> </ul> <p>Discharged client follow-up:</p> <ul style="list-style-type: none"> <li>• Discharge detail and further referral detail by primary diagnosis</li> </ul>

The resulting self-construed digital annual report database contains data from 45 locations of the autonomous Centers for Ambulatory Rehabilitation. Data from the CAR linked to university hospitals and

four autonomous CAR (two in Brussels, one in Flemish Brabant and one in West Flanders) are missing altogether. Also, data from one CAR are limited to one of two locations, with data available from the location in Flemish Brabant, but lacking for the location in the Brussels region. Finally, in most years, there are missing data for some varying CAR, resulting in totals between 40 (in 2016) and 44 CAR per year (in 2015 and 2018). Table 4.2 gives an overview of the total number of CAR locations in the database per province and per year.

Table 4.2 Number of (locations of the) Centers for Ambulatory Rehabilitation in the self-construed annual report database.

<i>Province</i>	2013	2014	2015	2016	2017	2018
Antwerp	6	6	6	5	6	6
East Flanders	20	20	21	20	20	21
Flemish Brabant	4	4	4	4	4	4
Limburg	3	3	3	3	3	3
West Flanders	11	10	9	8	10	10
<b>Total</b>	<b>44</b>	<b>43</b>	<b>43</b>	<b>40</b>	<b>43</b>	<b>44</b>

When presenting summary data aggregated over years in Section 3.3 below, all available data are used. However, considering that not all CAR locations are represented in the database, with most data missing from Flemish Brabant (and the Brussels Region) and from West Flanders in certain years, and with data missing from varying CAR in most years, results always have to be interpreted with care.

When showing time series data, only CAR with complete time series for the presented variables are included, so as to maximize comparability between years and showing evolutions more clearly. However, this selection comes with a cost to generalizability. For some variables more than one third to almost half of the CAR locations have missing data in at least one year between 2013 and 2018, leading to reported results based on 26 to 35 CAR locations. Table 4.3 gives an overview of the number and percentage of CAR locations with complete time series per province. When interpreting time series data reported by province in Section 3.2 below, the table can be used to evaluate representativeness for the different provinces.

Table 4.3 Numbers and percentages of CAR locations with complete times series for the period from 2013 to 2018 for relevant annual report variables

<b>Variables</b>	<b>Number and percentage of CAR locations with complete time series 2013-2018</b>																				
<b>Ongoing rehabilitation on December 31</b>																					
Active clients	<table border="1"> <thead> <tr> <th><b>35 CAR locations</b></th> <th><b>#</b></th> <th><b>%</b></th> </tr> </thead> <tbody> <tr> <td>Antwerp</td> <td>5</td> <td>83%</td> </tr> <tr> <td>East Flanders</td> <td>17</td> <td>81%</td> </tr> <tr> <td>Flemish Brabant</td> <td>4</td> <td>80%</td> </tr> <tr> <td>Limburg</td> <td>3</td> <td>100%</td> </tr> <tr> <td>West Flanders</td> <td>6</td> <td>50%</td> </tr> </tbody> </table>			<b>35 CAR locations</b>	<b>#</b>	<b>%</b>	Antwerp	5	83%	East Flanders	17	81%	Flemish Brabant	4	80%	Limburg	3	100%	West Flanders	6	50%
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Active client residence Active client mean waiting time	<table border="1"> <thead> <tr> <th><b>34 CAR locations</b></th> <th><b>#</b></th> <th><b>%</b></th> </tr> </thead> <tbody> <tr> <td>Antwerp</td> <td>5</td> <td>83%</td> </tr> <tr> <td>East Flanders</td> <td>16</td> <td>76%</td> </tr> <tr> <td>Flemish Brabant</td> <td>4</td> <td>80%</td> </tr> <tr> <td>Limburg</td> <td>3</td> <td>100%</td> </tr> <tr> <td>West Flanders</td> <td>6</td> <td>50%</td> </tr> </tbody> </table>	<b>34 CAR locations</b>	<b>#</b>	<b>%</b>	Antwerp	5	83%	East Flanders	16	76%	Flemish Brabant	4	80%	Limburg	3	100%	West Flanders	6	50%
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Current and previous years applicants waiting for examination on 31/12	<table border="1"> <thead> <tr> <th><b>26 CAR locations</b></th> <th><b>#</b></th> <th><b>%</b></th> </tr> </thead> <tbody> <tr> <td>Antwerp</td> <td>3</td> <td>50%</td> </tr> <tr> <td>East Flanders</td> <td>11</td> <td>52%</td> </tr> <tr> <td>Flemish Brabant</td> <td>4</td> <td>80%</td> </tr> <tr> <td>Limburg</td> <td>3</td> <td>100%</td> </tr> <tr> <td>West Flanders</td> <td>5</td> <td>42%</td> </tr> </tbody> </table>	<b>26 CAR locations</b>	<b>#</b>	<b>%</b>	Antwerp	3	50%	East Flanders	11	52%	Flemish Brabant	4	80%	Limburg	3	100%	West Flanders	5	42%
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## 3.1.2 Health insurance data

The Inter-Mutualistic Agency (IMA) manages the data collected by all health insurance funds in Belgium. In the IMA-database, a range of service-specific nomenclature codes for delivered services in the Centers for Ambulatory Rehabilitation are registered, making it possible to distinguish ambulatory and in-patient services (in the university hospital CAR), target groups or diagnoses, and examination, rehabilitation, and teacher group sessions. The permanent sample or EPS (see Chapter 1, Section 2.1) contains a representative sample of the individual IMA-database client records. Representativeness for CAR-clients is limited though, seeing that the number of cases relating to the Centers for Ambulatory Rehabilitation is quite small. As mentioned in Chapter 1, this is partly due to the sampling procedure with oversampling for elderly people, but not for the mainly young target population of the CAR. Tables 4.4 and 4.5 give an overview of the number of cases in the EPS for the ambulatory examination codes and the ambulatory rehabilitation codes, respectively. Extrapolation to the population was accomplished by using age and gender-specific weights (see Part II of this report).

Table 4.4 The number of unique clients and the total number of examination sessions in the Centers for Ambulatory Rehabilitation in the EPS-database with a comparison of extrapolated population estimates to the total number of examination sessions registered by NIHDI from 2013 to 2017.

<i>Examination sessions</i>	<b>2013</b>	<b>2014</b>	<b>2015</b>	<b>2016</b>	<b>2017</b>
EPS unique clients	128	118	121	115	123
EPS unique clients extrapolated	4418	4096	4197	4016	4260
EPS services	661	670	639	660	685
EPS services extrapolated	22345	23188	22349	22496	23626
NIHDI services	28163	30019	28930	28188	27838
<b>% EPS extrapolated/NIHDI</b>	<b>79%</b>	<b>77%</b>	<b>77%</b>	<b>80%</b>	<b>85%</b>

Table 4.5 The number of unique clients and the total number of rehabilitation sessions in the Centers for Ambulatory Rehabilitation in the EPS-database with a comparison of extrapolated population estimates to the total number of rehabilitation sessions registered by NIHDI from 2013 to 2017.

<i>Rehabilitation sessions</i>	<b>2013</b>	<b>2014</b>	<b>2015</b>	<b>2016</b>	<b>2017</b>
EPS unique clients	233	226	231	224	231
EPS unique clients extrapolated	6382	6240	6263	6061	6229
EPS services	9918	10165	9630	9474	8642
EPS services extrapolated	339200	346631	324925	319882	298746
NIHDI services	476727	494138	491983	479629	465801
<b>% EPS extrapolated/NIHDI</b>	<b>71%</b>	<b>70%</b>	<b>66%</b>	<b>67%</b>	<b>64%</b>

For both examination and rehabilitation sessions, the comparison between the number of extrapolated EPS services with the number of billed NIHDI services shows that extrapolation from the EPS sample strongly underestimates the actual number of services provided by the Centers for Ambulatory Rehabilitation.

In Table 4.6 the number of cases in the EPS for the ambulatory rehabilitation codes is shown for the six target groups or diagnoses with the largest number of cases in the EPS dataset.

Table 4.6 The number of unique clients and the total number of rehabilitation sessions by diagnosis in the Centers for Ambulatory Rehabilitation in the EPS-database with a comparison of extrapolated population estimates to the total number of rehabilitation sessions registered by NIHDI from 2013 to 2017.

<i>Autism</i>	<b>2013</b>	<b>2014</b>	<b>2015</b>	<b>2016</b>	<b>2017</b>
EPS unique clients	50	52	60	64	68
EPS unique clients extrapolated	1786	1908	2193	2295	2416
EPS services	2006	2250	2435	2630	2514
EPS services extrapolated	72467	79617	88338	93723	88804
NIHDI services	88801	105401	114198	116122	122463
<b>% EPS extrapolated/NIHDI</b>	<b>82%</b>	<b>76%</b>	<b>77%</b>	<b>81%</b>	<b>73%</b>
<i>ADHD</i>	<b>2013</b>	<b>2014</b>	<b>2015</b>	<b>2016</b>	<b>2017</b>
EPS unique clients	35	42	38	35	40
EPS unique clients extrapolated	1259	1563	1422	1280	1461
EPS services	1250	1525	1418	1075	1348
EPS services extrapolated	44657	56323	53808	39655	48582
NIHDI services	67675	77379	75692	71967	65959
<b>% EPS extrapolated/NIHDI</b>	<b>66%</b>	<b>73%</b>	<b>71%</b>	<b>55%</b>	<b>74%</b>
<i>Intellectual disability</i>	<b>2013</b>	<b>2014</b>	<b>2015</b>	<b>2016</b>	<b>2017</b>
EPS unique clients	50	49	43	38	41
EPS unique clients extrapolated	1786	1786	1604	1402	1502
EPS services	2297	2674	2374	1916	1860
EPS services extrapolated	78518	97801	88688	66705	65499
NIHDI services	102563	97515	94732	92327	88244
<b>% EPS extrapolated/NIHDI</b>	<b>77%</b>	<b>100%</b>	<b>94%</b>	<b>72%</b>	<b>74%</b>
<i>Complex developmental disorders</i>	<b>2013</b>	<b>2014</b>	<b>2015</b>	<b>2016</b>	<b>2017</b>
EPS unique clients	64	53	56	53	48
EPS unique clients extrapolated	2233	1929	2051	1909	1744
EPS services	2421	2263	2174	2270	1903
EPS services extrapolated	83764	80985	83343	82541	70880
NIHDI services	150647	140477	132844	127422	117628
<b>% EPS extrapolated/NIHDI</b>	<b>56%</b>	<b>58%</b>	<b>63%</b>	<b>65%</b>	<b>60%</b>
<i>Hearing impairment</i>	<b>2013</b>	<b>2014</b>	<b>2015</b>	<b>2016</b>	<b>2017</b>
EPS unique clients	15	17	15	15	12
EPS unique clients extrapolated	548	569	569	571	467
EPS services	900	946	906	836	812
EPS services extrapolated	33716	35386	34879	33538	32174
NIHDI services	34059	35443	36798	36028	35255
<b>% EPS extrapolated/NIHDI</b>	<b>99%</b>	<b>100%</b>	<b>95%</b>	<b>93%</b>	<b>91%</b>
<i>Acquired Brain Injury</i>	<b>2013</b>	<b>2014</b>	<b>2015</b>	<b>2016</b>	<b>2017</b>
EPS unique clients	6	7	12	11	6
EPS unique clients extrapolated	243	284	427	427	243
EPS services	441	332	403	384	110
EPS services extrapolated	17909	13488	14767	14767	4471
NIHDI services	10381	11207	11772	12306	12690
<b>% EPS extrapolated/NIHDI</b>	<b>173%</b>	<b>120%</b>	<b>125%</b>	<b>120%</b>	<b>35%</b>

As the small numbers of unique clients and the comparison between the number of extrapolated EPS services to the number of billed NIHDI services shows, representativeness is probably insufficient for most diagnoses. Percentages come closest to 100% for people with hearing impairment, which may not be surprising given that this group consists of relatively more people in older age categories. It is noteworthy that for some clients, services are billed under two or more different target group nomenclature codes.

Given that the complete IMA-database was not available and the representativeness of the permanent sample is considered insufficient for the Centers for Ambulatory Rehabilitation, reported health insurance data in the remainder of this section are mostly limited to an aggregated overview of the number of cases and costs per nomenclature code per year, obtained from the National Institute for Health and Disability Insurance (NIHDI).

### 3.2 Description of service use in the Centers for Ambulatory Rehabilitation

In this paragraph, we present an overview of the overall use of services in the Centers for Ambulatory Rehabilitation (3.2.1), the use per province (3.2.2), client characteristics (3.2.3), and service characteristics (3.2.4).

#### 3.2.1 Overall use of services in the Centers for Ambulatory Rehabilitation

Figure 4.1 shows the evolution of the number of clients receiving rehabilitation on December 31 in the Centers for Ambulatory Rehabilitation. As mentioned in Section 3.2.1, only centers with complete time series were considered (35 centers).

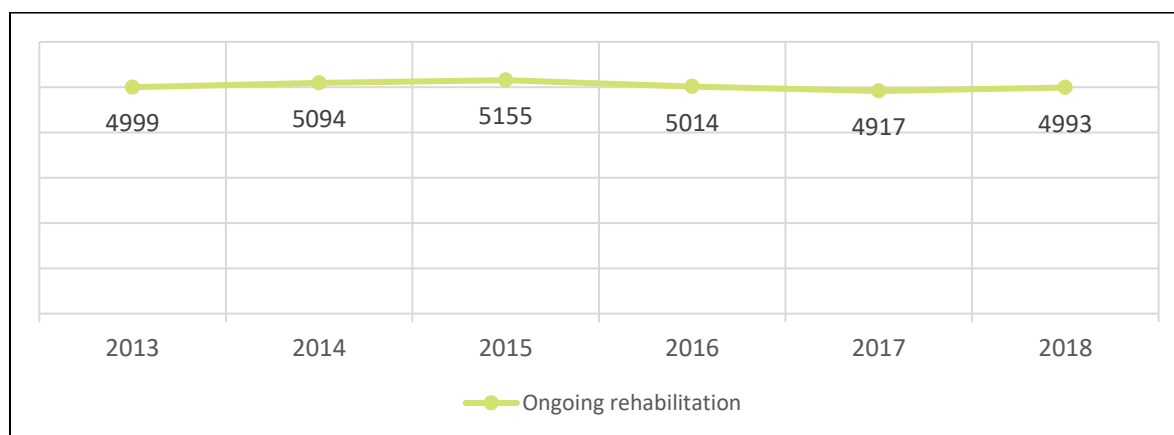


Figure 4.1 Evolution of the total number of clients with ongoing rehabilitation on December 31 in the Centers for Ambulatory Rehabilitation from 2013 to 2018 (CAR annual reports, data from 35 centers with complete time series for ongoing rehabilitation).

On December 31, around 5000 clients received rehabilitation in 35 CAR locations, with little evolution observed between 2013 and 2018. When extrapolating this number to 50 Dutch-speaking CAR locations, this would come down to a roughly estimated 7000 clients in ongoing rehabilitation treatment at a given point in time in the period between 2013 and 2018.

When adding the number of discharged clients in Figure 4.2, it becomes clear that the difference in the number of clients who ended their treatment during the year was limited as well, apart from 2017 and 2018, where this number seemed to lower slightly, altogether resulting in a rather stable, but somewhat decreasing total number of clients yearly passing through the 30 centers considered for the figure.

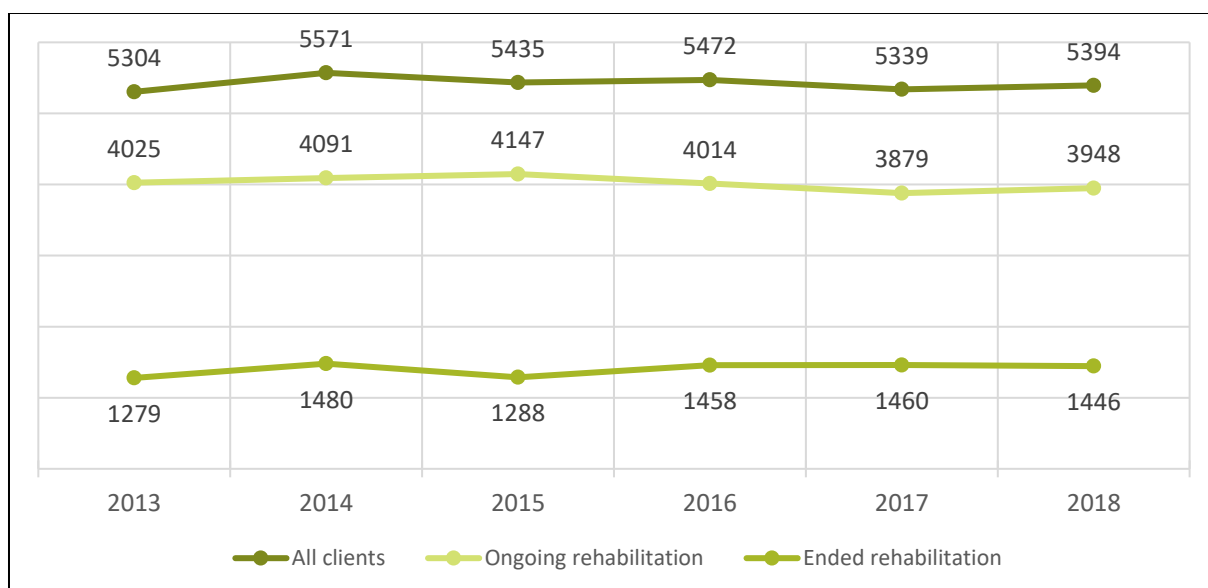


Figure 4.2 Evolution of the total number of clients, clients with ongoing rehabilitation on December 31, and discharged clients in the Centers for Ambulatory Rehabilitation from 2013 to 2018 (CAR annual reports, data from 30 centers with complete time series for ongoing rehabilitation and discharged clients).

Again, when roughly extrapolating this number to all Dutch-speaking CAR locations, we estimate around 9000 clients receiving rehabilitation treatment at some point in time each year. For the 47 autonomous CAR locations in the Flemish Region, the estimate amounts to an approximate 8500 clients. Comparison of this last estimate with the extrapolation to the entire Flemish population of the number of clients in the EPS (around 6200 or 70%, even with ambulatory sessions provided by university hospital CAR included in the data, see Table 4.4), suggests once more that the EPS sample cannot be considered representative for all clients in the Centers for Ambulatory Rehabilitation. We therefore report no further data from the EPS, unless no other comparable data are available.

In Figure 4.3 the number of ambulatory examination and rehabilitation sessions billed by the Centers for Ambulatory Rehabilitation to NIHDI from 2013 to 2018 is shown. The figure shows a declining trend in both examination and rehabilitation sessions since 2014, mirroring the less outspoken trend observed in the annual report data. It is not straightforward to compare these results, though, given that the NIHDI dataset contains data from all centers, including ambulatory sessions provided by the university hospital CAR.

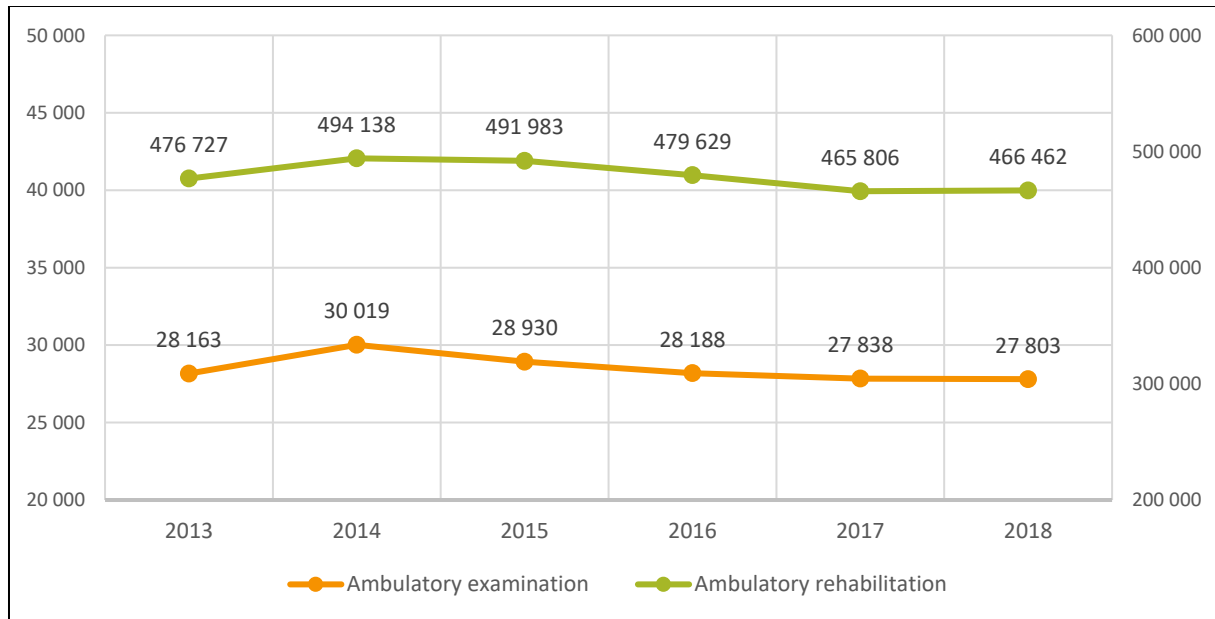


Figure 4.3 Evolution of the total number of ambulatory examination and rehabilitation sessions provided by the Centers for Ambulatory Rehabilitation (including university hospital CAR) from 2013 to 2018 (NIHDI health insurance data)

Contrary to ambulatory examination sessions in all centers, the number of in-patient examination sessions in the university hospital CAR more than doubled between 2013 and 2018. Rehabilitation treatment sessions on the other hand decreased from 2015 onwards.

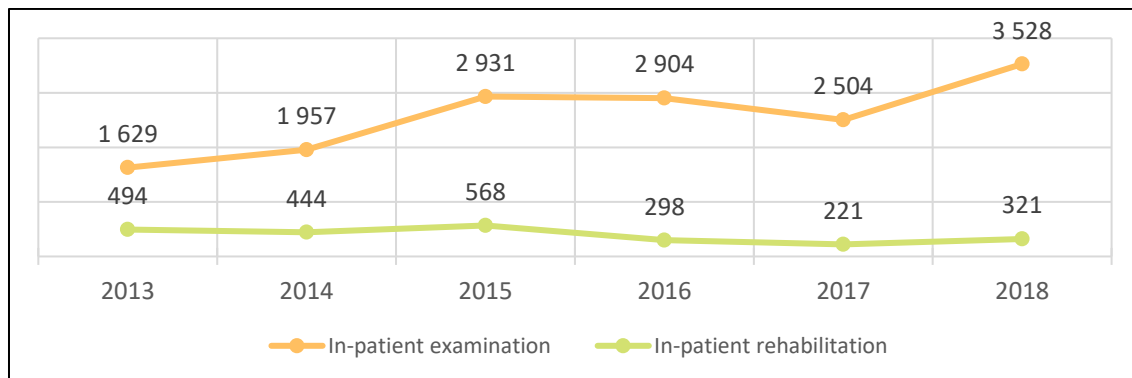


Figure 4.4 Evolution of the total number of in-patient examination and rehabilitation sessions provided by the Centers for Ambulatory Rehabilitation (university hospital CAR) from 2013 to 2018 (NIHDI health insurance data)

Both the aggregated annual report data and the NIHDI billed services data show that the capacity of the CAR certainly did not increase between 2013 and 2018. In addition, the number of new applicants showed no increasing trend either, as shown in Figure 4.5 below, based on the data of 26 centers with complete time series for ongoing rehabilitation, discharged clients, and new applications.

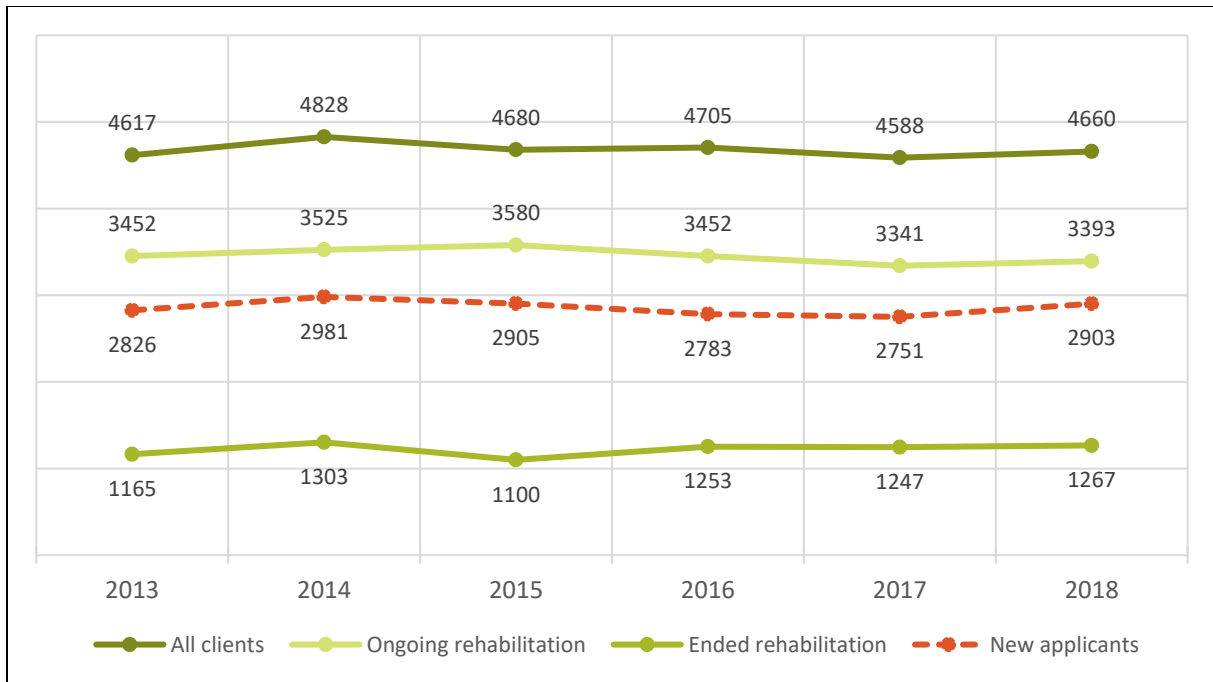


Figure 4.5 Evolution of the total number of clients, clients with ongoing rehabilitation on December 31, discharged clients, and new applicants in the Centers for Ambulatory Rehabilitation from 2013 to 2018 (CAR annual reports, data from 26 centers with complete time series for ongoing rehabilitation, discharged clients, and applications).

The more or less stable number of applications may not necessarily mean though that needs remained stable, as potential clients may less likely be inclined to apply when waiting lists become longer as a result of fixed, but insufficient capacity.

### 3.2.2 Use of the Centers for Ambulatory Rehabilitation per province

As predicted from the uneven spread of the CAR in Flanders described in Section 2, the distribution of the mean annual number of applying, discharged, and active clients differs considerably from the distribution of the population over the Flemish provinces. For Figure 4.6, all available data are considered, which means that there are differences in the actual (number of) CAR locations contributing to the mean annual numbers and that capacity is especially underestimated for Flemish Brabant and West Flanders. Notwithstanding this, the predominance of East Flanders (and to a lesser extent West Flanders) in the number of clients passing through the CARs each year is unmistakable.

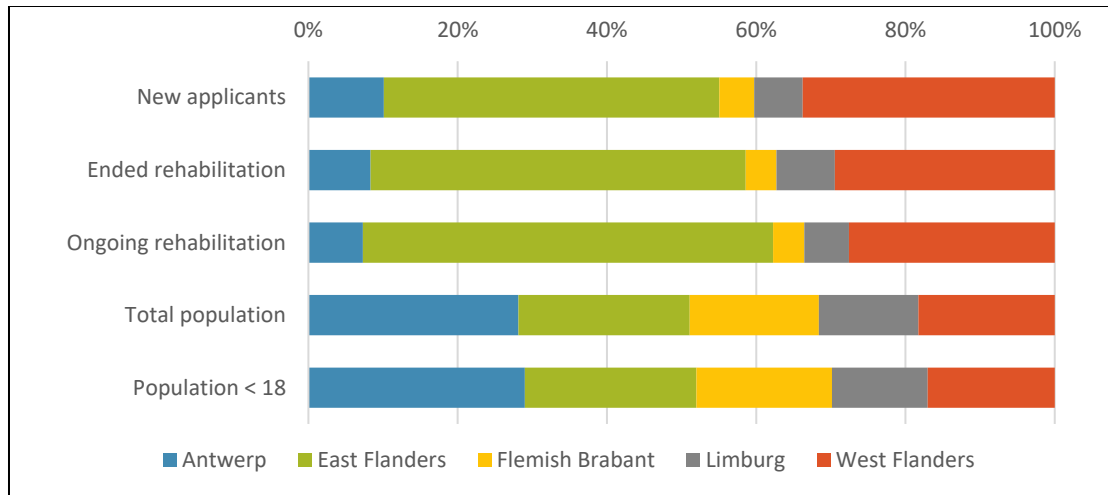


Figure 4.6 Comparison of the distribution of the mean annual number of clients per province applying for care, ending rehabilitation, and receiving rehabilitation on December 31 in the Centers for Ambulatory Rehabilitation with the mean annual total population and the mean annual population under 18 years per province between 2013 and 2018 (CAR annual reports, Population data: Federal Planning Bureau, Statbel).

The somewhat reduced share of East Flanders in the mean number of discharged clients and especially new applicants as compared to active clients in ongoing treatment at the end of the year may partly be due to the fact that relatively more data were missing for the former two variables in the East Flanders' locations than for the latter variable.

However, when calculating the ratio of applications to clients in ongoing treatment on December 31 for the 30 CAR with complete time series for both measures (Figure 4.7), it is clear that this ratio is relatively smaller and more stable in East Flanders than in other provinces or the Flemish Region as a whole, suggesting a quicker and steady turnover from application to rehabilitation and thus, shorter waiting times. In Antwerp the ratio was largest, but decreasing, whereas in West Flanders there was a recent increase. In Flemish Brabant the ratio of applicants to treated clients mounted until 2015, but decreased considerably thereafter. It is not straightforward to interpret these evolutions, though, as the ratio of application to rehabilitation may depend on several other factors besides regional availability (e.g. improved referral).



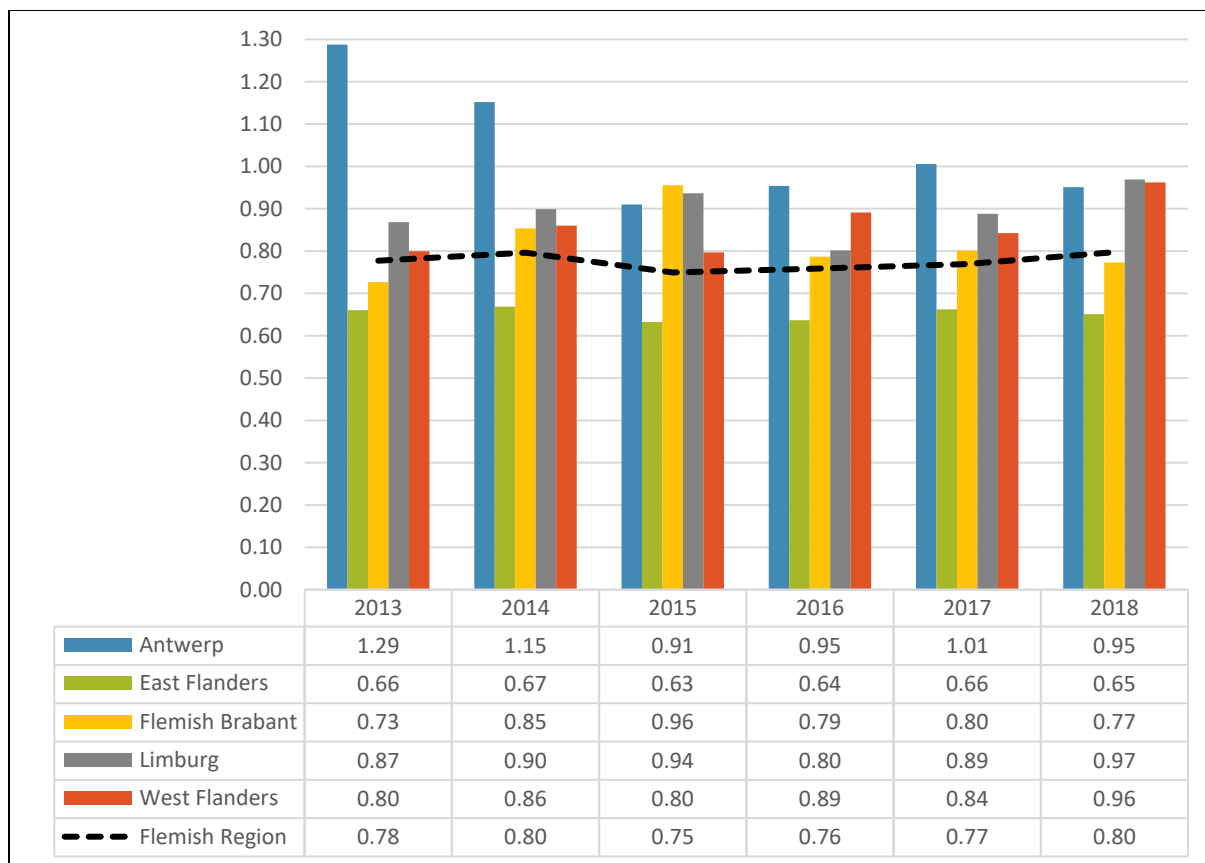


Figure 4.7 Evolution of the ratio of the total number of clients applying to the total number of clients in rehabilitation on December 31 in the Centers for Ambulatory Rehabilitation from 2013 to 2018, by province (CAR annual reports, data from 30 centers with complete time series for both ongoing rehabilitation and applications).

Due to the greater availability of CAR locations in East Flanders, clients in this province are more likely to live close to the CAR, even in the same municipality where they find treatment, with centers also accepting relatively many clients from other provinces on the other hand. This is shown in Figure 4.8, picturing the evolution of the percentage of clients in the Centers for Ambulatory Rehabilitation living in the province or municipality where the CAR is situated. Numbers are limited to 34 CAR locations with complete time series for client origin data of ongoing rehabilitations.

Overall, the majority of CAR service users are domiciled in the province where they receive rehabilitation. The provinces with the largest percentage of clients coming from a different province were Flemish Brabant (11 to 15%) and East Flanders (11 to 12%). In the latter province, approximately half of all CAR rehabilitation treatments involved clients from the same municipality, with the same picture emerging in Flemish Brabant since 2016. The Centers for Ambulatory Rehabilitation in Antwerp had the lowest number of clients from the same municipality (20 to 30%). Between 2013 and 2018, there was limited evolution, apart from the noticeable increase in clients from the same municipality in Flemish Brabant in 2016 and a somewhat smaller decrease in Limburg in 2016 and again in 2017.

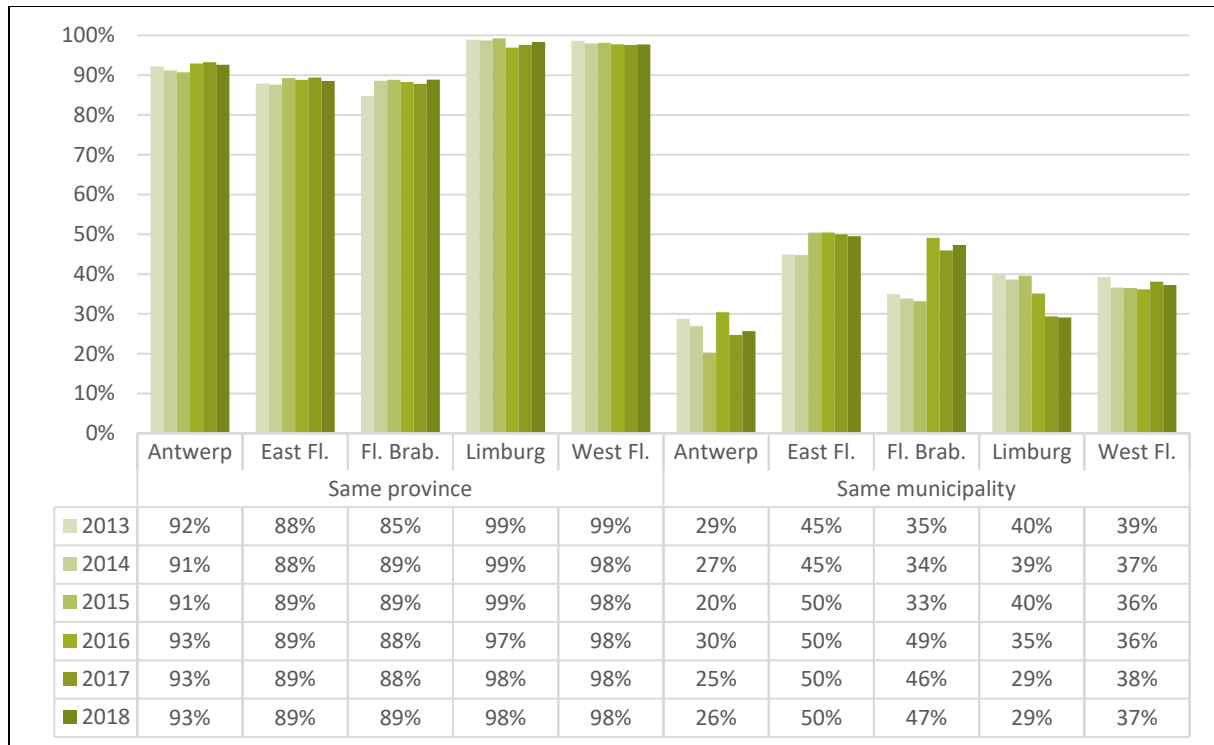


Figure 4.8 Evolution of the percentage of clients in the Centers for Ambulatory Rehabilitation coming from the same province or the same municipality, from 2013 to 2018, per province (CAR annual reports, data from 34 centers with complete time series for client origin data of ongoing rehabilitations).

A comparable picture emerges in the mobility estimations matrix (Table 4.7) based on the extrapolation of IMA EPS-data, with few people receiving services from a CAR in another province between 2010 and 2015. The largest mobility is observed in people who live in Antwerp, Flemish Brabant or West Flanders finding treatment in East Flanders, with comparable numbers from West Flanders to Antwerp in some years as well. According to the EPS-based estimations, people from East Flanders themselves hardly ever visited a CAR outside their province, again suggesting that supply in East Flanders was probably more adequate than in some of the other provinces. With respect to the data in Table 4.7 it is important to stress though that all EPS-estimates for CAR clients are based on a very small number of cases in the sample and that hypotheses based on these estimates have to be confirmed with more reliable data. As these data stem from the first EPS-export we received for this research project, they are limited to 2015. In the second EPS-export used for the final analyses reported in Part II, client domicile data were not available.

Table 4.7 Evolution of the mobility of clients between provinces in the Centers for Ambulatory Rehabilitation from 2010 to 2015 (EPS, population extrapolated).

Year	CAR location	Client domicile									
		Limburg		Antwerp		East Flanders		Flemish Brabant		West Flanders	
2010	Limburg	<b>202</b>	<b>2,0%</b>								
	Antwerp	81	0,8%	<b>889</b>	<b>8,8%</b>			40	0,4%	243	2,4%
	East Flanders			162	1,6%	<b>4992</b>	<b>49,1%</b>	40	0,4%	81	0,8%
	Flemish Brabant							<b>283</b>	<b>2,8%</b>		
	West Flanders									<b>3153</b>	<b>31,0%</b>
2011	Limburg	<b>162</b>	<b>1,7%</b>								
	Antwerp	81	0,9%	<b>1092</b>	<b>11,5%</b>					0,4	0,4%
	East Flanders			81	0,9%	<b>4225</b>	<b>44,5%</b>	81	0,9%	121	1,3%
	Flemish Brabant	40	0,4%					<b>445</b>	<b>4,7%</b>		
	West Flanders									<b>3134</b>	<b>33,0%</b>
2012	Limburg	<b>283</b>	<b>2,8%</b>								
	Antwerp	40	0,4%	<b>991</b>	<b>9,9%</b>			40	0,4%	283	2,8%
	East Flanders			121	1,2%	<b>4350</b>	<b>43,5%</b>	162	1,6%	121	1,2%
	Flemish Brabant	81	0,8%					<b>445</b>	<b>4,5%</b>		
	West Flanders									<b>3075</b>	<b>30,8%</b>
2013	Limburg	<b>283</b>	<b>2,7%</b>					40	0,4%		
	Antwerp	40	0,4%	<b>748</b>	<b>7,2%</b>					162	1,6%
	East Flanders			121	1,2%	<b>4571</b>	<b>44,1%</b>	243	2,3%	202	2,0%
	Flemish Brabant	40	0,4%	81	0,8%			<b>607</b>	<b>5,9%</b>		
	West Flanders									<b>3236</b>	<b>31,2%</b>
2014	Limburg	<b>283</b>	<b>2,7%</b>								
	Antwerp			<b>1010</b>	<b>9,5%</b>					40	0,4%
	East Flanders			81	0,8%	<b>4849</b>	<b>45,4%</b>	162	1,5%	202	1,9%
	Flemish Brabant	61	0,6%					<b>606</b>	<b>5,7%</b>		
	West Flanders					40	0,4%	40	0,4%	<b>3313</b>	<b>31,0%</b>
2015	Limburg	<b>242</b>	<b>2,2%</b>								
	Antwerp	40	0,4%	<b>1111</b>	<b>10,0%</b>					40	0,4%
	East Flanders			121	1,1%	<b>4745</b>	<b>42,7%</b>	40	0,4%	121	1,1%
	Flemish Brabant	40	0,4%					<b>565</b>	<b>5,1%</b>		
	West Flanders					0,4	0,4%			<b>3998</b>	<b>36,0%</b>

### 3.2.3 Characteristics of service users in the Centers for Ambulatory Rehabilitation

#### *Distribution of diagnoses*

As the CAR generally work at full capacity, the distribution of diagnoses taken at the same point in time each year gives a good indication of the distribution of diagnoses in the CAR in general. Figure 4.9 shows that clients with autism form the largest group when considering clients in treatment (around 25% of all clients). Other important diagnoses are ADHD or ADD and intellectual disability (each 16%), followed by speech disorders (12%). When considering new applications, the distribution of diagnoses changes

somewhat, with considerably less autism diagnoses (19%) and considerably more intellectual disability (22%) and, especially, learning disorder diagnoses (12% as compared to 6% treated clients). For both active clients and new applicants, the category ‘other/no diagnosis’ in Figure 4.8 contains less common diagnoses treated in the CAR (e.g. cerebral palsy, stuttering, behavioral disorders, depressive disorders, etc.). For new applications, it may also refer to uncertain diagnoses or applicants that haven’t been diagnosed yet.

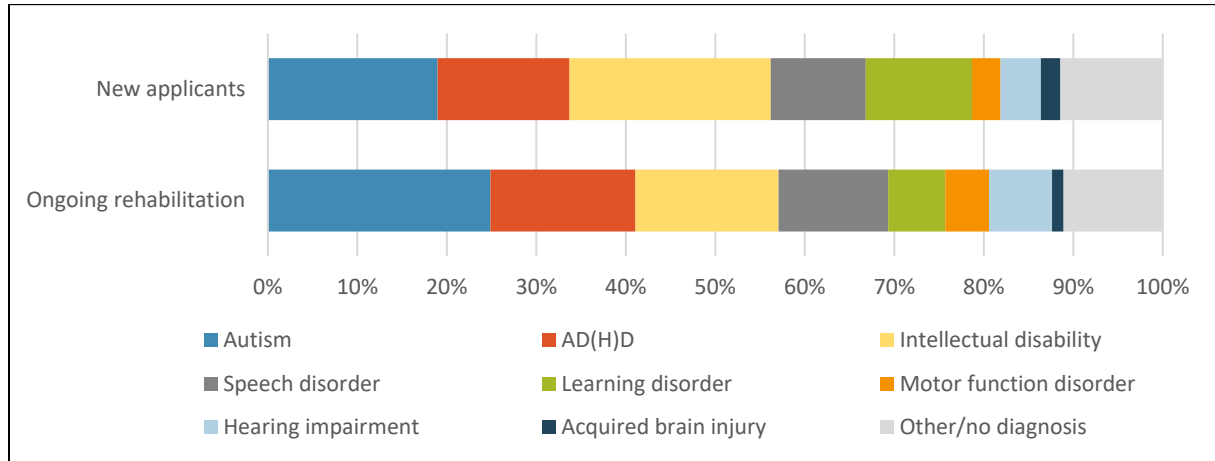


Figure 4.9 Distribution of diagnoses for new applicants and clients with ongoing rehabilitation on December 31 in the Centers for Ambulatory Rehabilitation between 2013 and 2018 (CAR annual reports).

In general, there are relatively more applicants with intellectual disability, learning disorders, and acquired brain injury as compared to clients in treatment with the same diagnoses. An obvious reason for this could be that multidisciplinary rehabilitation treatment in the CAR is relatively less often indicated for people with these disorders than for the other diagnoses. However, additional factors may play a role as well, including diagnoses changing after examination, application problem registration differences (in the annual reports, as well as in the recoding process performed for the purposes of this report), or actual differences in treatment duration or waiting time, resulting in an increased ratio of applications to ongoing treatment at a particular point in time.

A comparable figure picturing the distribution of diagnoses based on the NIHDI-service data is shown in Figure 4.10, with services divided into examination sessions and rehabilitation sessions. Only services billed under the ambulatory nomenclature codes are considered. The category ‘complex developmental’ refers to the presence of at least two complex developmental problems, belonging to the groups of spoken language and learning disorders, motor function disorders, attention and memory problems, auditory and visual perception problems, visual-spatial functioning problems, or psychosocial problems. The cerebral palsy, stuttering, behavioral problems, mood disorder, and other/suspected diagnosis categories taken together roughly correspond to the other/no diagnosis category in Figure 4.9. The swallowing/voice/... category refers to a group of disorders exclusively diagnosed and treated in the university hospital CAR, and is therefore not included in Figure 4.9.

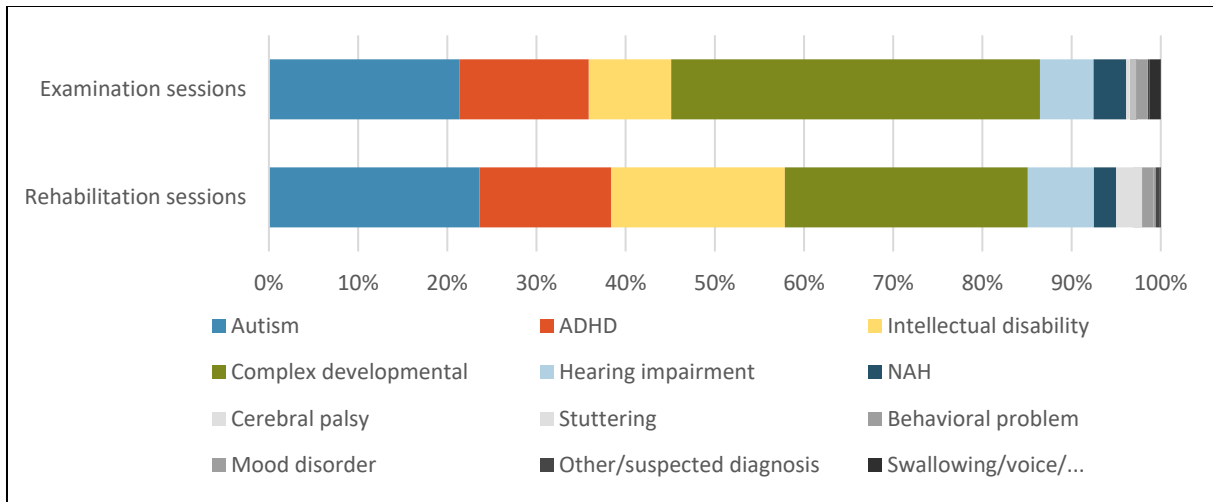


Figure 4.10 Distribution of diagnoses for ambulatory examination and rehabilitation sessions in the Centers for Ambulatory Rehabilitation between 2013 and 2018 (NIHDI health insurance data).

Figure 4.10 shows that relatively fewer examination sessions and relatively more rehabilitation sessions are billed for children and adolescents with autism and especially intellectual disabilities, and for people with hearing impairment, whereas the reverse is true for most other diagnoses. Several factors could be contributing to this picture, of which the most obvious ones pertain to diagnosis-specific differences in the length of the diagnostic process on the one hand and in the duration of treatment and the required frequency of treatment sessions on the other hand. In addition, examination may be more often performed beforehand by referring professionals for certain diagnoses, or multidisciplinary rehabilitation may not always be indicated after examination for other diagnoses.

When taking into account the diagnostic categorization differences, the distribution of diagnoses for clients in ongoing rehabilitation in Figure 4.9 and for rehabilitation sessions in Figure 4.10 is quite similar, despite the fact that the former figure refers to clients and is restricted to data from autonomous CAR, while the latter refers to billed services (sessions) and includes all CAR.

Figure 4.11 shows the evolution of diagnoses for active clients receiving rehabilitation on December 31 in the 35 Centers for Ambulatory Rehabilitation with complete time series for the ongoing rehabilitation variable. For autism, the most common diagnosis, the proportion of clients in treatment amounted from 20% of all clients in 2013 up to 29% in 2018, which represents a 43% increase in autism diagnoses in a five-year period. AD(H)D and intellectual disability represented each about 15% of diagnoses in 2018 as a result of a decreasing trend since 2013 (17% and 9% decrease, respectively). Other diagnoses showing a decreasing trend were speech, and especially, learning disorders (20% and 49% decrease, respectively), whereas the number of clients with hearing impairment increased with 18%.

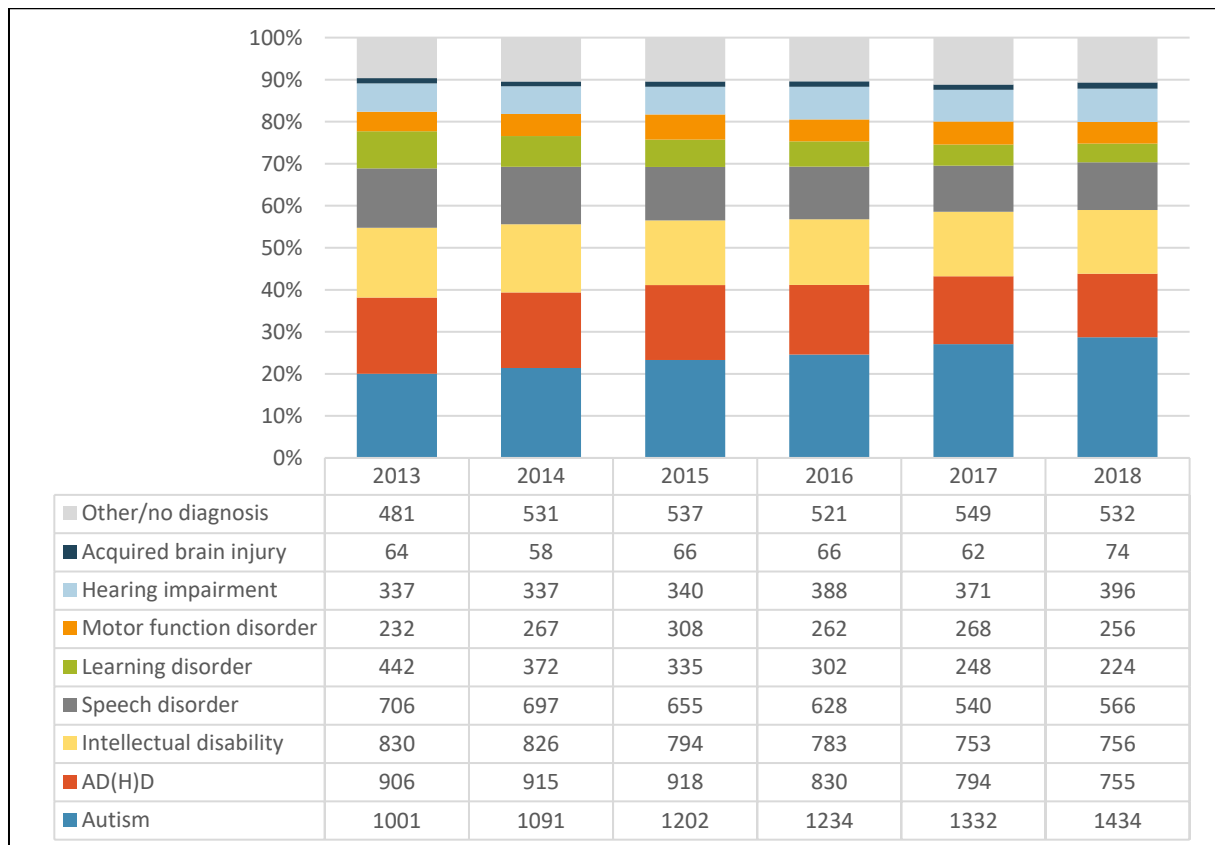


Figure 4.11 Evolution of the number and proportion of active clients per diagnosis on December 31 in the Centers for Ambulatory Rehabilitation from 2013 to 2018 (CAR annual reports, data from 35 centers with complete time series for ongoing rehabilitation).

In Figure 4.12 the evolution of diagnoses for people applying for care is shown. As expected, important diagnoses on the application file were autism, ADHD or ADD, and intellectual disability, with the autism diagnosis showing a strong increasing trend between 2013 and 2018 and AD(H)D showing a smaller decreasing trend. The strongest decrease in applications was seen for children with learning disorders.

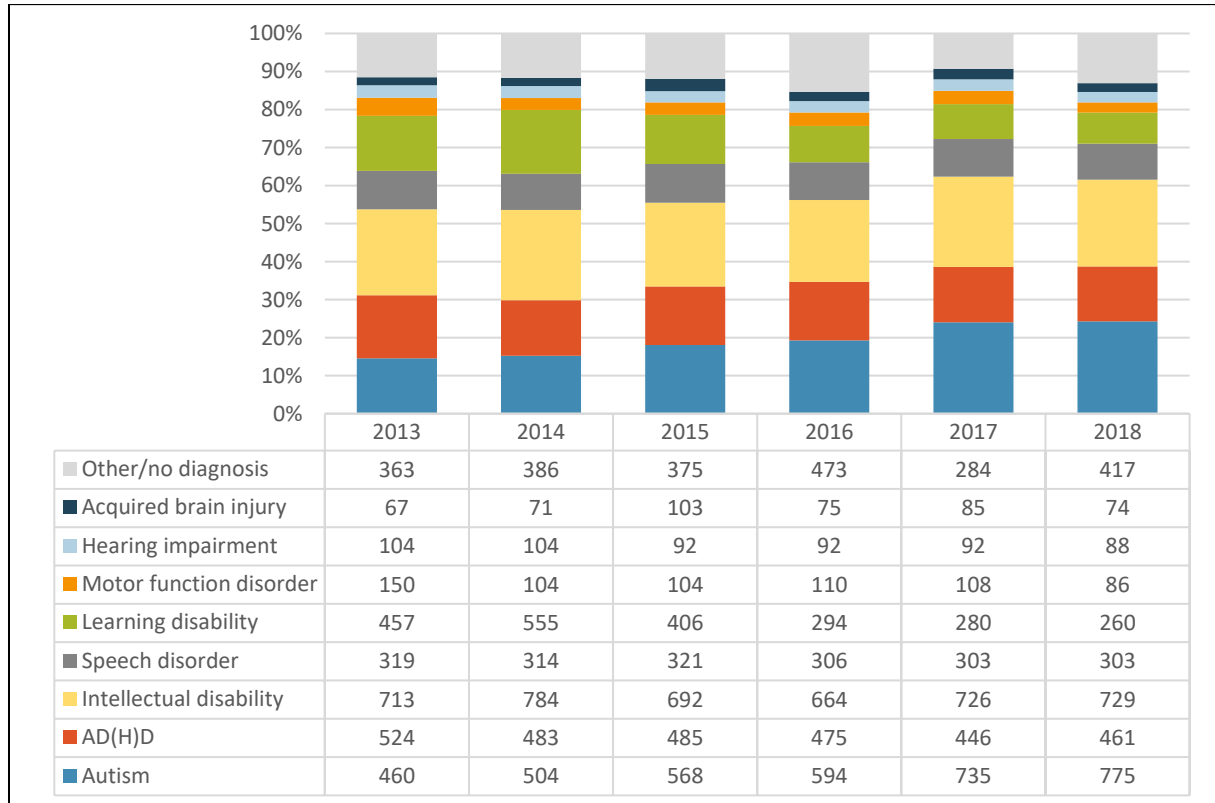


Figure 4.12 Evolution of the number and proportion of new applicants per diagnosis in the Centers for Ambulatory Rehabilitation from 2013 to 2018 (CAR annual reports, data from 30 centers with complete time series for applications).

In Figure 4.13 and 4.14 the evolution of diagnoses in the CAR are shown again, but this time based on the NIHDl data for rehabilitation and examination sessions, respectively.

Again, the increasing importance of the autism diagnosis is apparent, with a 48% increase in rehabilitation sessions and a 29% increase in examination sessions between 2013 and 2018. For ADHD, the number of rehabilitation and examination sessions decreased, following an increase in 2014. Rehabilitation sessions for intellectual disability diagnoses showed a 17% decrease between 2013 and 2018, but the number of examination sessions remained more stable, suggesting that rehabilitation treatment for this diagnosis was started for fewer examined clients or involved less sessions in more recent years.

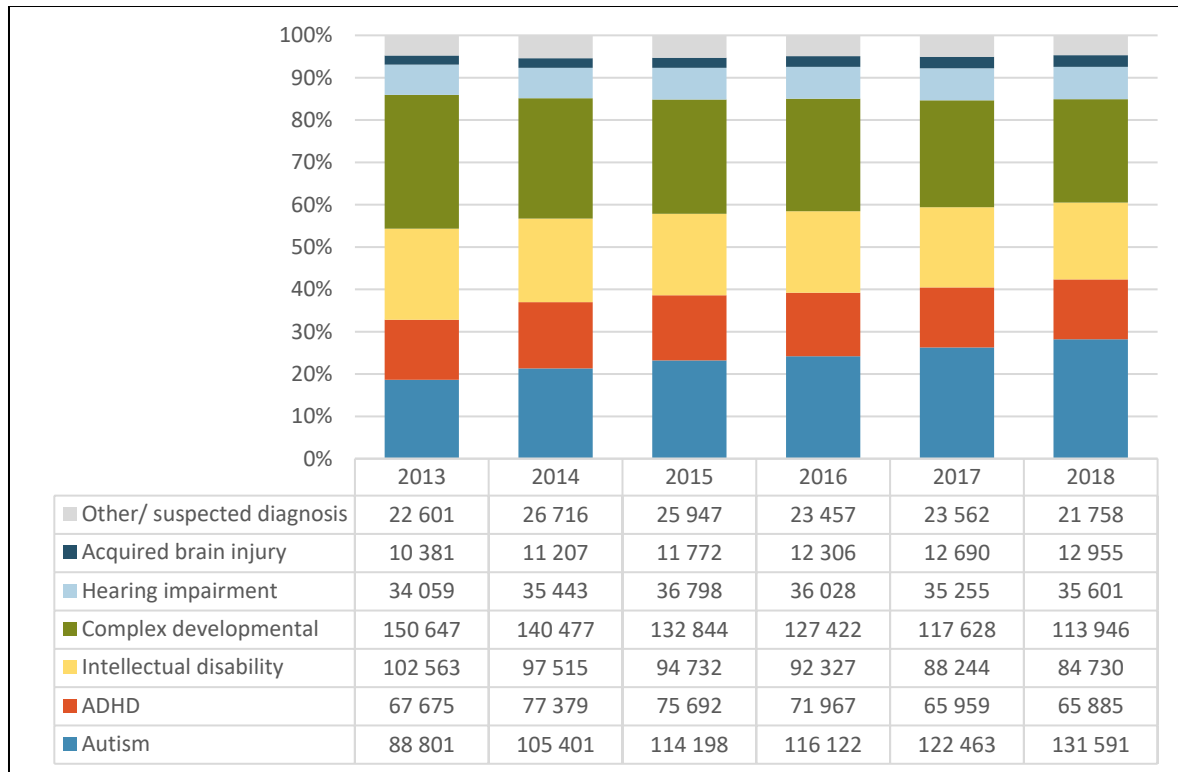


Figure 4.13 Evolution of the number and proportion of rehabilitation sessions per diagnosis in the Centers for Ambulatory Rehabilitation from 2013 to 2018 (NIHDI health insurance data).

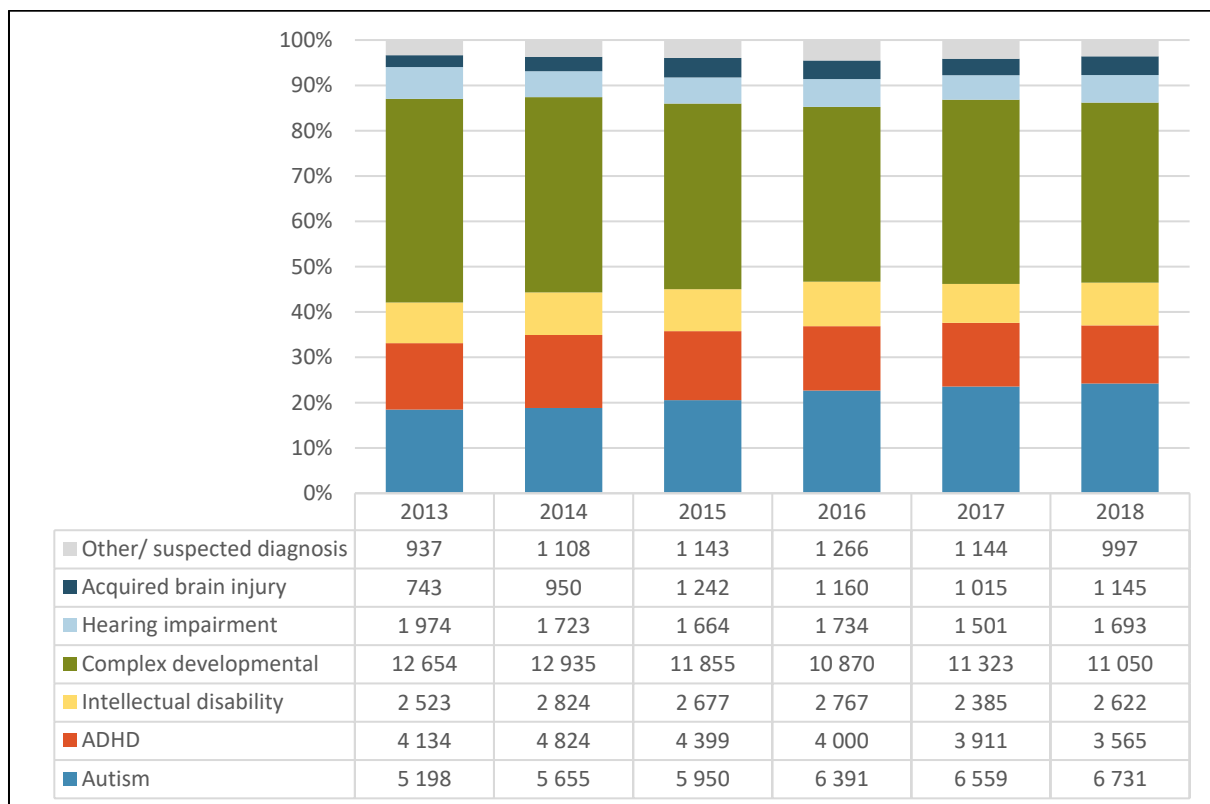


Figure 4.14 Evolution of the number and proportion of examination sessions per diagnosis in the Centers for Ambulatory Rehabilitation from 2013 to 2018 (NIHDI health insurance data).



The strongest decreasing trend in the number of billed rehabilitation and examination sessions was observed for the category of complex developmental disorders (24% and 13% decrease, respectively). This may not be so surprising, given that centers with a high proportion of clients in that category were obliged to gradually lower this proportion to a maximum of 30% since 2008, whereas CAR with a low proportion in 2008 were not allowed to exceed a restricted percentage based on that proportion in later years. When comparing Figure 4.13 with Figure 4.9, it seems that especially treatment for children and adolescents with learning and speech disorders was affected by these regulations. At the same time, referral became more adequate as well due to improved diagnostics at school and by the Centers for Student Guidance or CLB (Vervolsem, personal communication), thereby limiting examination in the Centers for Ambulatory Rehabilitation more and more to their actual target group of clients in need of a multidisciplinary approach, with other children and adolescents directly referred to speech therapists or other professionals.

#### *Age and gender distribution*

Most clients in the Centers for Ambulatory Rehabilitation are children below twelve years. Adolescents receive care for all common diagnoses as well, whereas rehabilitation for adults and elderly people is mainly limited to hearing impairment or acquired brain injury diagnoses. Figure 4.15 shows the evolution of the age distribution from 2013 to 2018, for clients in treatment on December 31 and for people applying for care. Fluctuations in time are limited and are generally similar for clients in treatment and for applications. However, for some diagnoses the age distribution itself differs somewhat (e.g. for speech disorders, motor function disorders, and hearing impairments), which may be the result of various factors, ranging from age-related differences in the required rehabilitation duration to differences in urgency, possibly reflected in disorder-specific waiting times.



Figure 4.15 Evolution of the age distribution per diagnosis of clients with ongoing rehabilitation on December 31 and new applicants in the Centers for Ambulatory Rehabilitation from 2013 to 2018 (CAR annual reports, data from 30 centers with complete time series for ongoing rehabilitation and applications).

Contrary to the age distributions, the gender distributions of clients receiving rehabilitation on the one hand and clients applying for care on the other hand are nearly identical for all diagnoses (Figure 4.16).

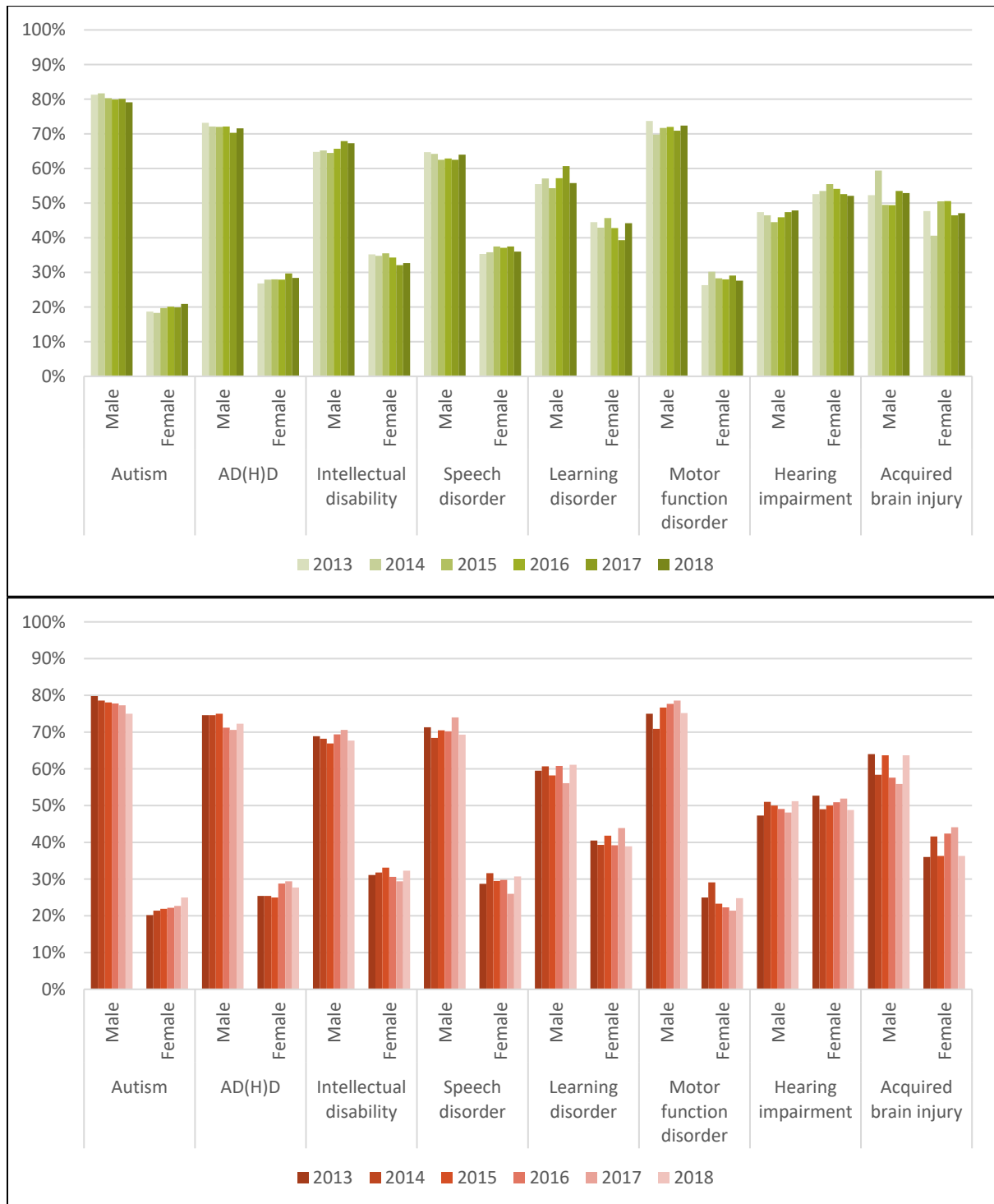


Figure 4.16 Evolution of the gender distribution per diagnosis of clients receiving rehabilitation on December 31 and new applicants in the Centers for Ambulatory Rehabilitation from 2013 to 2018 (CAR annual reports).

For all childhood- and adolescent-specific diagnoses in the Centers for Ambulatory Rehabilitation, the proportion of boys is higher than the proportion of girls, most noticeably so for the most common diagnoses of autism and AD(HD), and to a lesser extent for learning disorders. This strong predominance of boys over

girls in autism and ADHD is consistent with literature concerning these conditions (Begeer et al., 2013; Polanczyk et al. 2007). However, for both diagnoses the proportion of boys seemed to decrease slightly in favor of girls. For clients of all ages diagnosed with hearing impairment or acquired brain injury, the gender difference is much smaller than for the other diagnoses.

#### *Regional distribution of diagnoses*

Figures 4.17 and 4.18 compare provinces with respect to the aggregated number and proportion of clients receiving rehabilitation for specific diagnoses on December 31 or clients applying for care between 2013 and 2018 in the Centers for Ambulatory Rehabilitation. The other/no diagnosis category is not included.

Both figures show a considerable difference in the distribution of diagnoses, for the more common diagnoses as well as for the rarer ones. As regional differences are not expected for these diagnoses (see Appendix 1), the reasons for this varying picture may be the result of several, mainly supply-related factors. First and foremost, as a result of the origin of the Centers for Ambulatory Rehabilitation through the merging of two different types of centers (the so-called NOK and PSY centers) with specific target groups (in addition to the main diagnoses target groups) in 2010, many CAR are still more or less specialized in rehabilitation treatment for certain diagnoses (e.g. hearing impairment in the CAR originating from NOK centers). Seeing that these historical NOK and PSY centers were unevenly divided over the Flemish Region (Scheiris e.a, 2008), it is not surprising that the distribution of diagnoses in the CAR still varies from province to province.

In addition, the observed regional differences in both figures below may also be partly due to missing data for certain centers (including the CAR linked to university hospitals), some of which are possibly specialized in diagnoses that are underrepresented in the current data. For example, clients with hearing impairment or acquired brain injury in Flemish Brabant may be treated mainly by the university hospital CAR in the province, thus explaining the low numbers for these diagnoses in Figure 4.17.

Finally, other factors contributing to regional differences in the distribution of diagnoses in general as well as differences for applications on the one hand and treated clients on the other hand, may include registration differences (e.g. the lacking acquired brain injury diagnostic category in Limburg may not be registered separately), practice differences (e.g. in referral instances or in the CAR themselves), or could be due to other supply-related reasons, such as the availability of alternative services, or the availability and accessibility of the CAR locations themselves (with limited coverage possibly leading to longer waiting lists and diminished treatment of less urgent diagnoses).

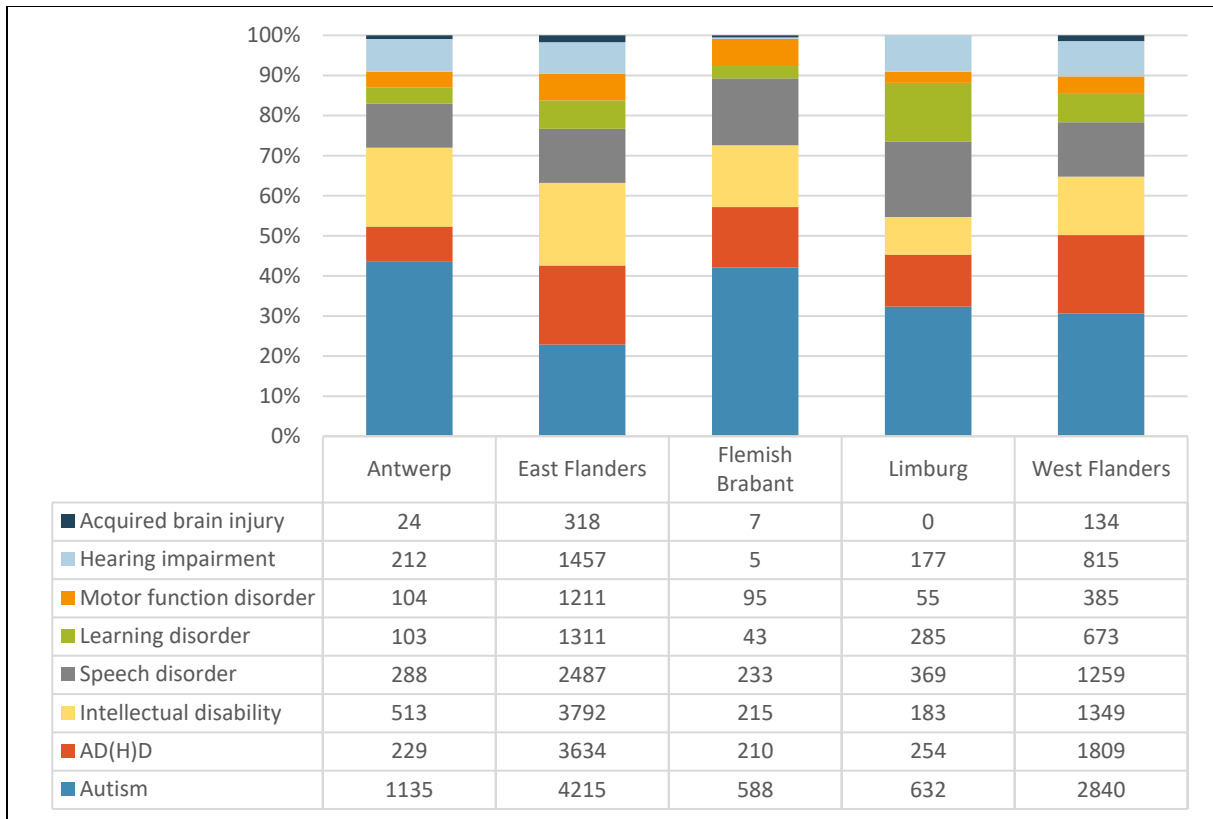


Figure 4.17 Total number and proportion of diagnoses per province for clients receiving rehabilitation on December 31 2013 to 2018 in the Centers for Ambulatory Rehabilitation (CAR annual reports).

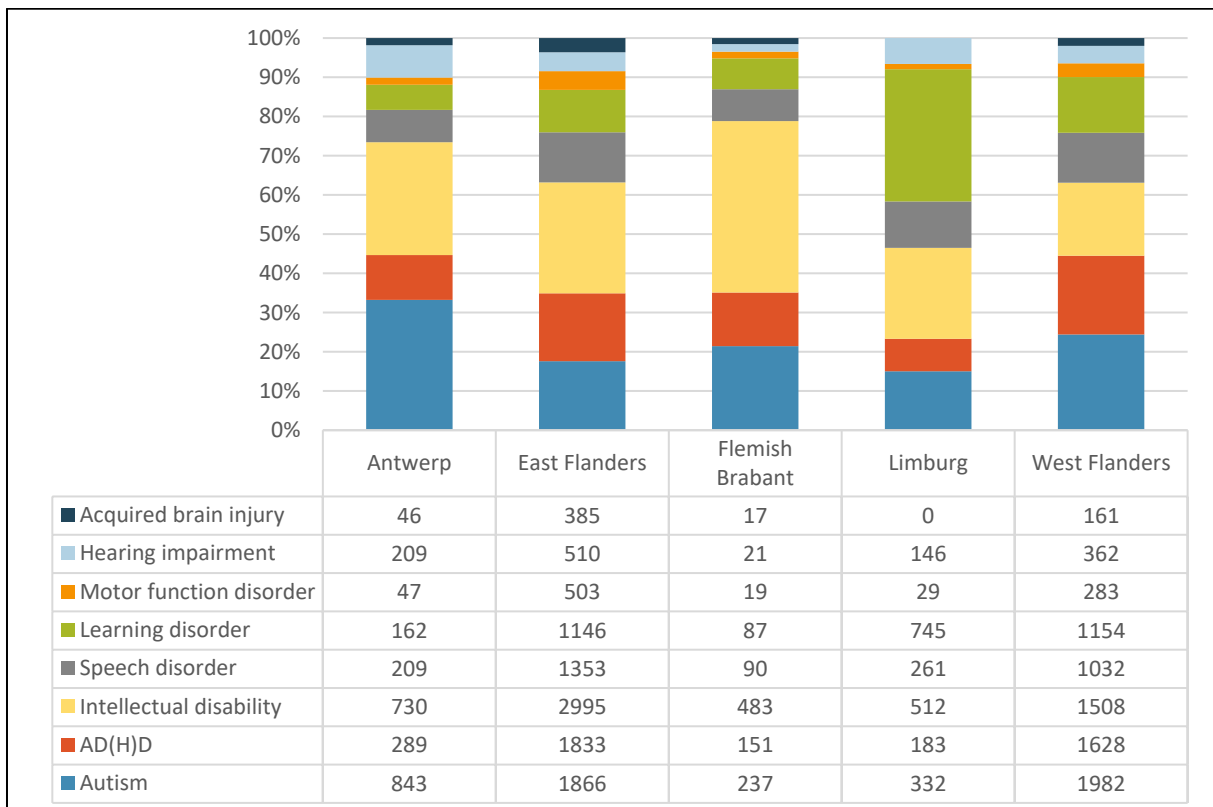


Figure 4.18 Total number of diagnoses per province for clients applying for care between 2013 and 2018 in the Centers for Ambulatory Rehabilitation (CAR annual reports).

In Figures 4.19 and 4.20 the evolution of the three most common diagnoses in the Centers for Ambulatory Rehabilitation is shown per province. In all provinces, the number of clients diagnosed with autism was higher in 2018 than in 2013, whereas rehabilitation for clients with AD(H)D or intellectual disability remained rather stable (Antwerp, Flemish Brabant, and Limburg) or decreased (East and West Flanders).

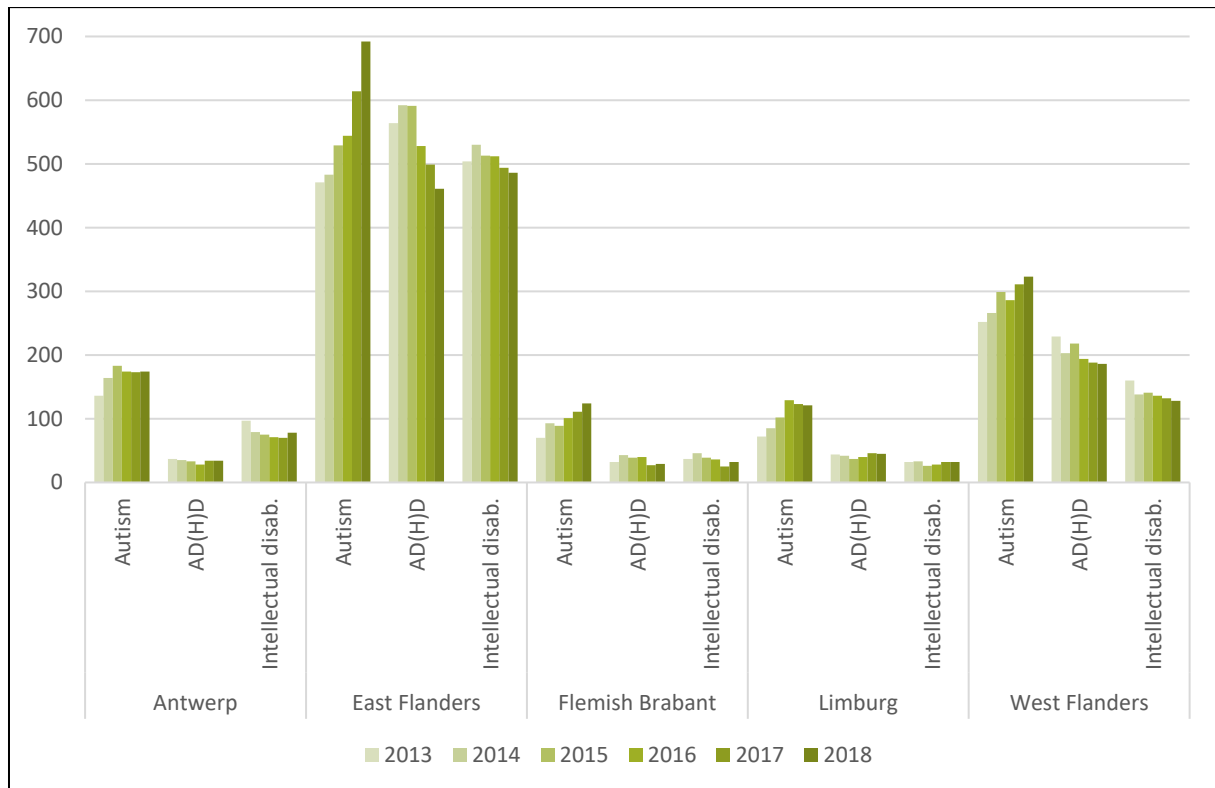


Figure 4.19 Evolution of the most common diagnoses (autism, AD(H)D, intellectual disability) per province for clients in the Centers for Ambulatory Rehabilitation on December 31 from 2013 to 2018 (CAR annual reports, data from 35 centers with complete time series for ongoing rehabilitation).

When looking at applications, the rise of autism is even more clear, with numbers doubling between 2013 and 2018 in East Flanders and Flemish Brabant, and mounting strongly in West Flanders as well.

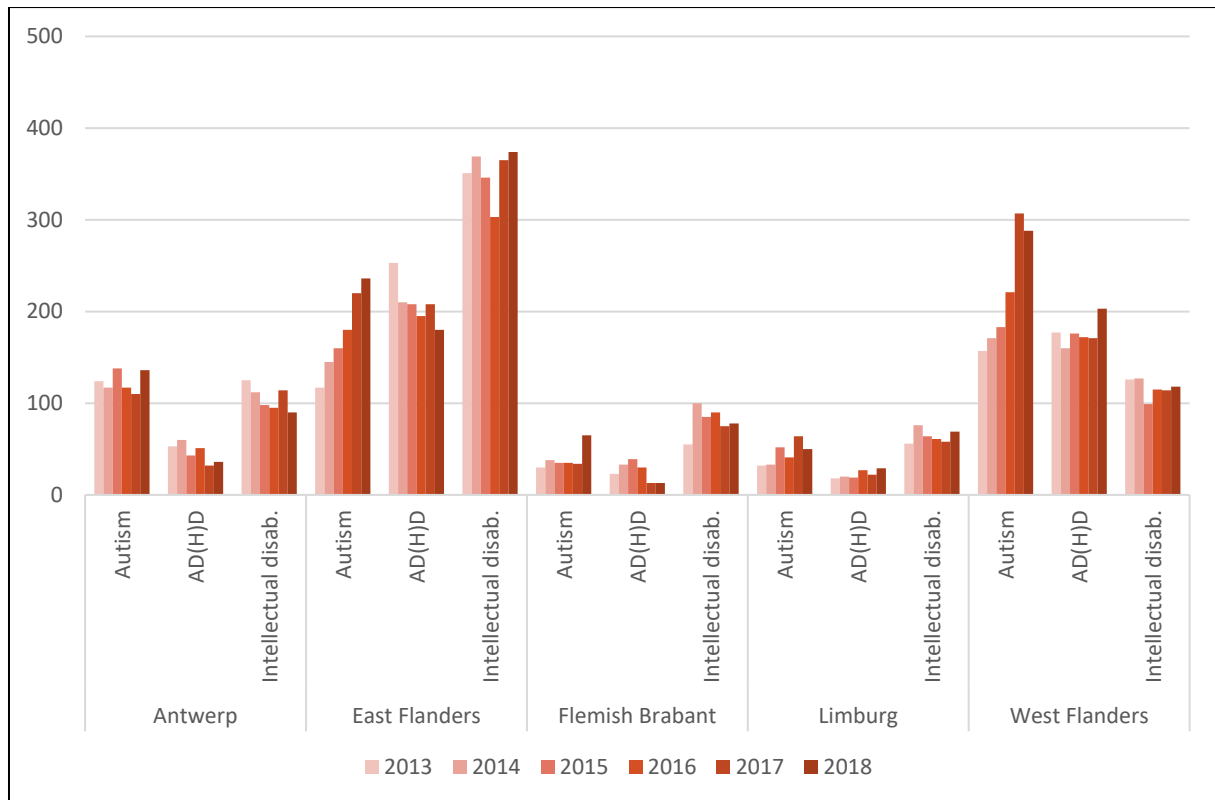


Figure 4.20 Evolution of the most common diagnoses (autism, AD(H)D, intellectual disability) per province for clients applying for care in the Centers for Ambulatory Rehabilitation from 2013 to 2018 (CAR annual reports, data from 30 centers with complete time series for applications).

### 3.2.4 Service characteristics in the Centers for Ambulatory Rehabilitation

The evolution of the trajectory of people applying for care in the Centers for Ambulatory Rehabilitation is summarized in a few percentages shown in Figure 4.21, referring to the situation on December 31 of each year. In 2013, 35% of all new applicants were examined, while 40% were still waiting for an examination. However, in 2018 the former percentage had already dropped to 30% and the latter percentage mounted to 51%, suggesting gradually longer waiting times between application and examination. Approximately 12% of all applicants dropped out before (9 to 11%) or during examination (1 to 3%), with little evolution in these percentages between 2013 and 2018. The remainder of the applicants received rehabilitation without examination, usually following referral after previous examination and diagnosis by a specialist or in hospital. The percentage of applicants in this groups was somewhat lower in recent years.

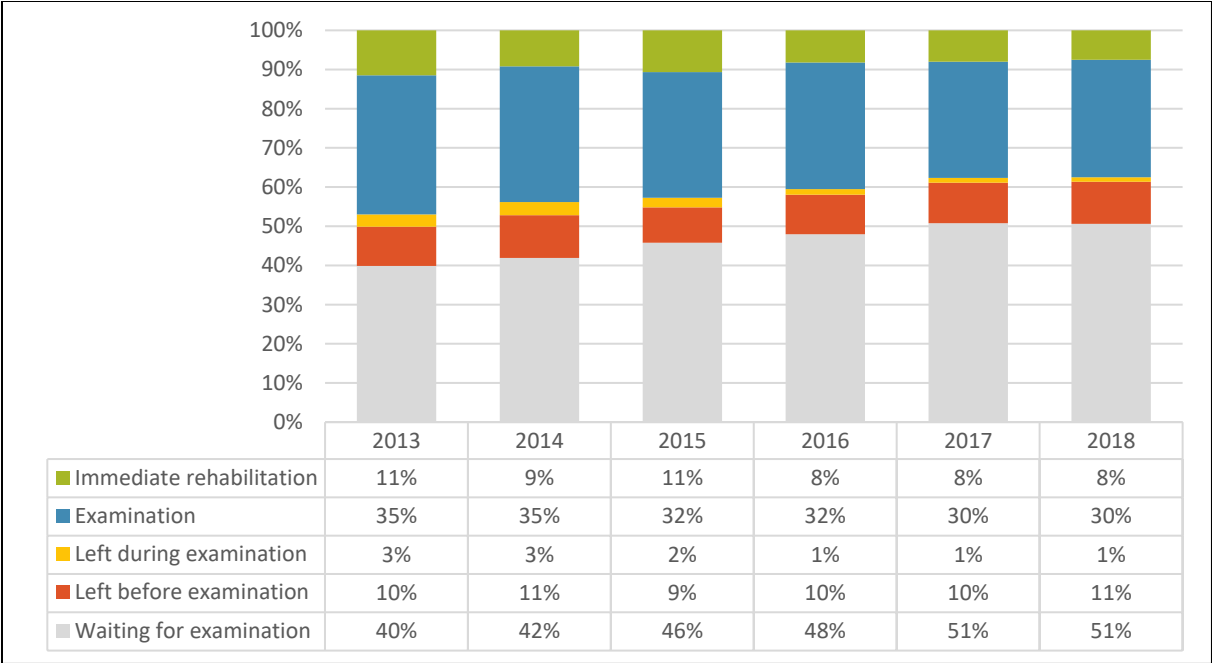


Figure 4.21 Evolution of the trajectory of people applying for care in the Centers for Ambulatory Rehabilitation from 2013 to 2018 (CAR annual reports, data from 34 CARs with complete time series for the application follow-up variables).

Despite the increasing proportion of applicants still waiting for examination at the end of the year, the total number of applications did not seem to increase significantly (see Figure 4.3), which may be the result of different factors, including a forced waiting list stop or a self-limiting process where people refrain from applying when waiting lists are too long



Figure 4.22 summarizes the evolution of the trajectory of applicants with an examination started between 2013 and 2018 in the Centers for Ambulatory Rehabilitation. The proportion of examined clients for whom further treatment in the CAR was indicated mounted from 62% in 2013 to 67% in 2018. More than half of the examined clients already started rehabilitation before the end of each year, whereas the proportion of clients still waiting for treatment fluctuated around 12%. In 2018, 6% of the examinations were discontinued by the CAR without referral and 15% of the examined clients were referred for treatment elsewhere (e.g. when rehabilitation is not possible or when the multidisciplinary approach in the CAR is not appropriate). The total proportion of discontinued examinations and referred clients lowered in recent years, suggesting better-targeted referral.

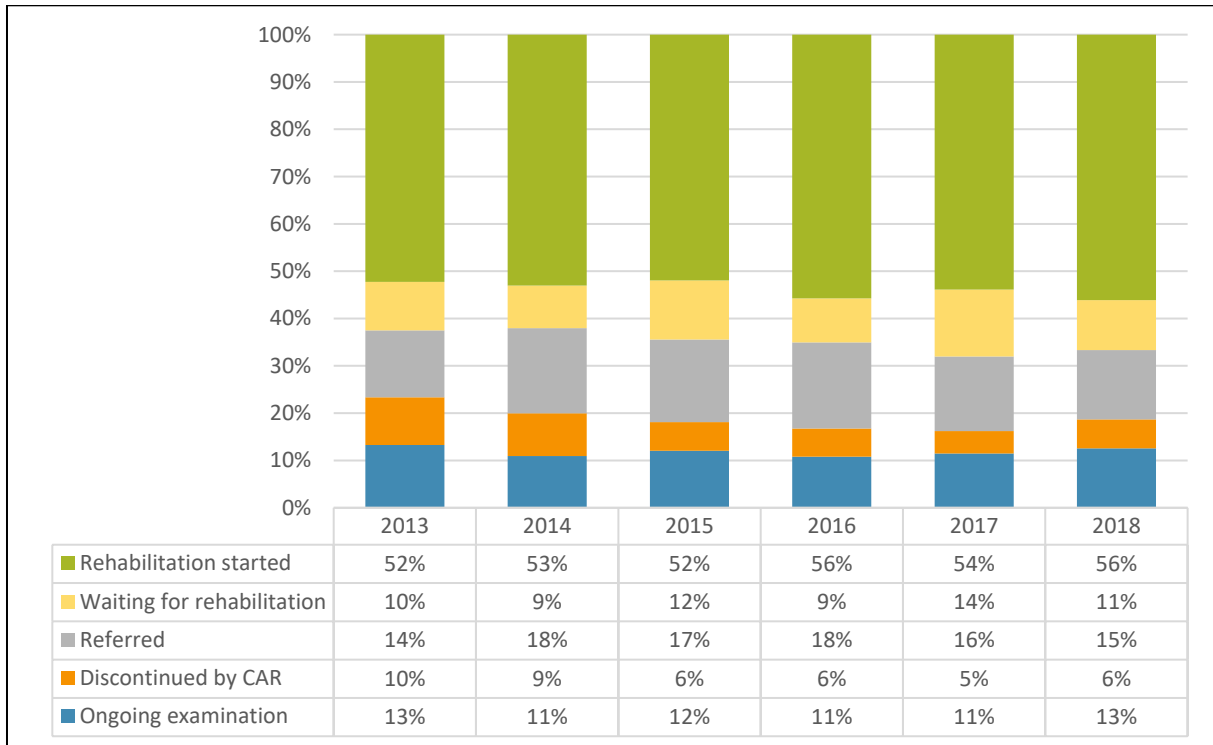


Figure 4.22 Evolution of the trajectory of clients receiving an examination in the Centers for Ambulatory Rehabilitation from 2013 to 2018 (CAR annual reports, data from 27 CARs with complete time series for the examination follow-up variables).

Figure 4.23 shows an increasing trend in the total number of applicants waiting for examination on December 31 in the Centers for Ambulatory Rehabilitation. Current year applications, as well as applications from previous years are included in the data. The number of people waiting more than doubled between 2013 and 2014 in Flemish Brabant, and in West Flanders numbers increased substantially in 2016. Only in Antwerp there was a lower number of people waiting for examination at the end of the year in 2018 then in 2013. As the capacity of the CAR in Flanders was stable during this period, the increasing trend in Figure 4.22 can be considered an indication of increasing waiting lists. Nevertheless, as mentioned above the number of applications itself remained rather constant, suggesting that the increased number of people waiting for examination may be caused by longer treatment duration or longer duration of the examination process itself (e.g. due to the gradual shift in the distribution of diagnoses, or as a result of longer waiting times between sessions in centers where capacity is constantly exceeded).

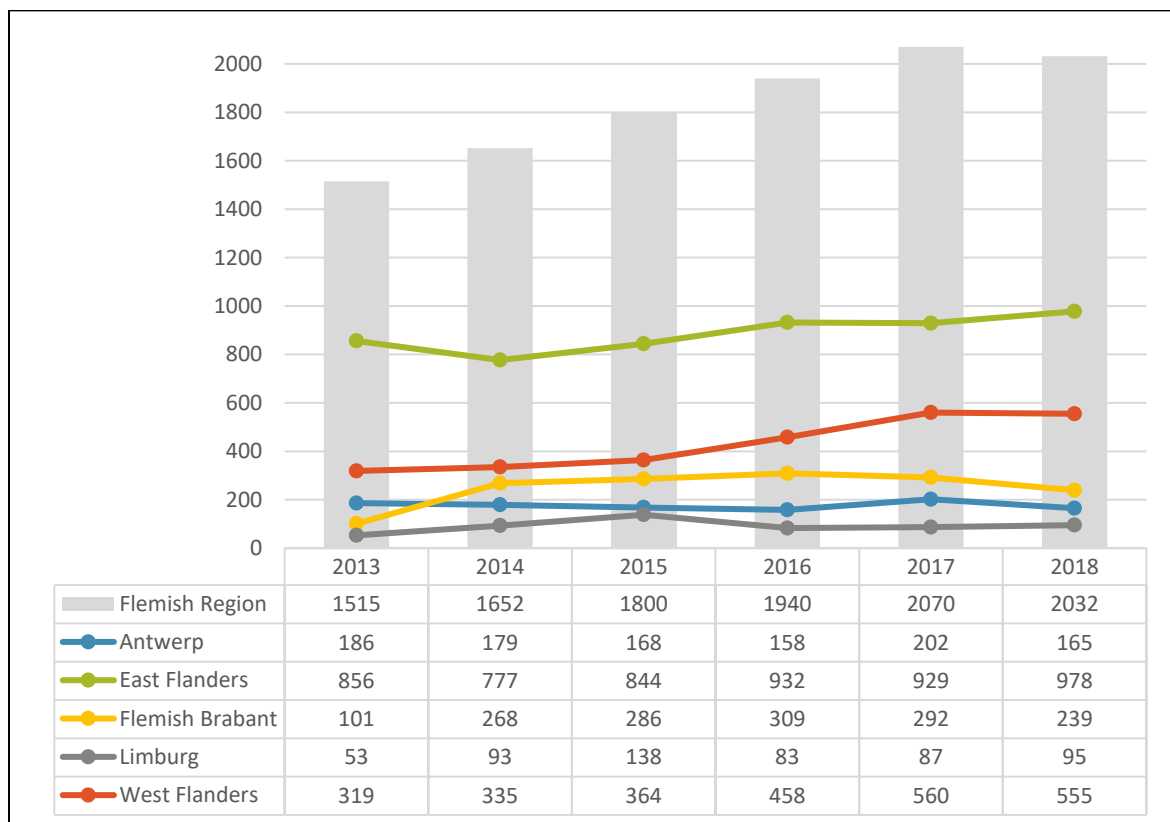


Figure 4.23 Evolution of the total number of people waiting for examination on December 31 in the Centers for Ambulatory Rehabilitation from 2013 to 2018 per province (CAR annual reports, data from 26 CAR with complete time series for the waiting for examination variable for current and previous years applicants).

For most diagnoses, the waiting time in months between applying and the start of rehabilitation increased from 2013 to 2018 as shown by the trends in Figure 4.24. Centers with missing data for all diagnoses in certain years were removed from the dataset, leaving 34 CAR with complete time series for the waiting time variable. The median and percentiles in the figure are calculated based on the mean waiting time per center per diagnosis. Certain diagnoses, however, did not occur in the remaining CAR at all or in some years. This means that calculations may be made on as little as four centers for some diagnoses in certain years (e.g. acquired brain injury in 2017 and 2018) to all 34 centers for other diagnoses.

Waiting times for clients with acquired brain injury and hearing impairment were the shortest, whereas waiting times for learning disorders were the longest, with half of the CAR showing a mean waiting time of more than 15 months and one fourth a mean waiting time of more than 20 months in 2018. For clients diagnosed with autism or AD(H)D mean waiting times amounted to more than ten months for at least half of the CAR in 2018, a three month increase when compared to 2013. The increase in waiting times for clients with intellectual disability was less outspoken and went from a median mean waiting time of seven months in 2013 to eight months in 2018. In Figure 4.24 the AD(H)D diagnoses includes both ADHD and ADD for some centers and only ADD for other centers.

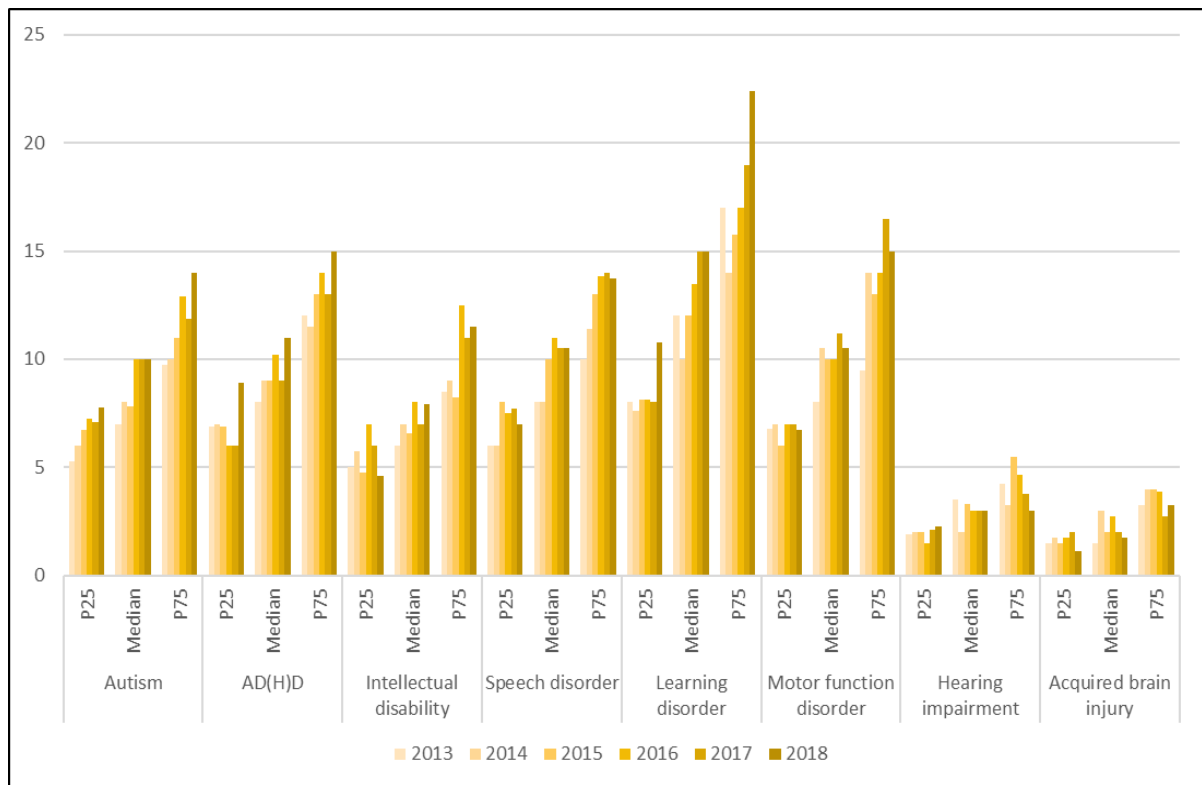


Figure 4.24 Evolution of the waiting time (in months) between application and rehabilitation per diagnosis in the Centers for Ambulatory Rehabilitation from 2013 to 2018 (CAR annual reports, data from 34 CAR with complete time series for the mean waiting time variable).

Figure 4.25 shows the same data for the three main diagnoses, with medians calculated per province. All provinces show an increase in waiting times between application and rehabilitation for autism, with the strongest increase observed in West Flanders and Flemish Brabant in 2018. Waiting times also mounted strongly for clients diagnosed with AD(H)D for both provinces and Antwerp, but remained more constant in Limburg and East Flanders. For clients with intellectual disability, there was a decrease in waiting times in Antwerp in recent years and a limited increase in the other provinces. Given that even for the main diagnoses, some mean waiting time data were missing for certain years, in addition to the missing years for all diagnoses, these results have to be interpreted with care, though.

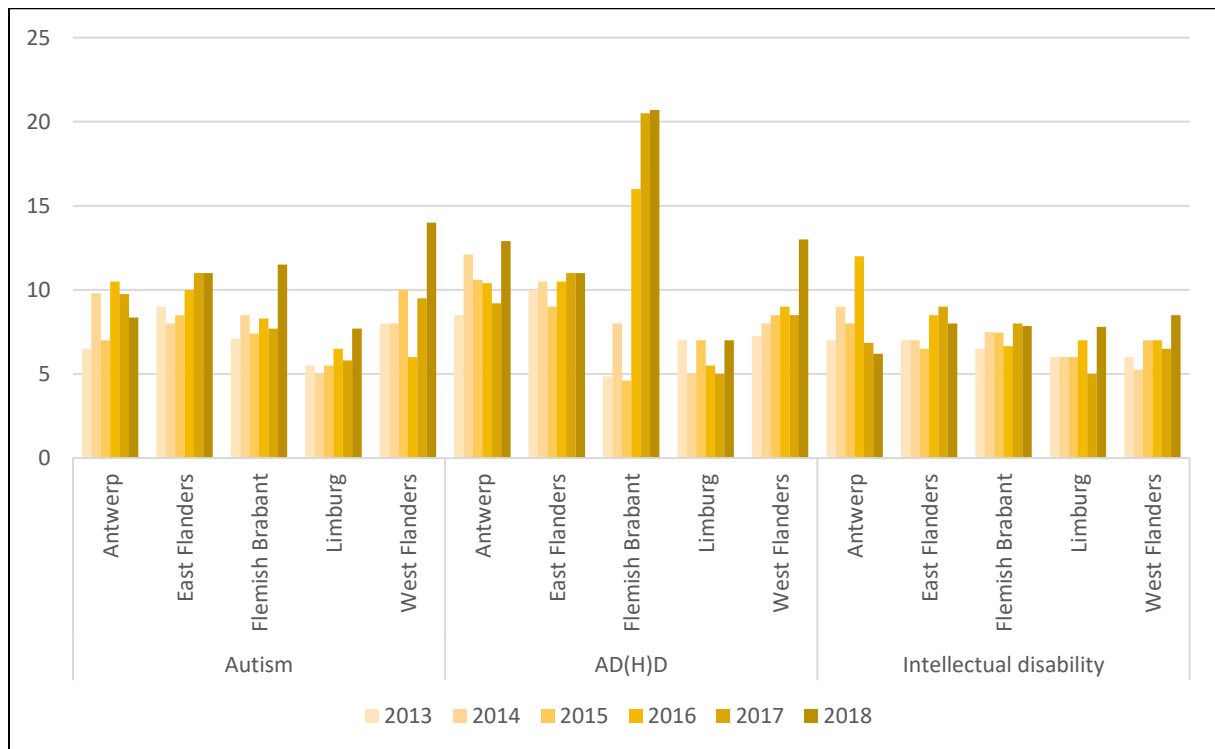


Figure 4.25 Evolution of the median mean waiting time (in months) between application and rehabilitation for people with autism, AD(H)D, or intellectual disability in the Centers for Ambulatory Rehabilitation per province, from 2013 to 2018 (CAR annual reports, data from 34 CAR with complete time series for the mean waiting time variable).

The evolution of the duration of rehabilitation treatment per diagnosis is shown in Figure 4.26. As for the waiting time figures above, centers with missing data for all diagnoses in certain years were removed from the dataset, leaving 30 CAR locations with complete time series for the rehabilitation duration variable. Again, certain diagnoses did not occur in the remaining CAR at all or in some years, leading to calculations based on as little as two centers for some diagnoses in certain years (e.g. acquired brain injury in 2014) to all 30 centers for other diagnoses.

The median of the average rehabilitation treatment duration per center was lower in 2013 than in 2018 for every diagnosis and mostly ended up between 30 to 40 months in the latter year. This increase is not necessarily the reflection of an increasing total number of sessions, but may also be the result of increasing waiting times between sessions. When capacity is stretched to its limits, clients with urgent rehabilitation needs may be given priority at the expense of less urgent sessions being pushed backwards.

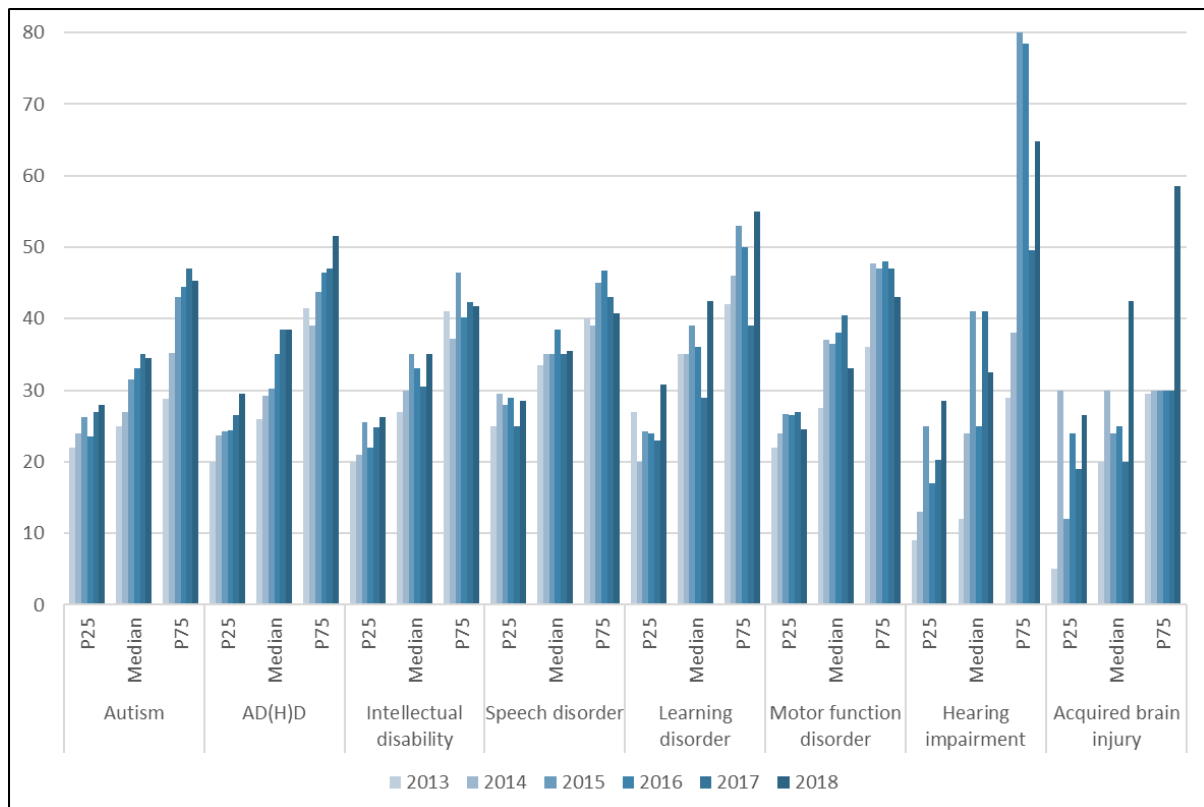


Figure 4.26 Evolution of the rehabilitation duration (in months) per diagnosis in the Centers for Ambulatory Rehabilitation from 2013 to 2018 (CAR annual reports, data from 30 CAR with complete time series for the mean rehabilitation duration variable).

### 3.3 Description of costs in the Centers for Ambulatory Rehabilitation

Given the limited representativeness of the EPS sample for the Centers for Ambulatory Rehabilitation, the description of costs is solely based on the aggregated NIHDI-data, containing total costs per nomenclature code per year.

Figures 4.27 and 4.28 show the evolution of total costs and the evolution of calculated costs per case for examination and rehabilitation sessions. As expected, total costs were higher in 2018 than in 2013 for both examination (9%) and rehabilitation sessions (8%), although fluctuations were limited in between these

years. The cost per case gradually increased for rehabilitation sessions and remained rather constant for examination sessions until 2016.

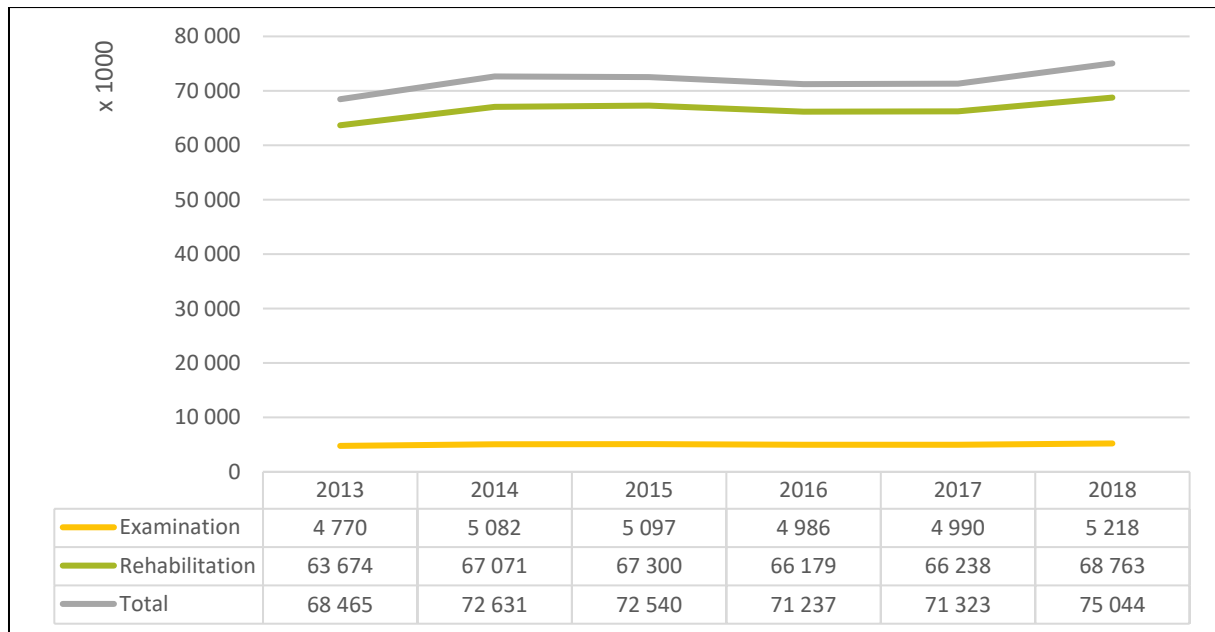


Figure 4.27 Evolution of total costs for examination and rehabilitation sessions provided by the Centers for Ambulatory Rehabilitation from 2013 to 2018, with totals including costs for teacher group sessions and catch-up fees (NIHDI health insurance data).

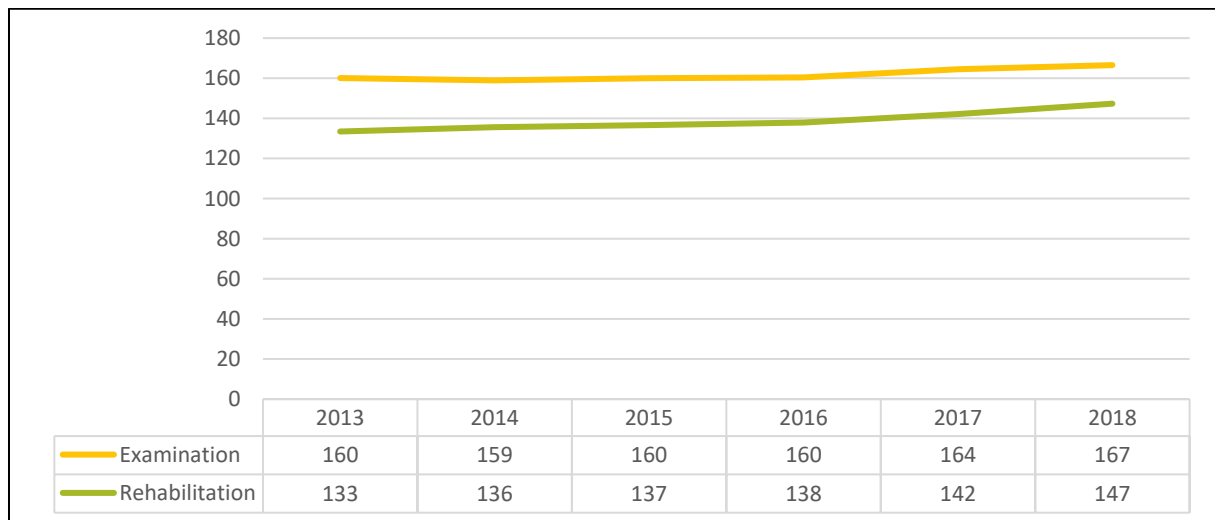


Figure 4.28 Evolution of costs per case for examination and rehabilitation sessions provided by the Centers for Ambulatory Rehabilitation from 2013 to 2018 (NIHDI health insurance data).

Figure 4.29 shows the evolution of total costs per main target group or diagnosis in the Centers for Ambulatory Rehabilitation. Costs for all three service types (examination sessions, rehabilitation sessions, and teacher group sessions) are added together.

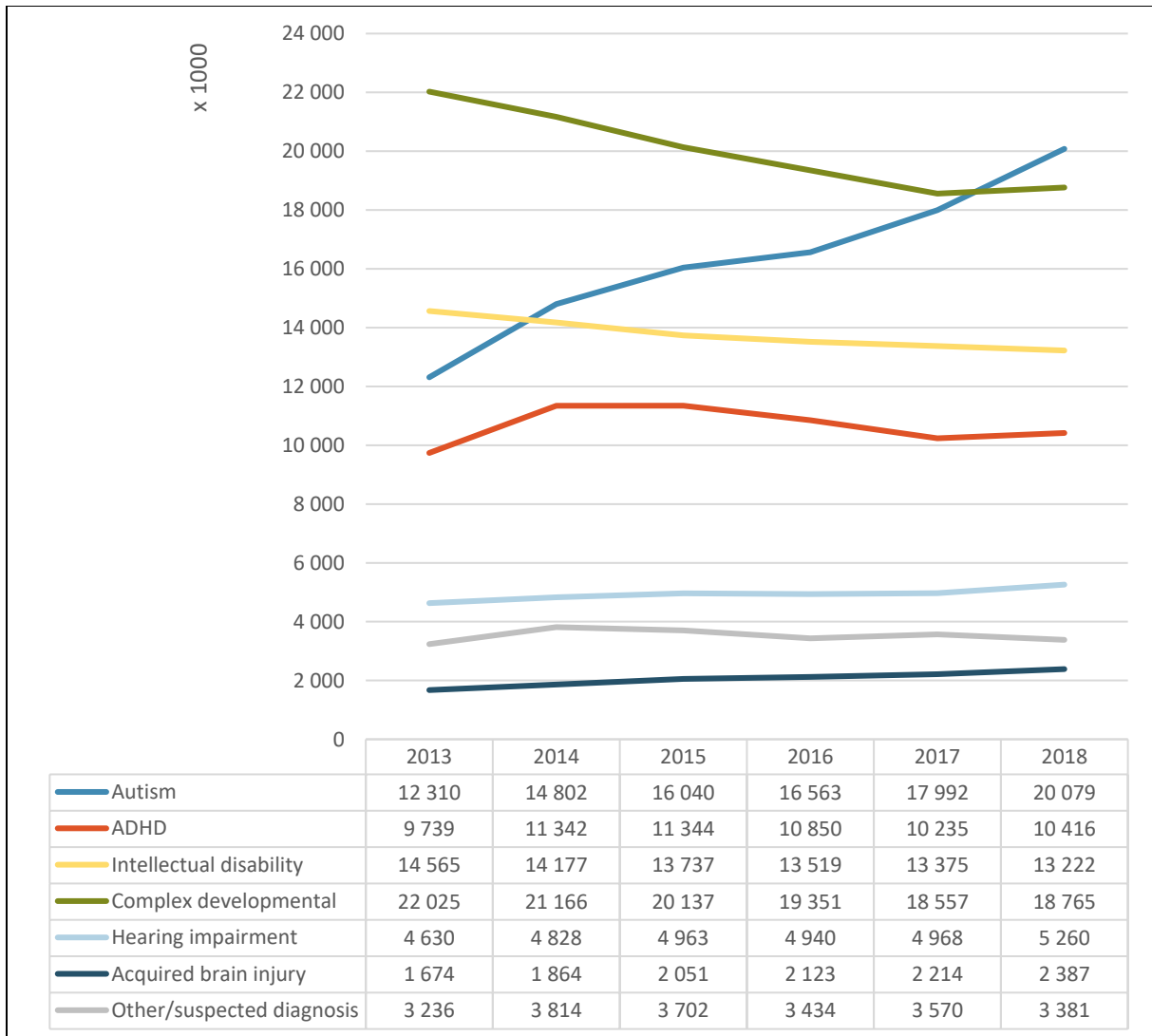


Figure 4.29 Evolution of total costs per diagnosis for all services provided by the Centers for Ambulatory Rehabilitation from 2013 to 2018 (NIHDI health insurance data).

From 2013 to 2018, total service costs for the target group of children and adolescents with autism in the Centers for Ambulatory Rehabilitation augmented with 63%. Over the same five-year time period, costs for complex developmental disorders and intellectual disability decreased with 15% and 9%, respectively. Also, rising costs were apparent for services to clients with Acquired Brain Injury (43% increase) and hearing impairment (14% increase).

## **4 Projection of future needs, service use, and costs in the Centers for Ambulatory Rehabilitation**

The incomplete, aggregated data presented in Section 3 of this chapter are not sufficient to construct a full explanatory, model for the Centers for Ambulatory Rehabilitation than can be used for projecting future needs, service use, and costs.

From the reported results, it is clear that the Centers for Ambulatory Rehabilitation are a typical example of actual service use reflecting supply restrictions rather than needs. The CAR are unequally spread over the Flemish Region and are mainly concentrated in East and West Flanders. However, this regional spread is historically grown rather than determined by a regional differentiation in needs. Despite the more or less stable trend in the number of people applying for treatment, waiting lists and waiting times to treatment increased between 2013 and 2018, suggesting insufficient capacity, especially in provinces with less coverage. As a result, the total number of clients in treatment hardly changed, but the importance of different target diagnoses shifted, with autism diagnoses increasing the most.

In order to shed some light on care needs independent of current service use, we searched for population prevalence data for two important diagnoses in the Ambulatory Centers for Rehabilitation: Autism Spectrum Disorder (ASD) and Attention-Deficit Hyperactivity Disorder (ADHD). However, the summary in Appendix 1 concerning both types of developmental disorders shows that reliable prevalence data for the Flemish population of children and adolescents are scarce and time series are not available. Moreover, national and international estimates vary greatly as a result of methodological differences, changing inclusion criteria and definitions, etc., making it difficult to interpret results and generalize findings.

### **4.1 Prediction models for service use in the Rehabilitation Centers for Addiction**

Notwithstanding the shortcomings of the aggregated service use data obtained from the CAR annual reports described in Section 3 of this chapter, as well as the prevalence data summarized in Appendix 1, a few simple regression models are listed in Appendix 4, with the total number of clients on waiting lists, waiting times per diagnosis (autism and ADHD/ADD), and clients receiving treatment on December 31 as dependent variables. Given the unequal spread of the Ambulatory Centers for Rehabilitation, province dummies are included as explanatory variables in every model. In addition, year dummies are added as a first step to investigate possible time trends.

Then, in a second step, time dummies are replaced by estimates of the population of children and adolescents in Flanders with autism or AD(H)D, using a general international meta-analysis estimate for ASD (MacKay, 2016) and ADHD (Polanczyk, 2008; 2014) and primary care registration estimates for ADHD in the Netherlands, reported by the NIVEL institute (Nielen, et al., 2021), however, given the short overlapping time series of three years (2016 to 2018), datasets are quite small for the latter estimates. Further details concerning all prevalence estimates are summarized in Appendix 1.

As expected from the description of service use in Section 3, province dummies produced significant effects in all models, whereas year dummies contributed to explaining the number of people on waiting lists, waiting times for autism and ADHD treatment, and the number of children and adolescents receiving treatment for autism on December 31, with all of these variables increasing with time. Obviously, this was not the case for the total number of active clients on December 31, given the lack of evolution in the total capacity of the Centers for Ambulatory Rehabilitation.



Inclusion of the international meta-analysis-based prevalence estimates reflecting the demographic evolution instead of the year dummies led to similar results, with increasing numbers in the population explaining increasing mean waiting times, increasing numbers of clients with autism and ADHD on waiting lists, and increasing numbers of active clients with autism. As the number of active clients with ADHD decreased with time, this variable is negatively related to the increasing ADHD prevalence estimates. However, given the increase of other diagnoses (mainly autism) and the constant insufficient capacity of the Centers for Ambulatory Rehabilitation, effects of increasing numbers of children and adolescents with ADHD in the population could never emerge in the presented regression models, again showing that service use data in a context of restricted supply cannot be used to project the future.



## Chapter 5

### The Rehabilitation Centers for Addiction

The Rehabilitation Centers for Addiction provide care to people with addiction problems. The main focus is on illegal substance and medication abuse, but clients with addiction to alcohol are treated as well. In Flanders, there are 11 organizations with a rehabilitation agreement, offering one or more types of addiction care programs in one or more locations throughout the Flemish Region. Program types roughly divide into ambulatory treatment, short-term in-patient treatment (mainly detoxification programs or crisis care), and long-term in-patient care.

Activities performed in the Rehabilitation Centers for Addiction are billed to the health insurance funds of the clients and were financed by the Federal Government through the National Institute for Health and Disability Insurance or NIHDI (Rijksinstituut voor ziekte- en invaliditeitsverzekering or RIZIV) until 2018. Since January 2019, financing was taken over by the Flemish Government.

Rehabilitation activities are registered in the IMA-health insurance database managed by the Inter-Mutualistic Agency (IMA) and in the European Treatment Demand Indicator (TDI) database, managed by the Belgian Health Institute Sciensano.

In this chapter, we describe the Rehabilitation Centers for Addiction in more detail, focusing on target group, objectives, and organizational structure (section 1), financing and costs (section 2), and available data concerning use and costs (section 3). Finally, in section 4 we present the first steps in an approach to projecting future needs, use and costs based on the information in the previous sections and external information.

#### 1 Target group, objectives, and organizational structure

The Rehabilitation Centers for Addiction are specialized rehabilitation facilities for drug treatment, with a clearly defined target group and a distinctive therapeutic approach. In this section, we discuss target group and objectives (1.1) and the organizational structure (1.2) of the Rehabilitation Centers for Addiction, mainly based on information of the [Flemish Agency for Care and Health](#) and the [Flemish Association of Treatment Centers for Addiction Care](#) (VVBV), the umbrella organization of all Rehabilitation Centers for Addiction.

##### 1.1 Target group and objectives

The target group of the Rehabilitation Centers for Addiction are adults and adolescents with addiction to – mostly illegal – psycho-active substances. All rehabilitation agreements explicitly list intended diagnoses in terms of the DSM-IV codes pertaining to specific substance dependence disorders, extended with codes for substance abuse disorders in case of low-threshold addiction care programs. Codes referring to alcohol dependence are not included in the listed diagnoses, but in several rehabilitation agreements it is stated that exceptionally, and if appropriate, the facility can also take in clients primarily addicted to alcohol. Although this statement is not included in every agreement, all centers do seem to treat some clients with alcohol registered as primary drug (according to TDI-registration, see Section 3: Data on service use and costs).

Most clients of the Rehabilitation Centers for Addiction are referred by the Belgian Justice Department or different care instances, such as hospitals, general practitioners, and other medical or psychosocial services. Even so, in many programs, clients presenting themselves or applying on the advice of family and friends are accepted as well.

The program starts with an intake or orientation phase, followed by the approval from the advisory physician of the clients' health insurance fund. When treatment is warranted, a treatment plan is drawn up, with treatment objectives specified. During treatment, evolution in light of the treatment plan is evaluated regularly in view of continuation, adjustment, or termination of treatment, with clients actively involved in the decision. In case of termination, the center helps clients search for appropriate follow-up at home or by other services.

In general, the ultimate objective of all programs in the Rehabilitation Centers for Addiction is to facilitate social reintegration of clients by helping them manage and overcome addiction problems in a defined period. This objective is translated into different program types and treatment methods depending on the specific needs of the client, and involving the clients' context when indicated.

Treatment in the Rehabilitation Centers for Addiction is offered by a multidisciplinary team of physicians, psychiatrists, psychologists, specialized educators, social workers, etc., as many clients with addiction problems suffer from additional medical or psychosocial problems as well.

Roughly program types in the Rehabilitation Centers for Addiction divide into three main categories: ambulatory programs, in-patient crisis or detoxification programs, and long-term therapeutic in-patient programs.

Interventions in ambulatory programs include medical, psychological, and social therapeutic or counselling sessions, family counselling, and group sessions or group activities. In addition, opioid substitution treatment may be provided. Part of ambulatory care is offered by the low-threshold Medical Social Day Care Centers (Medisch-sociale opvangcentra or MSOC). These centers are specifically aimed at drug users that are not or insufficiently reached by the other programs.

In-patient crisis or detoxification programs are reserved for clients in a serious medical, psychological or social crisis as a result of psycho-active substance use. The immediate goal is stabilization of the crisis situation, preferably combined with physical detoxification. The European Monitoring Centre for Drugs and Drug Addiction defines detoxification as a short-term medically supervised intervention aimed at the reduction and cessation of substance use, with support provided to alleviate withdrawal symptoms or other negative effects. (EMCDDA, 2021a). Crisis care programs are short-term programs, aimed at relatively rapid discharge, often with referral to appropriate ambulatory or in-patient addiction treatment follow-up programs in the same center.

In long-term in-patient programs, clients live in the treatment facility or therapeutic community for several weeks or months, with prior detoxification or abstinence from drug use as a prerequisite for entry. Psychosocial interventions, counselling programs, and activities in these programs are aimed at reintegration into society, without the need for further drug use.

## 1.2 Organizational structure

In January 2019, 13 conventions closed with 11 Flemish organizations recognized by NIHDI as Rehabilitation Centers for Toxicomania (NIHDI code 773), were taken over by the Agency for Care and Health of the Flemish Government, with modalities regarding target group, treatment programs, capacity, financing, staffing requirements, etc. written down in 13 new rehabilitation agreements.

In all Rehabilitation Centers for Addiction, multidisciplinary teams offer different types of ambulatory or in-patient programs at different locations throughout Flanders.

Five of these centers are Medical Social Day Care Centers (MSOC), providing low-threshold ambulatory care at different locations within each province:

- [MSOC Flemish Brabant](#), with four centers located in Leuven, Diest, Vilvoorde, and Tienen
- [Free Clinic MSOC Antwerp](#), with an additional antenna in Boom (in collaboration with other ambulatory Rehabilitation Centers for Addiction).
- [MSOC Ghent](#), with three additional antennas in Sint-Niklaas, Lokeren, and Zele
- [MSOC Ostend](#), with two additional antennas in Roeselare and Kortrijk
- [CAD MSOC Limburg](#) in Hasselt, Genk, and Tongeren, and six additional antennas throughout the province

The remaining six rehabilitation centers offer different programs of ambulatory and/or in-patient care. Ambulatory programs include day care centers and programs offering specialized ambulatory interventions. In-patient programs can be divided into short-term crisis care and long-term therapeutic programs.

- One center, [De Sleutel](#), has 3 separate rehabilitation agreements with the Flemish Government, concerning:
  - Ambulatory day care centers in three provinces, with facilities in the provinces of Antwerp (two locations), East Flanders, and West Flanders.
  - An in-patient crisis care center, a long-term care therapeutic community, and a long-term care therapeutic community for clients with a double diagnosis in East Flanders.
  - A specific care program for adolescents (12 to 18 years) in East Flanders
- Three rehabilitation centers, [De Kiem](#) (East Flanders), [De Spiegel](#) (Flemish Brabant), and [Kompas](#) (West Flanders) each consist of an ambulatory program, an in-patient crisis program, and a long-term therapeutic community program. In addition, De Kiem provides a small in-patient mother-child program.
- [Katarsis](#) in the province of Limburg only offers in-patient crisis and long-term therapeutic care. This means that in this province, all ambulatory services within the rehabilitation framework are provided by the MSOC.
- Finally, in Antwerp, [ADIC](#) has a rehabilitation agreement for short-term crisis care and long-term in-patient care. Both program types each consist of two programs, one of which is aimed at mothers, who are admitted with their child.

A 14<sup>th</sup> rehabilitation agreement will be made up with a new in-patient facility ['t Kader](#) in the region De Kempen in the province of Antwerp, which will start in 2021 and provide long-term treatment for clients with intellectual disabilities and short-term crisis care.

Some of the centers with rehabilitation agreements with the Flemish Agency for Care and Health, also provide additional programs financed by other instances, such as the federal Justice Department, local governments, etc. Apart from one specific short-term residential care program (by ADIC in Antwerp), these are all ambulatory programs, sometimes aimed at specific client groups. Examples are the Judicial

Alternative Measures Programs (GAM) in several centers, the ADIC ambulatory program, the Free Clinic PROject program for women and their children, the Kompas outreach program, etc.

The Rehabilitation Centers for Addiction have a long tradition of sectoral and intersectoral cooperation with other services (e.g. shared care with general practitioners for opioid substitution treatment, referral by the justice sector, follow-up by the welfare or employment sector, etc.) and are embedded in regional care networks, such as the care circuits in mental health care. Specific to addiction care, however, is that distancing clients from their home drug environment may be an important step in the recovery process. Therefore, clients should have the choice to seek treatment outside their regional care network as well (VVBV, 2019).

In addition to the Rehabilitation Centers for Addiction, important contributors to the care landscape for specialized addiction treatment include the Centers for Mental Health Care (CGG, see Chapter 2), as an alternative for ambulatory treatment, Units for Psychiatric Emergency Interventions (EPSI) and psychiatric wards (PAAZ) in general hospitals, mainly for crisis care, and psychiatric hospitals, offering crisis care and long-term treatment, sometimes followed by semi-residential or day-clinic after care (also see, [VAD, 2021a](#)).

In Section 3 of this chapter we provide more detailed information on the characteristics of target clients and the number of treatment episodes started in the different program types in the Rehabilitation Centers for Addiction and other facilities offering addiction treatment in the Flemish provinces, based on available data sources.

## **2 Financing and costs**

Yearly, the Rehabilitation Centers for Addiction realize around 150.000 addiction rehabilitation services for an estimated 10.000 clients (VVBV, 2019) and a total budget of approximately 28.000.000 Euro.

In ambulatory settings rehabilitation services are defined either in terms of treatment sessions or in terms of rehabilitation weeks (mostly MSOC). For services defined in terms of sessions, the reference category is a one-hour individual treatment session. Rehabilitation weeks consist of at least one individual session or two group sessions, with an additional minimum of three on-site administrations of substitution medication in case of opioid substitution treatment. Rehabilitation services defined in terms of sessions and in terms of weeks cannot be combined in the same week. Fees per rehabilitation week or session cover all operating costs of the facility, (personnel) costs for care and rehabilitation activities administered by the rehabilitation centers' staff, and costs for toxicological analyses performed on samples taken within the rehabilitation center. Costs for pharmaceutical products are generally not included and reimbursed separately. All included and excluded costs are specified in the [rehabilitation agreements](#) with the centers (Agentschap Zorg en Gezondheid, 2021). In specific cases, reimbursement for travelling costs to the ambulatory facilities is provided as well.

In in-patient settings rehabilitation services are defined in terms of stay-days in the rehabilitation facility, with the different rehabilitation agreements specifying costs included in the total fee per day. In general operating-costs of the facility and most provisions (stay-costs, diagnostics, addiction interventions, pharmaceutical products, etc.) are covered.

As part of the multidisciplinary team in the Rehabilitation Centers for Addiction, medical doctors and psychiatrists receive a fixed salary instead of being compensated based on performance (individual consultations).

In all centers with rehabilitation agreements, the third-party payment system is applied. At present, client contributions are limited to 1,88 Euro per session or per week in ambulatory settings and 16,57 Euro per day in in-patient settings. For clients with enhanced reimbursement status (e.g. due to low income), ambulatory treatment is free and in-patient treatment amounts to 5,89 Euro per day.

For the additional costs associated with performed rehabilitation services, the Rehabilitation Centers for Addiction apply for financial compensation to the health insurance funds of their clients. The Agency for Care and Health of the Flemish Government is responsible for calculating the financial compensations since January 2019 only. Even so, fees, billing capacity and rules for indexation haven't changed from the years before under federal government responsibility and continue to be based on real annual costs (e.g. personnel costs, operating costs, investment costs, costs for activities). The amount of the financial compensation is contractually established in annexes to the individual rehabilitation agreements with the Flemish Government. Separate Flemish subsidies that were granted to the Rehabilitation Centers for Addiction before 2019 are since then included in this amount.

The normal billing capacity with a 100% coverage of costs is set at 90% of the realizable capacity of the facility. In case of exceedance of normal billing capacity to a maximum of 98% of the realizable capacity, 50% or 25% of costs are covered, depending on the realized capacity or occupancy rate in previous years (with exceedance of 94% in previous years leading to 25% coverage). On the one hand, financing is negatively impacted when the normal 90% billing capacity is not attained (e.g. due to temporary therapeutically indicated absence of clients throughout treatment episodes), making centers inclined to assure sufficient coverage of personnel and other costs by exceeding their capacity. On the other hand, financial compensation from the health insurance funds is not available and client contributions are not permitted when occupancy rates exceed the maximum billing capacity of 98%, which is sometimes reached towards the end of the year by some centers. (Pauwelyn, 2016). However, facilities may still bill care for clients without health insurance status to other instances, but are not allowed to exceed the realizable capacity of the facility as a result of this.

In addition to the Flemish Government financing, some of the Rehabilitation Centers for Addiction offer additional programs, funded by other instances, such as local governments or the federal Justice Department. Moreover, the MSOC are co-financed by the federal Home Affairs Department, with the realizable capacity depending on both the Flemish and federal financial sources. As a result, only two thirds of all personnel costs in the Rehabilitation Centers for Addiction are covered by the Flemish financing through the Agency for Care and Health (VVBV, 2019), with the remaining third funded by the other instances mentioned above, project subsidies, and as part of employment programs.

### 3 Data on service use and costs in the Rehabilitation Centers for Addiction

In the first paragraph of this section, we present the available data sources containing information on the activities of the Rehabilitation Centers for Addiction. In the next two paragraphs, we describe current service use (3.2) and costs (3.3), based on these data sources.

#### 3.1 Data sources

All rehabilitation facilities register clients and rehabilitation services daily and have to keep these data available. In addition, an annual report and a detailed personnel overview must be sent to the Agency for Care and Health each year. However, all this information is not consolidated into readily available electronic databases.

This means that, at present, we found only two data sources containing relevant information on use and costs in the Rehabilitation Centers for Addiction: The health insurance data (3.1.1) and the data registered for the European Treatment Demand Indicator (3.1.2).

##### 3.1.1 Health insurance data

The Inter-Mutualistic Agency (IMA) manages the data collected by all health insurance funds in Belgium. With respect to care in the Rehabilitation Centers for Addiction, a limited number of specific pseudo-nomenclature codes are utilized and registered in the IMA-database. In addition, codes referring to medication for substitution treatment based on Methadone are available.

The specific pseudo-nomenclature codes for the Rehabilitation Centers for Addiction are quite general and provide information on the number and cost of rehabilitation services per client per setting (ambulant or in-patient). These nomenclature codes changed in 2020, as a result of the responsibility transfer from the federal to the Flemish Government in 2019.

Table 5.1 Rehabilitation Centers for Addiction pseudo-nomenclature codes

NIHDI-codes (until 01/2020)	Flemish codes (from 02/2020)	
772074 / 772085	251174 / 251185	Addiction rehabilitation services (ambulant/in-patient): normal rehabilitation fee (i.e. within normal billing capacity; 100%)
775515 / 775526	253996 / 254007	Addiction rehabilitation services (ambulant/in-patient): reduced rate (50% or 25%), in case of exceedance of normal billing capacity
783915 / 783926	/	Addiction rehabilitation services (ambulant/in-patient): catch-up fees (regularizations)

As mentioned in the financing and costs section above, rehabilitation services in ambulatory settings are defined either in terms of rehabilitation weeks or individual rehabilitation or treatment sessions. Services in in-patient settings are defined in terms of stay-days.

In theory, the permanent sample (EPS) from the IMA-database contains the information described above, as well as information on substitution treatment medication. However, due to the limited number of relevant cases in the EPS, extrapolation to the entire client population of the Rehabilitation Centers for



Addiction would not be reliable, as Table 5.2 and 5.3 illustrate for the years between 2013 and 2017. The tables give an overview of the number of unique clients for ambulatory and in-patient addiction rehabilitation programs in the EPS and an estimation of the total number of clients and services in the Flemish population aged 15 to 64 years, using general weights for the whole group. The resulting EPS-based estimated number of services is then compared to the actual total number of services registered by the National Institute for Health and Disability Insurance (NIHDI).

Table 5.2 The number of unique clients and the total number of services in ambulatory Rehabilitation Centers for Addiction in the EPS-database, with a comparison of extrapolated population estimates to the total number of services registered by NIHDI from 2013 to 2017.

<i>Code 772074+775515 (ambulatory)</i>	<b>2013</b>	<b>2014</b>	<b>2015</b>	<b>2016</b>	<b>2017</b>
EPS unique clients	72	75	78	77	77
EPS unique clients extrapolated	2926	3052	3175	3132	3138
EPS services	997	977	912	1088	946
EPS services extrapolated	40516	39754	37118	44254	38553
NIHDI services	88643	85511	83747	91766	84729
<b>% EPS extrapolated/NIHDI</b>	<b>46%</b>	<b>46%</b>	<b>44%</b>	<b>48%</b>	<b>46%</b>

Table 5.3 The number of unique clients and the total number of services in in-patient Rehabilitation Centers for Addiction in the EPS-database with a comparison of extrapolated population estimates to the total number of services registered by NIHDI from 2013 to 2017.

<i>Code 772085+775526 (in-patient)</i>	<b>2013</b>	<b>2014</b>	<b>2015</b>	<b>2016</b>	<b>2017</b>
EPS unique clients	15	14	15	17	16
EPS unique clients extrapolated	610	570	611	691	652
EPS services (days)	1345	1307	962	1491	1199
EPS services extrapolated	54659	53182	39153	60646	48863
NIHDI services (days)	62593	66932	65871	61052	65017
<b>% EPS extrapolated/NIHDI</b>	<b>87%</b>	<b>79%</b>	<b>59%</b>	<b>99%</b>	<b>75%</b>

For ambulatory addiction care, the number of services is clearly underestimated when extrapolating from the EPS-database. Percentages are higher for in-patient services, but given the low number of unique clients in the database, combined with the considerable variability in the number of stay-days per client (from 1 day to 355 days in the present sample), the extrapolated numbers cannot be considered reliable estimates either. It is noteworthy that all clients with in-patient nomenclature codes in the EPS, were also registered for ambulatory services. The substitution treatment medication nomenclature code was present for one client only in the EPS in the five-year period between 2013 and 2018.

Given that the complete IMA-database was not available and the representativeness of the permanent sample is considered insufficient, reported health insurance data in the remainder of this section are limited to an aggregated overview of the number of cases and costs per nomenclature code per year, obtained from the National Institute for Health and Disability Insurance (NIHDI).

### 3.1.2 TDI-register

The Belgian TDI-registration collects information on the number and characteristics of clients with drug addiction problems entering into specialized treatment programs and facilities. The TDI or Treatment Demand Indicator is one of five key epidemiological indicators, used by the [EMCDDA](#) (European Monitoring Centre for Drugs and Drug Addiction) for monitoring the European drug situation. In Flanders, data were collected since 1988, but standardized registration started only in 2011, with Sciensano becoming responsible for the Belgian TDI-register. The most recent update to the registration protocol was used from 2015. In addition to the Rehabilitation Centers for Addiction, the TDI-register includes data from other facilities involved in addiction treatment, such as the Centers for Mental Health Care (mandatory since 2013) and hospitals (mandatory since 2015).

The TDI-register consists of individual client records, limited to newly started treatment episodes. The end of a treatment episode is defined as an interruption of face-to-face contact for a minimum of six months in the case of ambulatory treatment or discharge with no further admissions planned in the case of residential treatment. Repeated ambulatory treatment episodes in the same treatment program within six months are registered only once at the first face-to-face contact even when extending over several years. In other words, episodes that started in previous years are not counted again.

To count unique clients and keep track of clients over different episodes or different treatment programs and centers, the national insurance number of clients is registered. However, according to a recent Sciensano report (Antoine, 2019), around 20% of episodes involve unknown clients, due to their right to insist on anonymous registration. This overall percentage largely remained constant between 2015 and 2019 for Belgium as a whole, but varies between regions. For example, in 2018 approximately 15% of registrations in Flanders were anonymous, as compared to 29% in the Walloon Region and 35% in Brussels. Also, within Flanders, percentages varied from 6% in Flemish Brabant, 9% in West Flanders and 13% in East Flanders to 26% in Antwerp and 28% in Limburg. In addition, anonymous registration depends on the type of service as well, with a mere 4% in crisis care up to 13% in long-term in-patient care, 15% in day care centers and 37% in other ambulatory programs. Anonymous episodes are counted as separate clients, which may lead to an overestimation of the number of clients.

Table 5.4 provides an overview of potentially relevant use variables in the TDI-database. The database mainly contains socio-economical and epidemiological client variables. Treatment characteristics, such as waiting time, duration of treatment, number of sessions, treatment results, etc. are not included, apart from a limited number of variables pertaining to treatment antecedents. Living distance from the treatment center is also listed, but is not consistently registered by every center.

Table 5.4 Treatment Demand Indicator variables (Sciensano)

Variables	Values / clarification
<b>Program description</b>	
Center name/ID	
Program name/ID	
Program type	Values: <ul style="list-style-type: none"> <li>• Outpatient, low-threshold</li> <li>• Outpatient, specialized day center</li> <li>• Outpatient, specialized consultations</li> <li>• Outpatient, center for mental health care</li> </ul>

Variables	Values / clarification
	<ul style="list-style-type: none"> <li>• Outpatient, other</li> <li>• Inpatient, low-threshold</li> <li>• Inpatient, crisis unit</li> <li>• Inpatient, treatment program/therapeutic community</li> <li>• Inpatient, psychiatric hospital</li> <li>• Inpatient, psychiatric unit in a general hospital</li> <li>• Inpatient, general hospital</li> <li>• Inpatient, other</li> </ul>
Location variables	Variables: Region, province, district
<b>Client description (socio-economical)</b>	
Client national number	Clarification: Recommended, but anonymous registration allowed
Client NIHDI number	
Nationality	
Client gender	
Client age (category)	
Client living situation (Where?)	Values: Stable accommodation, unstable accommodation, homeless, institution, prison, other, unknown
Client living situation (With whom?)	Values: Alone, with partner, parents, other relative, friends or other persons, other, unknown
Client living situation (With children?)	Values: Yes, no, unknown
Education level	Values: No, primary, secondary, higher, other, unknown
Work status	Values: Regularly employed, occasionally employed, unemployed, student, disabled, homemaker, pensioner, other, unknown
Income status	Values: Salary, unemployment benefit, pension, sickness-disability benefit, living wage, child benefit, student scholarship, no income, other, unknown
<b>Client description (epidemiological, addiction profile)</b>	
Problem drug variables	Variables: Opioids, cocaine, other stimulants, hypnotics/sedatives, hallucinogens, volatile inhalants, cannabis, alcohol, other problem substance + specific opioids, types of cocaine, stimulants, hypnotics/sedatives, hallucinogens, types of cannabis (see primary drug) Values: Yes, no, unknown
Primary drug	Values: Not applicable, opioid category, heroin, methadone misused, buprenorphine misused, fentanyl misused, other opioids, cocaine category, powder cocaine, crack cocaine, other cocaine, stimulants other than cocaine category, amphetamines, methamphetamines, MDMA or derivatives, mephedrone, other stimulants, hypnotics/sedatives category, barbiturates misused, benzodiazepines misused, GHB/GBL, other hypnotics/sedatives misused, hallucinogens category, LSD, ketamine, other hallucinogens, volatile inhalants, cannabis category, marijuana, hash, other cannabis, alcohol, other substance Clarification: One answer allowed, with category answer used when the specific primary drug is unknown.
Other addiction profile variables	Primary drug route of administration, Primary drug use frequency, Age first primary drug use, Injecting status, Age first injection, last injection

Variables	Values / clarification
<b>(Previous) treatment description</b>	
Referral	Values: Self-referral, referral from family, friends, general practitioner, other drug treatment center, hospital, other medical/psychosocial service, court, other, unknown
Previous treatment	Values: Yes, no, unknown
Previous substitution treatment	Values: Yes, no, unknown
Previous substitution treatment variables	Variables: Methadone treatment, buprenorphine treatment, other opioids treatment, other substitution treatment
Age (category) first substitution treatment	
Treatment start date	
Diagnostic	Values: Intoxication, misuse, addiction, other, unknown
Treatment objective	Values: No objective, stabilization of consumption, substitution treatment, reduction of consumption, withdrawal, other, unknown
Distance to treatment center	From domicile to treatment centers (in km). Registration is not mandatory.

Apart from the Sciensano reports describing all addiction treatment programs in Belgium, analyses on the TDI-data are also performed by the VAD (Flemish Center of Expertise on Alcohol and Other Drugs), resulting in factsheets concerning the Flemish programs only (VAD, 2021b) and by the umbrella organization of all Rehabilitation Centers for Addiction (VVBV), resulting in periodic overviews limited to data from the rehabilitation centers only (e.g. Van Deun, 2015; 2016;2017; 2019).

The individual records TDI-database was not available for this project. Therefore, the description of service use in the Rehabilitation Centers for Addiction in the next paragraph of this section, is based on the analysis of aggregated data per rehabilitation program per center, derived from the TDI-database and provided by Sciensano.

### 3.2 Description of service use in the Rehabilitation Centers for Addiction

We first describe the overall use of services in the Rehabilitation Centers for Addiction (3.2.1) and the use of specific services (3.2.2), with a comparison to other services in the Flemish Region (3.2.3). Next, we focus on use per province (3.2.4) and client characteristics (3.2.5).

#### 3.2.1 Overall use of the Rehabilitation Centers for Addiction

As mentioned above, due to the limited number of relevant cases in the EPS of the IMA-database, health insurance data regarding drug addiction related rehabilitation services, could not be analyzed in detail for this report. However, from the National Institute for Health and Disability Insurance (NIHDI) we obtained an aggregated overview of the number of cases per nomenclature code per year. Figure 5.1 summarizes these data, comparing ambulatory services (in terms of sessions or weeks) to in-patient services (in terms of stay-days). Cases with nomenclature codes for regularizations (catch-up fees) are not considered, as

these codes may not actually refer to separate care services for the clients in question or refer to the year in which they were listed.

The figure shows that the total number of in-patient rehabilitation services billed to the health insurance funds remained rather constant from 2008 to 2017, with fluctuations in certain years, but no general increasing or decreasing trends. For the ambulatory rehabilitation services, however, there were noticeable peaks in 2012 and 2016, each time followed by a decrease, but on a higher level than before 2012.

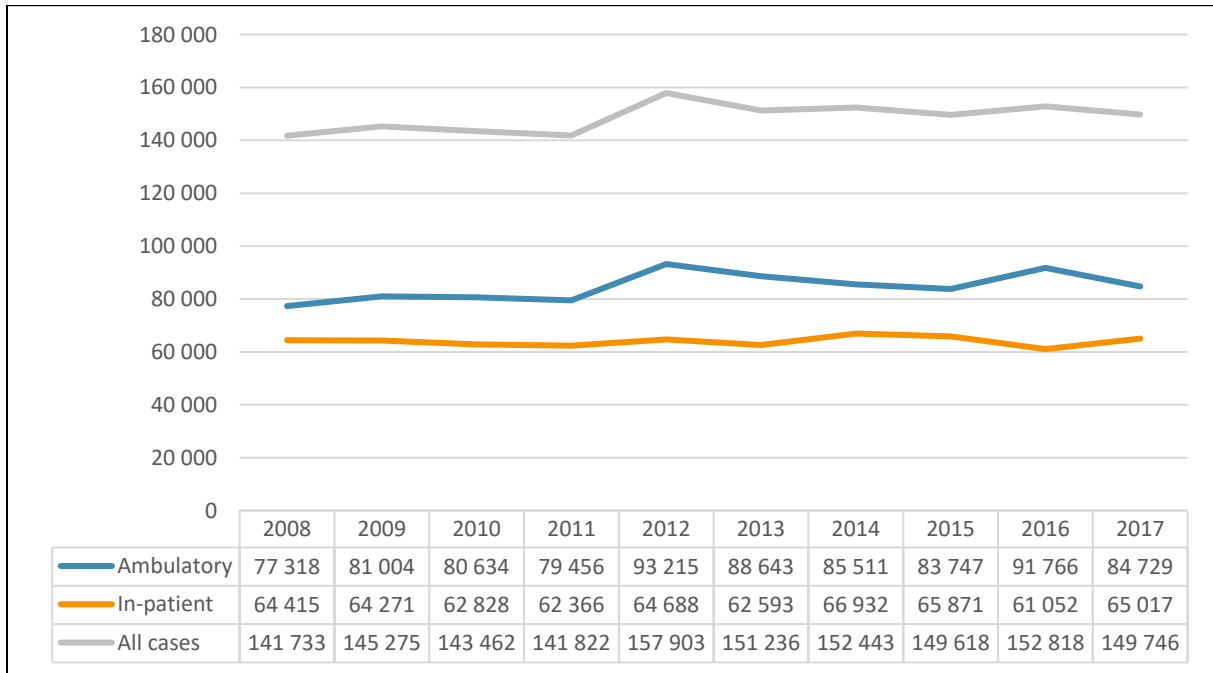


Figure 5.1 Evolution of ambulatory and in-patient rehabilitation services provided by the Rehabilitation Centers for Addiction from 2008 to 2017 (NIHDI health insurance data).

In Figure 5.2 below, we compare the number of services billed at the normal 100% rate with services billed at a reduced rate (50 or 25%) as a result of exceeding 90% of the realizable capacity.

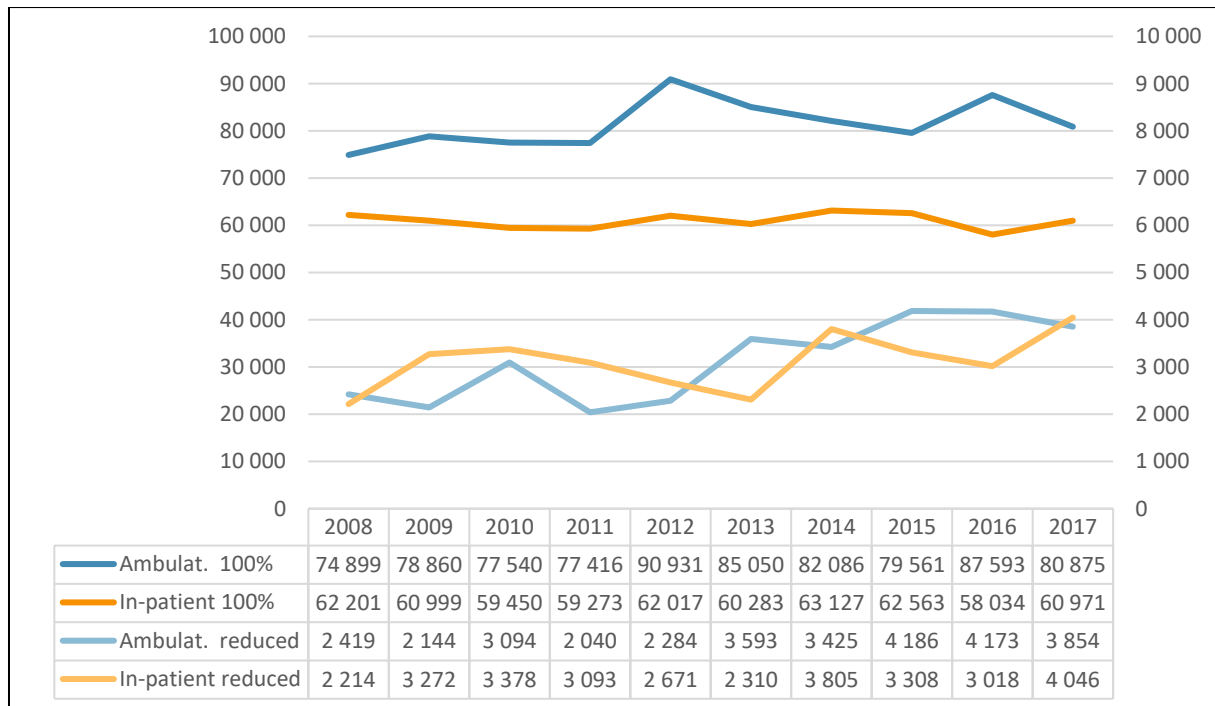


Figure 5.2 Evolution of ambulatory and in-patient rehabilitation services provided by the Rehabilitation Centers for Addiction from 2008 to 2017, by nomenclature code referring to the normal 100% or reduced fee (NIHDI health insurance data).

The figure shows that the peaks in ambulatory services in 2012 and 2016 are especially visible in the evolution of services billed at 100% (i.e. within 90% of the realizable capacity). Although there were capacity enhancements in ambulatory programs in 2009 and 2010 (Van Deun, 2012), since then capacity largely remained constant (Van Deun, 2014). Fluctuations and peaks following 2011 should thus be the result of other factors, with some centers billing less than 90% of their realizable capacity in certain years as an obvious one.

Billing less than 90% doesn't necessarily mean that supply was sufficient in the catchment area of the centers, but may have several reasons, such as clients cancelling or missing appointments, the proportion of treatment sessions for clients financed by other instances (e.g. clients with no health insurance status), or temporary therapeutically indicated absences during the course of treatment (in in-patient programs). Moreover, the occurrence of services billed at a reduced rate in every year indicates that at least some centers regularly exceed normal billing capacity as well. The number of reduced rate cases also seemed to increase slightly over the years, suggesting that facilities were more and more likely to exceed 90% of their realizable capacity.

When comparing delivered services according to the NIHDI health insurance data with newly started treatment episodes and clients according to the TDI-register (Figure 5.3), the latter data seem to show a more obvious increasing trend since 2011 than the NIHDI data, with peaks in 2013, 2015, and 2017.

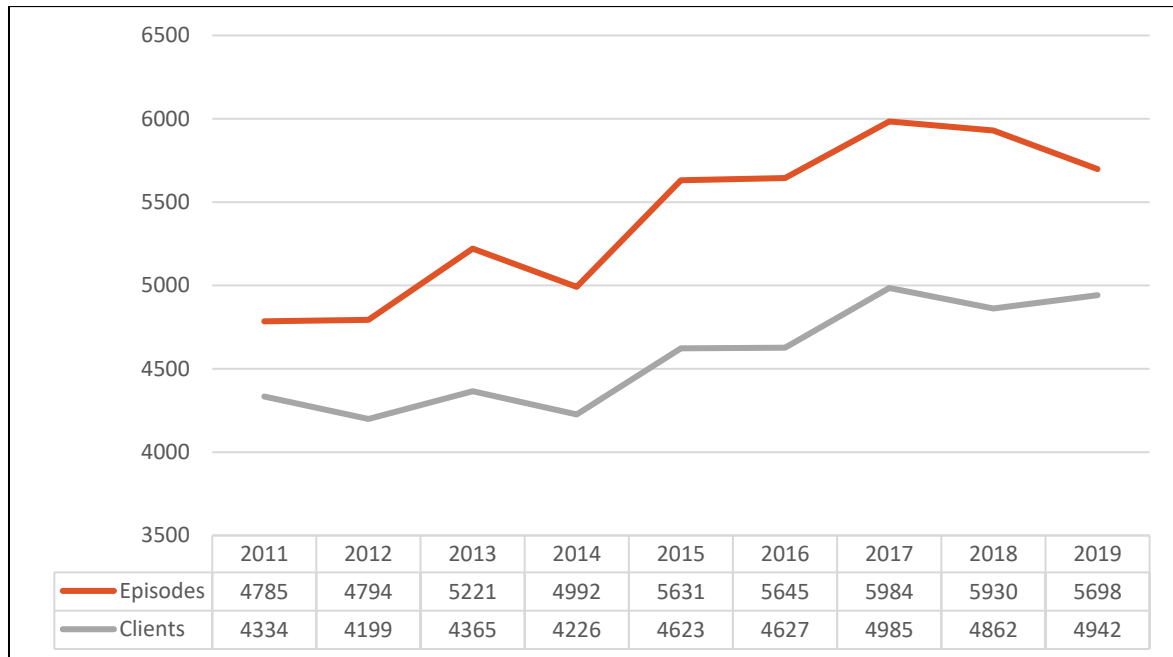


Figure 5.3 Evolution of newly started treatment episodes and clients in the Rehabilitation Centers for Addiction from 2011 to 2019 (Sciensano, TDI aggregated data)

However, the largest increase in the number of new clients and episodes in 2015, does not reflect an actual capacity enhancement, but is the result of the first-time inclusion into the TDI-dataset of existing alternatively financed services offered by the Rehabilitation Centers for Addiction (e.g. treatment programs financed by local governments or Judicial Alternative Measures Programs financed by the Justice Department). Before 2015 only services falling within NIHDI-financing were registered (Van Deun, 2015). The increase in the number of clients and episodes in 2017 was due to the same reason, when a few smaller alternatively financed programs added to the dataset.

It is not clear what happened in 2013, though, with the number of episodes increasing relatively more than the number of clients. This enlarged difference between the number of episodes and the number of clients may partly be due to registration particularities. In general, the number of clients is less reliable than the number of episodes, and even more so in the earlier years of registration with certain centers registering anonymously altogether, often due to technical problems.

Given the above considerations, we will mostly use episodes data from the NIHDI/Flemish Government financed programs only when describing service use in the Rehabilitation Centers for Addiction, thereby allowing for better comparison with the NIHDI health insurance data and ensuring more reliable time trend descriptions.

Figure 5.4 shows the evolution of newly started episodes for all NIHDI/Flemish Government financed programs and for ambulatory and in-patient programs separately. The figure shows a limited increase of episodes between 2011 and 2017, suggesting that the increase of episodes in all programs as shown in Figure 5.3 was not exclusively attributable to the addition of alternatively financed programs into the TDI-dataset. Ambulatory episodes were almost entirely responsible for the observed increase, seeing that the number of newly started in-patient episodes decreased slightly from 2013 onwards, with the lowest number of new intakes in 2019.

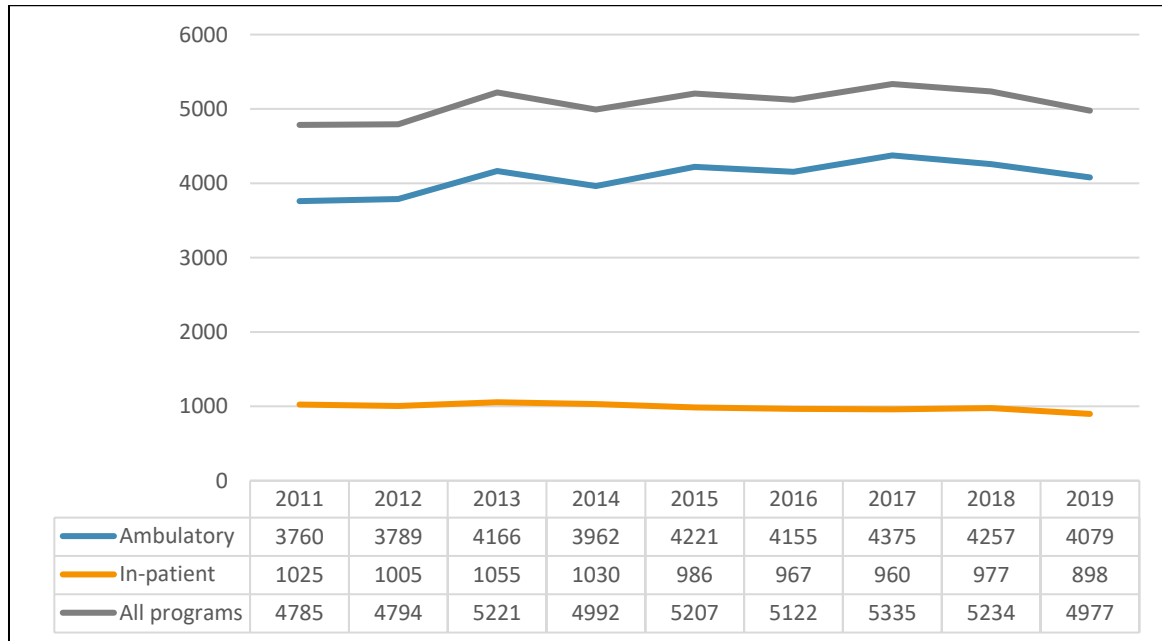


Figure 5.3 Evolution of newly started ambulatory and in-patient episodes in NIHDI (2011-2018) or Flemish Government (2019) financed programs in the Rehabilitation Centers for Addiction (Sciensano, TDI aggregated data)



As a rough approximation to understanding the evolution of newly started episodes (i.e. first services in a treatment episode) in NIHDI-financed programs in relation to all delivered services, we compared the TDI year totals to the NIHDI health insurance data in Figure 5.5.

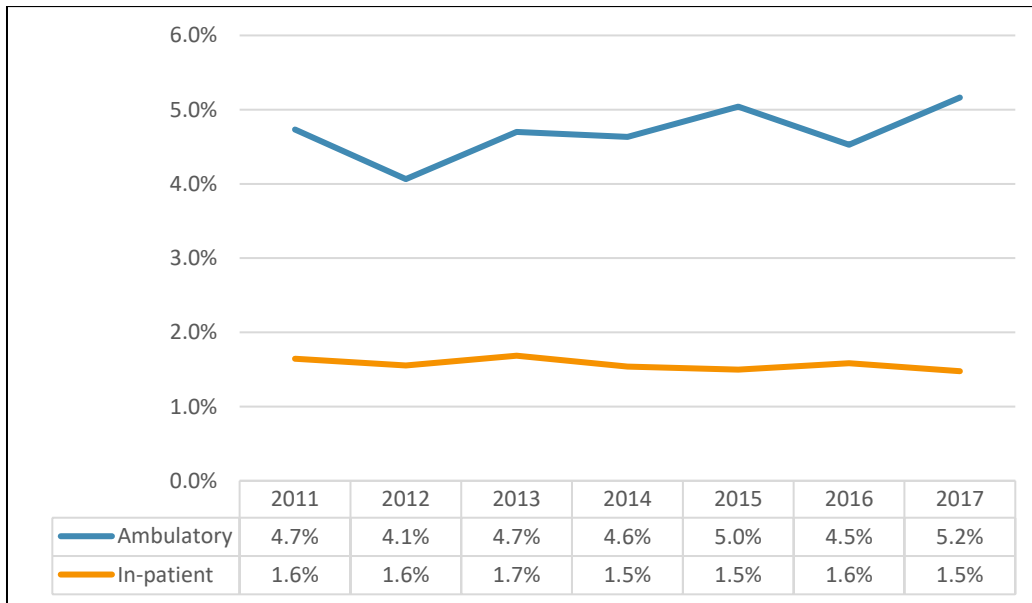


Figure 5.4 Proportion of first ambulatory and in-patient services in a treatment episode (Sciensano, TDI aggregated data) in relation to all rehabilitation services (NIHDI health insurance data) in the Rehabilitation Centers for Addiction from 2011 to 2019 (NIHDI/Flemish Government financed program only).

The figure shows there was a slight increase in the proportion of first services in ambulatory episodes in relation to all delivered ambulatory services between 2011 and 2017, whereas for in-patient programs, if anything, the reverse was true. In other words, more ambulatory episodes were initiated in comparison to ongoing episodes, while personnel and treatment capacity remained constant. This suggests a reduction in treatment duration, which may be the result of several factors, such as the pressure of waiting lists due to an increased demand, changing treatment approaches or client profiles, etc. However, in view of lacking readily available data sources with respect to treatment duration and waiting lists, these hypotheses cannot be corroborated at this time.

### 3.2.2 Use of specific rehabilitation services in the Rehabilitation Centers for Addiction

As explained in the first section of this chapter, rehabilitation programs offered by the Rehabilitation Centers for Addiction can be divided roughly into different types: ambulatory MSOC, ambulatory day care centers or specialized consultations, short-term in-patient crisis programs, and long-term in-patient programs. In the figure below, we compare newly started episodes in different program types, financed by NIHDI (until 2018) or the Flemish Government (2019).

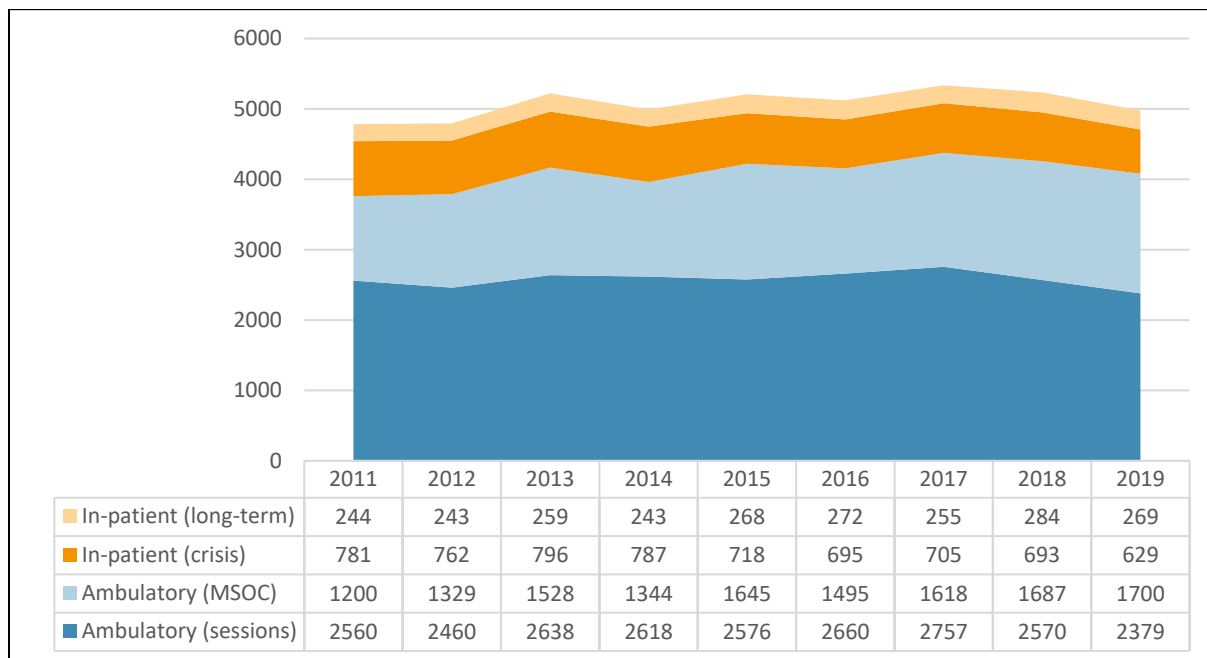


Figure 5.5 Evolution of newly started episodes in the Rehabilitation Centers for Addiction from 2011 to 2019 by program type (NIHDI/Flemish Government financed programs only; Sciensano, TDI aggregated data)

Slightly more than one third of new ambulatory episodes were offered in the MSOC, whereas the other two thirds took place in specialized consultations and day care centers. This doesn't necessarily mean that the total capacity in the MSOC was only half of the total capacity in the other ambulatory centers. According to VVBV, the umbrella organization of the rehabilitation centers (Van Deun, 2014), relatively more clients receive long-term continuous treatment in the MSOC compared to other ambulatory programs, leading to a smaller proportion of newly started in comparison to ongoing episodes.

In the ambulatory MSOC centers there was a gradual increase of newly started episodes with time, resulting in 500 more episodes in 2019 than in 2011. In the other ambulatory programs 2017 showed the highest number of new episodes, followed by a decrease in 2018 and 2019. Closer inspection of the data per center shows that this recent decrease almost exclusively reflected the decrease in one large rehabilitation center.

The number of new episodes in long-term in-patient care programs (mainly therapeutic communities) showed limited fluctuation over time. In short-term in-patient crisis care programs (mainly detoxification treatment), the number of new episodes seemed to decrease somewhat in recent years. Typically, the proportion of newly started as compared to ongoing episodes is larger in crisis care than in other care programs.

As mentioned above, both ambulatory sessions programs and in-patient crisis care programs financed by the NIHDI/ Flemish Government are complemented by alternatively financed programs. Table 5.5 shows the number of newly started episodes in these programs between 2015 and 2019, with three additional ambulatory programs included from 2017 onwards.

Table 5.5 Evolution of newly started episodes in alternatively financed programs offered by the Rehabilitation Centers for Addiction from 2015 to 2019 (Sciensano, TDI aggregated data)

<b>Alternatively financed programs</b>	<b>2015</b>	<b>2016</b>	<b>2017</b>	<b>2018</b>	<b>2019</b>
Ambulatory (sessions)	139	202	345	385	415
In-patient (crisis)	285	321	304	311	306

In the next paragraph, we compare all programs in the Rehabilitation Centers for Addiction with other ambulatory (mainly CGG) or in-patient (mainly psychiatric hospitals) drug addiction treatment programs.

### 3.2.3 Comparison with use of other services in the Flemish Region

In addition to the Rehabilitation Centers for Addiction, other services in Flanders provide addiction treatment as well. Ambulatory care is available in the Centers for Mental Health Care (CGG) and in two psychiatric day hospitals with very limited treatment capacity. In-patient care is available in psychiatric hospitals and in (psychiatric wards) in general hospitals. In both the CGG and hospital care, the focus is slightly different than in the Rehabilitation Centers for Addiction: All substance dependencies are treated, but alcohol addiction is most prominent in CGG and hospital clients (see Section 3.2.4 for characteristics of service users).

Figures 5.7 and 5.8 show the number of ambulatory treatment episodes in the Rehabilitation Centers for Addiction in comparison with the other ambulatory and in-patient addiction treatment services in Flanders. Services are compared from 2015 onwards, with most ambulatory treatment programs included in the TDI-register and mandatory registration for hospitals starting in that year.

Approximately 70% of new ambulatory addiction treatment episodes were offered by the Rehabilitation Centers for Addiction. The Centers for Mental Health Care accounted for almost 30% of newly started episodes, and psychiatric day hospitals for less than 1%. Whereas new ambulatory episodes increased slightly in the Rehabilitation Centers, with approximately 3% more registered episodes in 2019 than in 2015, there was a noticeable decrease in the CGG in the same period. The latter finding is in line with the decline in substance-related diagnoses and addiction as registered intake problem in the electronic patient files of the CGG (see Figure 2.34 in Chapter 2).

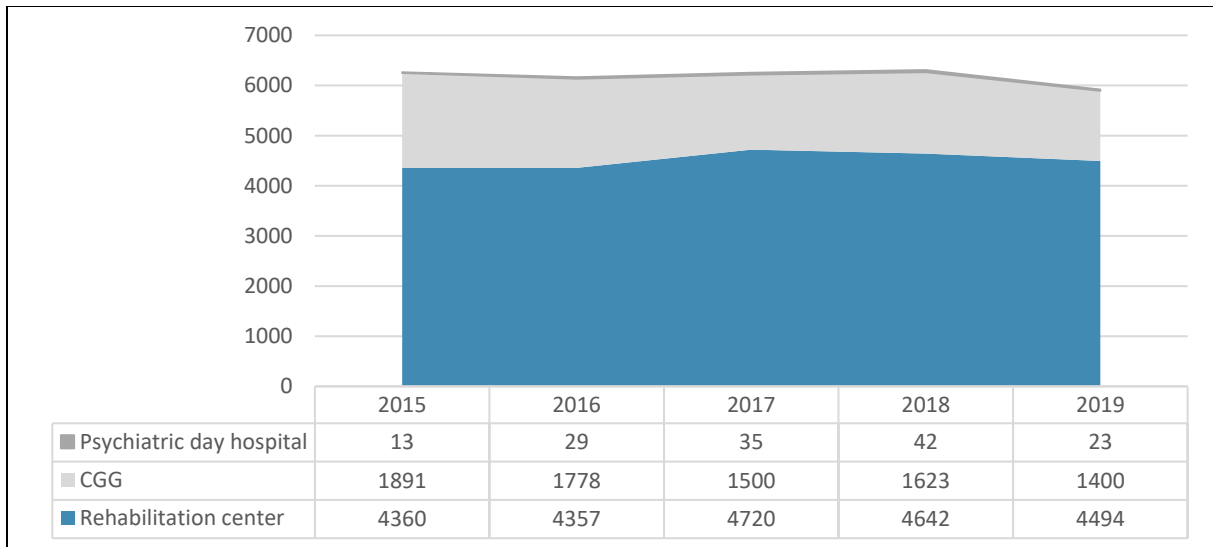


Figure 5.6 Evolution of newly started ambulatory addiction treatment episodes in the Flemish Region from 2013 to 2019, by service type (TDI aggregated data).

Contrary to ambulatory treatment, in-patient addiction treatment predominately took place in psychiatric hospitals and (psychiatric wards in) general hospitals, with the Rehabilitation Centers for Addiction accounting for an approximate 10% of all newly started episodes between 2015 and 2019.

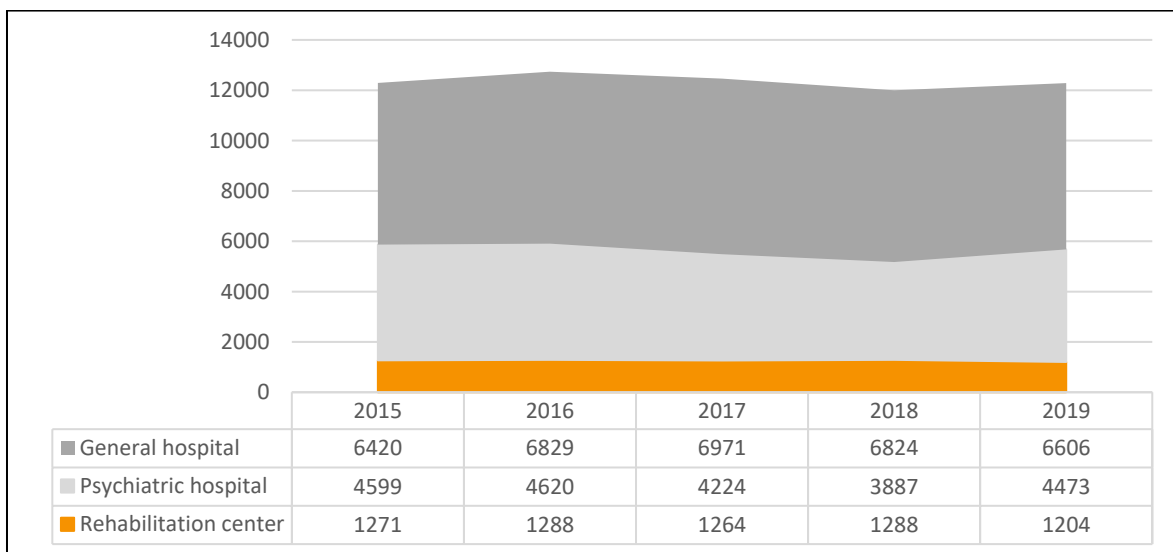


Figure 5.7 Evolution of newly started in-patient addiction treatment episodes in the Flemish Region from 2015 to 2019, by service type (Sciensano, TDI aggregated data).

### 3.2.4 Use of Rehabilitation Centers for Addiction per province

In this paragraph we focus on regional differences in the overall use of addiction rehabilitation services by comparing newly started episodes in the Flemish provinces. Figure 5.9 shows the aggregated number of all new episodes started between 2011 and 2019 in the different program types of the Rehabilitation Centers for Addiction per province. For the category of ambulatory programs in day centers and specialized sessions, almost 70% of province data are unknown, referring to episodes offered by one large rehabilitation center, spread over four day centers in three provinces: one in East and West Flanders and two in Antwerp. Since data in the TDI-register are aggregated over provinces for this center, total numbers per province cannot be obtained.

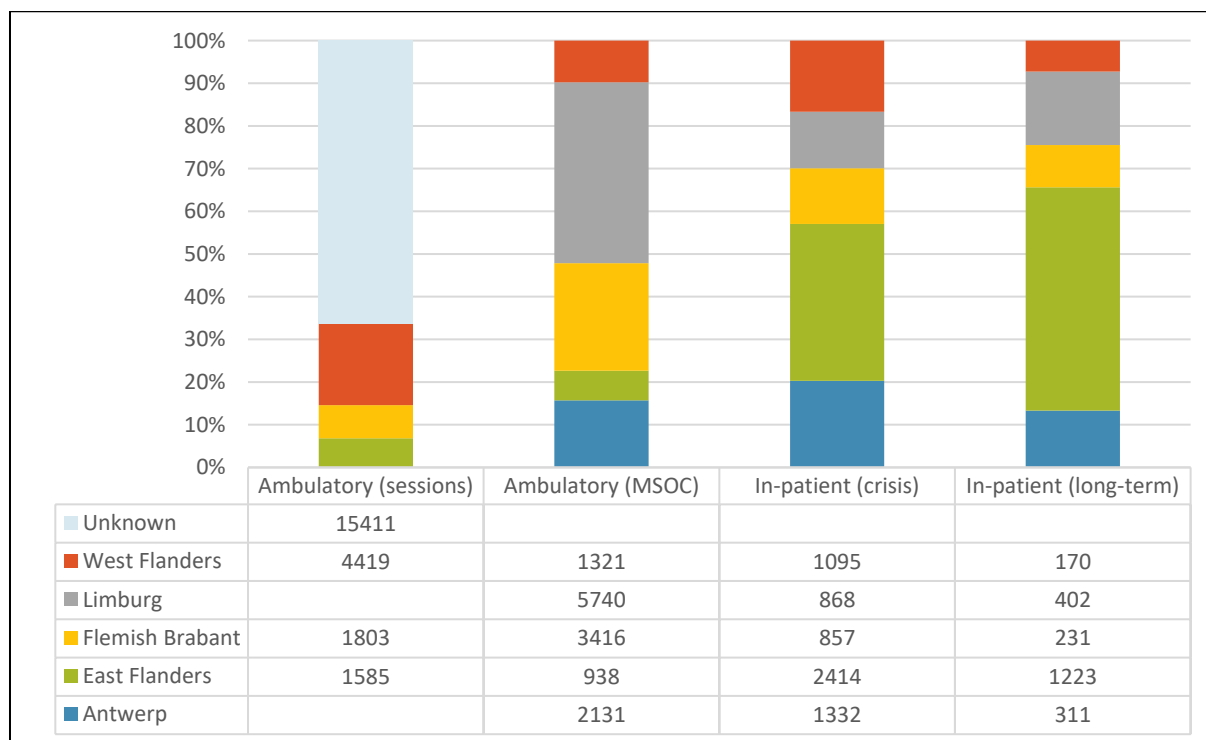


Figure 5.8 Total number and proportion of newly started episodes between 2011 and 2019 in the Rehabilitation Centers for Addiction, per province and by program type (NIHDI/Flemish Government financed programs only; Sciensano, TDI aggregated data).

Ambulatory rehabilitation treatment for addicts in day centers and specialized sessions is offered in all provinces, except for Limburg where all ambulatory addiction rehabilitation takes place in the MSOC. In Flemish Brabant, almost two thirds of new episodes are started in the MSOC, whereas in West Flanders, East Flanders, and probably Antwerp as well, the MSOC seem to play a relatively smaller role, compared to other available ambulatory services. However, as mentioned above, conclusions with respect to capacity are not straightforward based on newly started episodes, seeing that the proportion of new episodes as compared to ongoing episodes may vary according to program type.

Approximately half of long-term in-patient rehabilitation care and more than one third of in-patient crisis care for addicts takes place in East Flanders. Less than 10% of long-term episodes are started in West Flanders and Flemish Brabant, less than 15% in Antwerp and approximately 20% in Limburg. Crisis care is offered the least in Flemish Brabant and Limburg (less than 15%), followed by West Flanders (17%) and Antwerp (20%). Especially for in-patient care, this regional imbalance in care provision, may not necessarily be a problem for all clients living in provinces with less addiction care capacity. Sometimes, distancing

clients from the home-context is considered a necessary step in breaking with the addiction habit and may thus be part of the addiction treatment itself.

Figures 5.10 and 5.11 below show the evolution over time of newly started ambulatory and in-patient episodes per province. As a rough approximation, we divided the number of ambulatory episodes with unknown province evenly over the four rehabilitation day centers that registered these episodes together, attributing a quarter of the unknown episodes to both East and West Flanders and half of them to Antwerp.

Whereas the number of new ambulatory episodes remained constant or decreased somewhat in East Flanders, West Flanders and Antwerp, there was a noticeable increase in Limburg and especially Flemish Brabant, with the number of new ambulatory episodes almost doubling between 2011 and 2019.

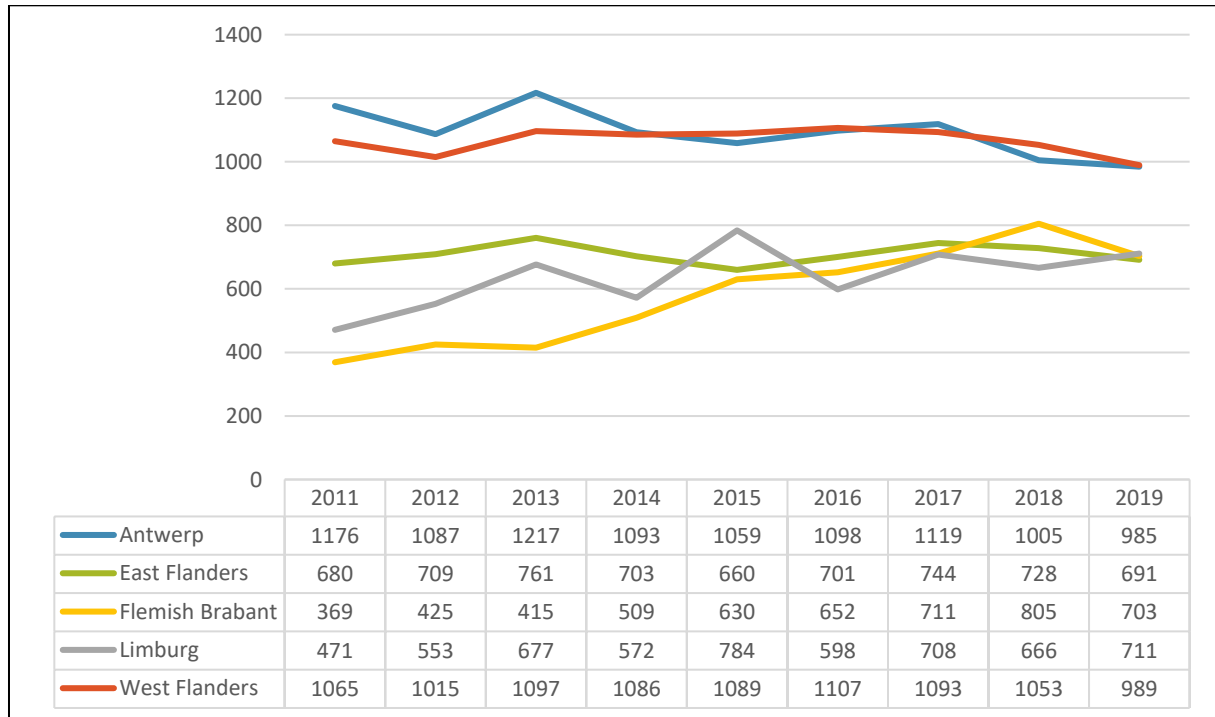


Figure 5.9 Evolution of newly started ambulatory episodes from 2011 to 2019 in the Rehabilitation Centers for Addiction, by province (NIHDI/Flemish Government financed programs only; Sciensano, TDI-aggregated data)

For newly started in-patient episodes, Figure 5.11 shows a gradual decrease in East Flanders, a small increase in Limburg and Flemish Brabant and minor fluctuations in the other provinces.

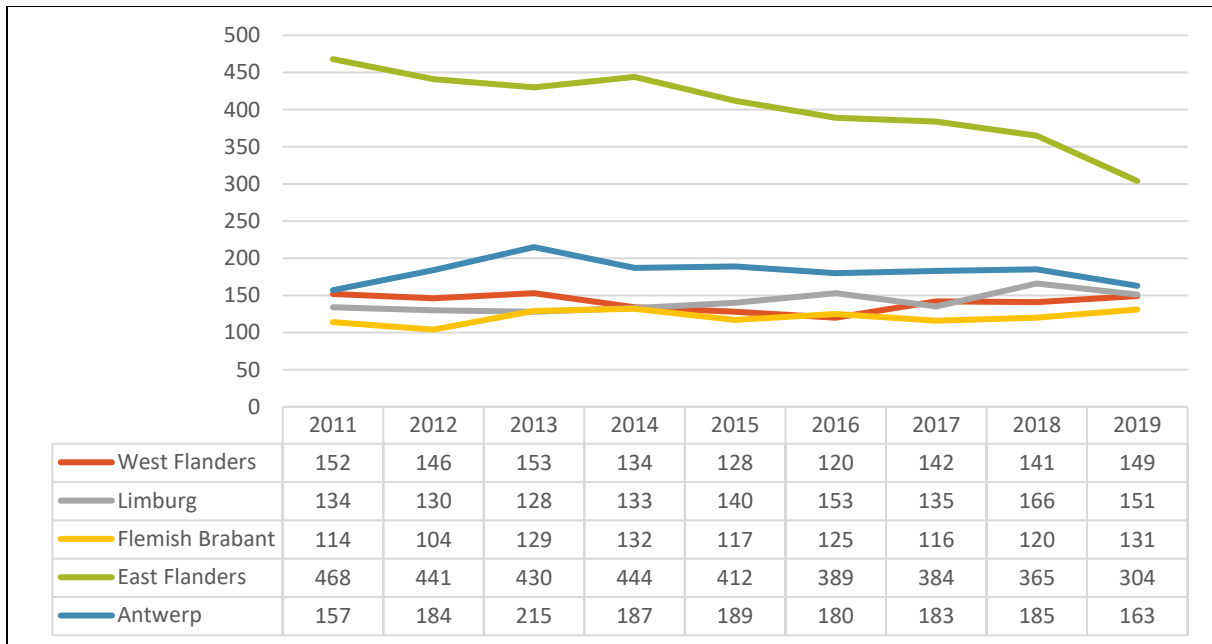


Figure 5.10 Evolution of newly started in-patient episodes from 2011 to 2019 in the Rehabilitation Centers for Addiction, by province (NIHDI/Flemish Government financed programs only; Sciensano, TDI aggregated data).

In Figures 5.12 and 5.13, the number of newly started episodes in the ambulatory and in-patient programs in the Rehabilitation Centers for Addiction are compared to the population of twelve years or older in the Flemish provinces.

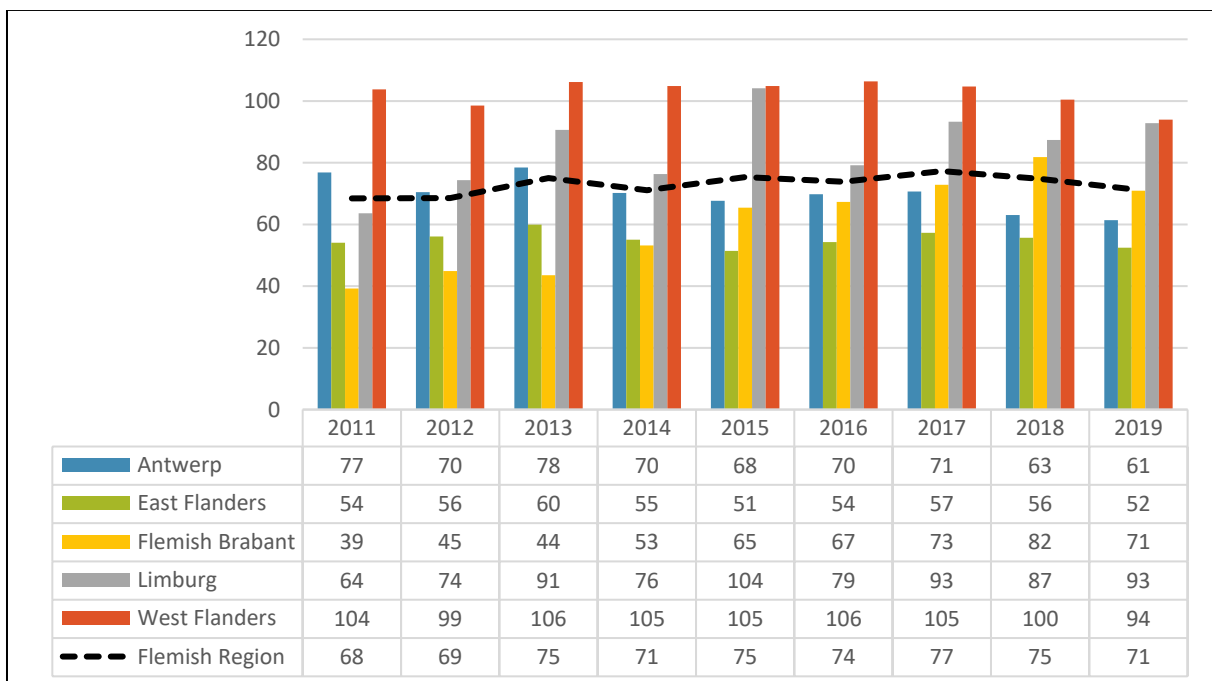


Figure 5.11 Evolution of the number of newly started episodes offered in the ambulatory programs of the Rehabilitation Centers for Addiction per 100.000 inhabitants (12 years or older) from 2011 to 2019, by province (Sciensano, TDI aggregated data; Population data: Federal Planning Bureau, Statbel).

Around 70 care periods per 100.000 inhabitants per year were registered in the NIHDI/Flemish Government financed ambulatory rehabilitation programs for addicts in Flanders between 2011 and 2019, with a

maximum of 77 in 2017. The ratio was highest in West Flanders in all years, followed by Limburg. In Flemish Brabant there was a noticeable increase in the proportion of newly started ambulatory episodes in comparison to the population until 2018, whereas in Antwerp there was more of a decreasing trend. In 2019, East Flanders ended up with the lowest ratio of newly started care periods (52 per 100.000), followed by Antwerp.

Contrary to this, the number of newly started in-patient episodes per 100.000 inhabitants was markedly higher in East Flanders than in the other Flemish provinces, especially in earlier years, with a ratio of 37 in 2011 as compared to ratios between 10 and 20 in the rest of Flanders. In most provinces the number of newly started in-patient episodes fluctuated somewhat over time, with more of an increasing trend in Limburg and a decreasing trend in East Flanders.

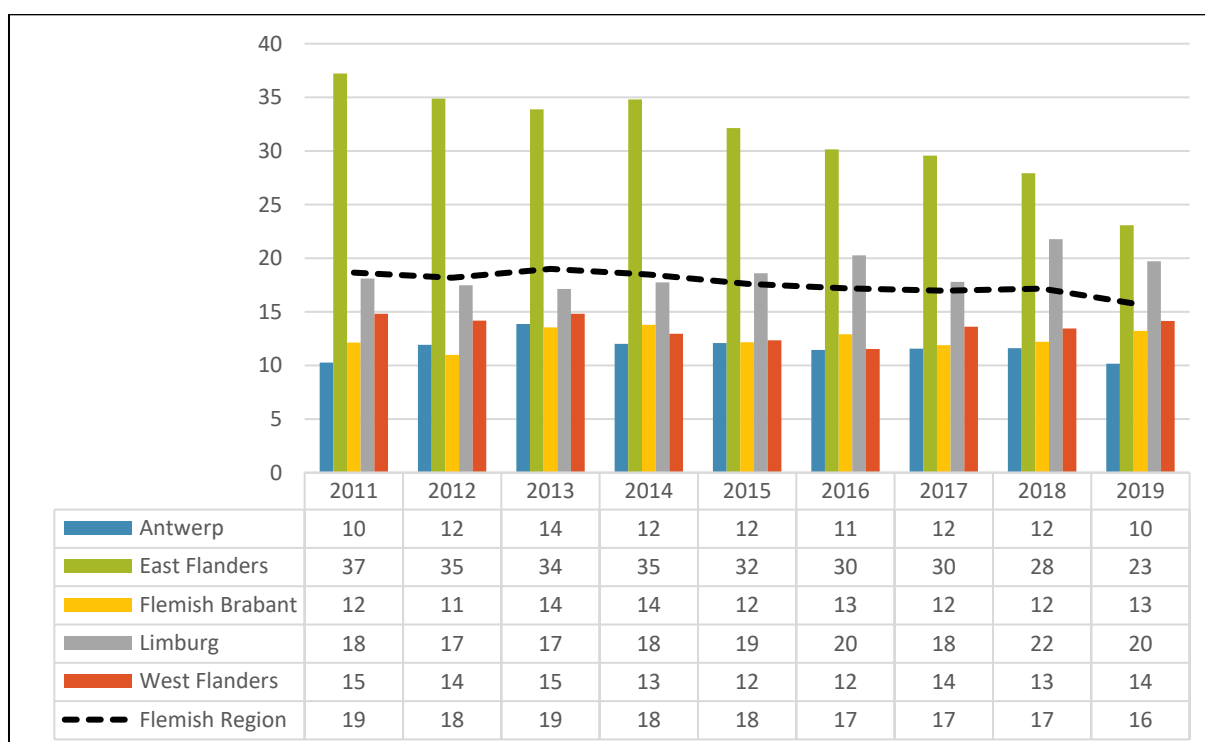


Figure 5.12 Evolution of the number of newly started episodes offered in the in-patient programs of the Rehabilitation Centers for Addiction per 100.000 inhabitants (12 years or older) from 2011 to 2019, by province (Sciensano, TDI aggregated data; Population data: Federal Planning Bureau, Statbel).

The proportion of new care episodes per province described in the figures above probably reflects supply rather than need, especially in in-patient programs. Provinces with relatively more capacity may serve more clients from other provinces, resulting in more care episodes for clients from further away.

Although not mandatory for the TDI, the majority of government financed programs in the Rehabilitation Centers for Addiction register distance between the clients' residence and the rehabilitation center, especially from 2013 onwards. Nevertheless, in most years, numbers were still missing for a few varying programs, making the evolution of new episodes over the years difficult to interpret. Therefore, in relating distance to program type and province, the number of episodes were aggregated over time, starting from 2013.

As shown in Figure 5.14, around 60% of new episodes in the MSOC and 50% in other ambulatory programs were started for clients living less than 10km from the center. In both program types, distance to the treatment center was less than 30km in approximately 90% of new episodes. For in-patient programs, a



different picture emerged, with more than 40% of newly started episodes for clients living at a distance of more than 50km away from the center and more than 50% living more than 40km away, reflecting the unequal regional spread of in-patient facilities. However, as mentioned above, treatment in centers located further away from the home context may not always be due to the lack of facilities nearby, but could also be part of the addiction treatment process.

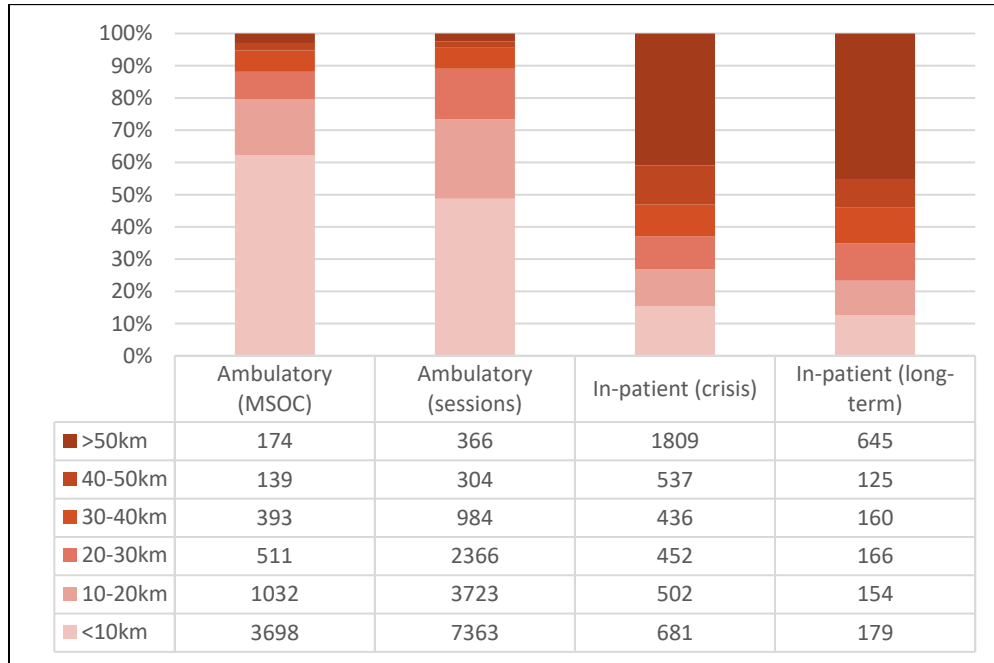


Figure 5.13 Total number of newly started episodes between 2013 and 2019 in the Rehabilitation Centers for Addiction, by distance and per program type (NIHDI/Flemish Government financed programs only; Sciensano, TDI aggregated data).

For the ambulatory programs, distance in relation to province is shown in Figure 5.15 below. Again, the episodes of one large ambulatory day center with unknown province were attributed to East and West Flanders and Antwerp as explained above. This approximation may lead to a slightly distorted picture, making the interpretation for the respective provinces somewhat uncertain.

Distance to the rehabilitation center varied slightly from province to province, with less than 50% of newly started episodes for clients living less than 10km away in East Flanders and Flemish Brabant to almost 60% in Antwerp. Larger distances from more than 20 or 30km were most frequent in East Flanders (around 30 and 15%, respectively) and least frequent in Limburg and Flemish Brabant (around 20 and 10%, respectively).

For in-patient programs (Figure 5.16), the largest distances were registered in East Flanders, with more than half of newly started episodes started by clients living at least 50km from the in-patient facility and almost two thirds living more than 40km away. Given the fact that East Flanders accounts for approximately half of long-term and one third of crisis in-patient rehabilitation care, it is not surprising that more clients come from further away.

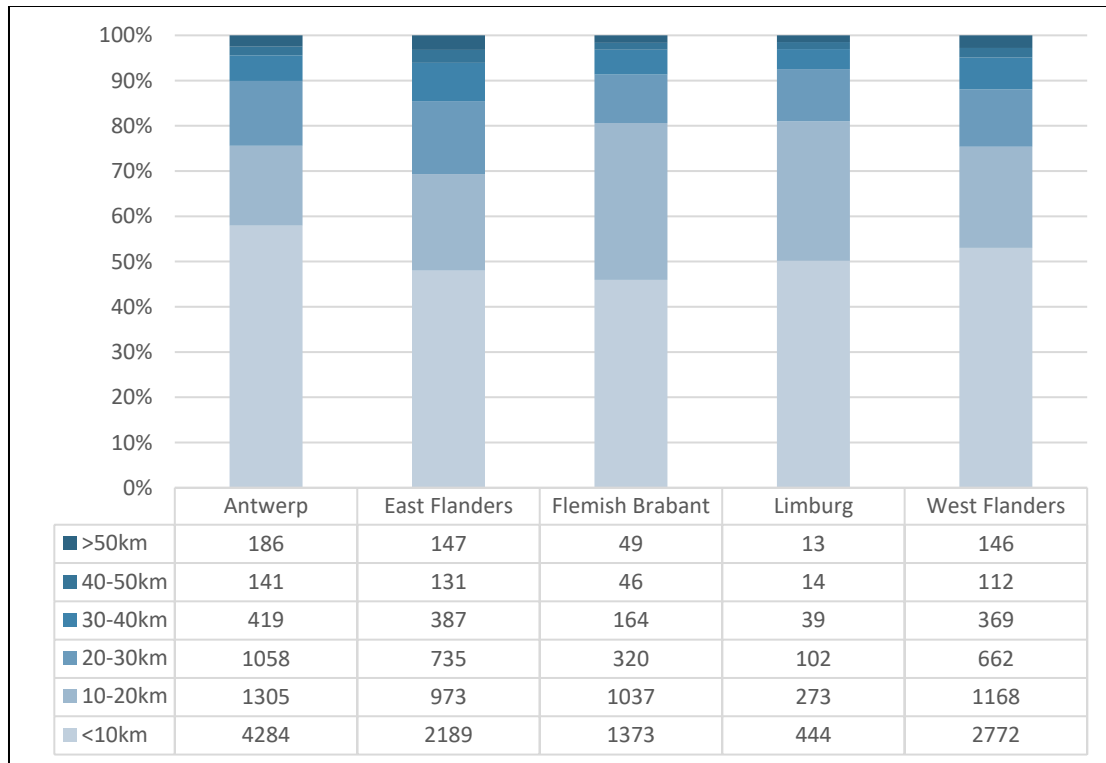


Figure 5.14 Total number of newly started episodes between 2013 and 2019 in the ambulatory programs of the Rehabilitation Centers for Addiction, by distance and per province (NIHDI/Flemish Government financed programs only; Sciensano, TDI aggregated data).

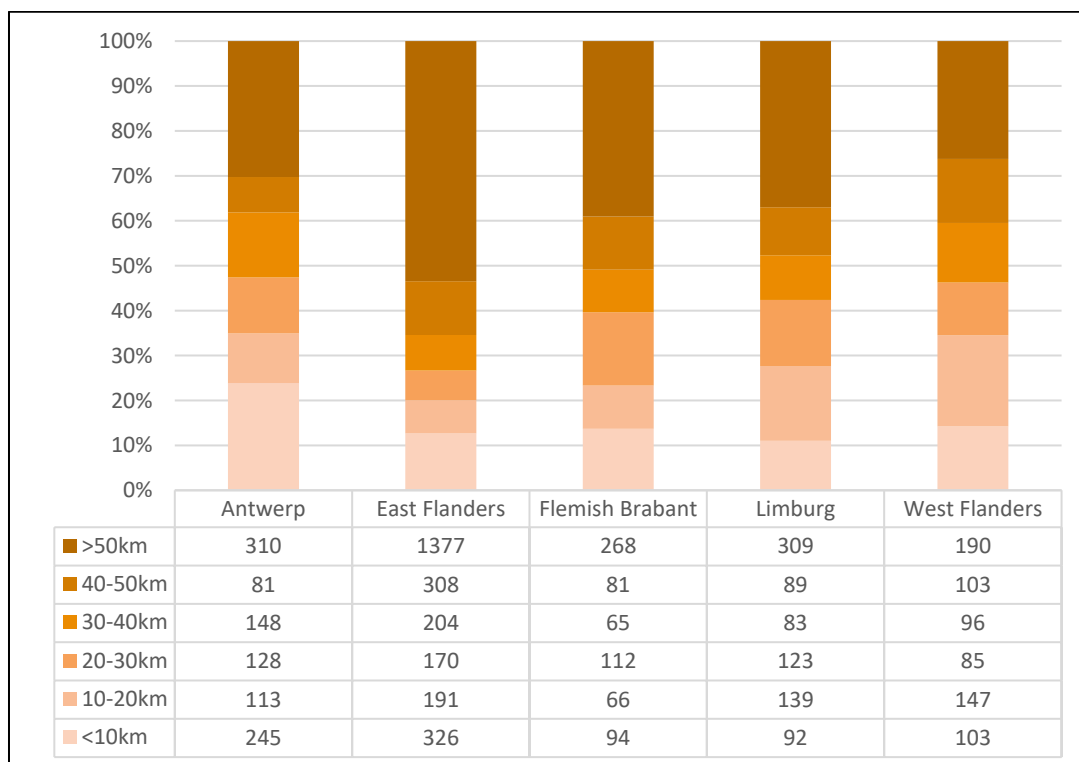


Figure 5.15 Total number of newly started episodes between 2013 and 2019 in the in-patient programs of the Rehabilitation Centers for Addiction, by distance and per province (NIHDI/Flemish Government financed programs only; Sciensano, TDI aggregated data);

In order to shed more light on provision imbalances throughout Flanders, it may also be insightful to compare the distribution of different program types offered by the Rehabilitation Centers for Addiction with the distribution of other addiction treatment services. Although target groups differ to a certain degree, availability of other services may compensate unfulfilled demand.

Figures 5.17 and 5.18 below show the proportion of new episodes started in the Rehabilitation Centers for Addiction compared to other addiction treatment services between 2015 and 2019. The episodes in the rehabilitation centers are divided in NIHDI or Flemish Government financed programs and alternatively financed programs. Once more, the episodes with unknown province were attributed to East and West Flanders and Antwerp as explained above.

Between 2015 and 2019 around 90% of new ambulatory addiction treatment episodes were provided by the Rehabilitation Centers for Addiction in Flemish Brabant and West Flanders. In the other provinces, the ambulatory rehabilitation programs accounted for approximately two thirds (Antwerp and East Flanders) or less than 60% (Limburg) of the newly started episodes in this period.

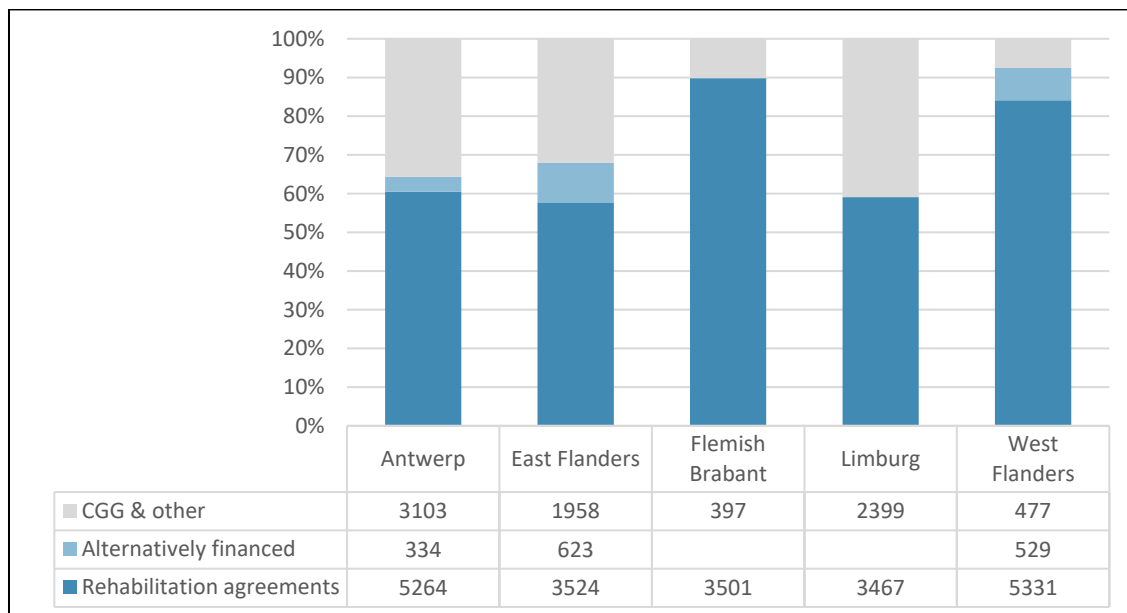


Figure 5.16 Total number and proportion of new ambulatory addiction treatment episodes by type of facility and by province between 2015 and 2019 (Sciensano, TDI aggregated data).

The proportion of new in-patient addiction treatment episodes in the Rehabilitation Centers for Addiction between 2015 and 2019 varied from approximately 3% in West Flanders, 8% in Limburg and 10% in East Flanders and Flemish Brabant to more than 25% in Antwerp. Largely two thirds of the episodes in the Rehabilitation Centers for Addiction in Antwerp, however, were registered as part of a specific short-term in-patient addiction rehabilitation care program financed by the local government in the city of Antwerp.

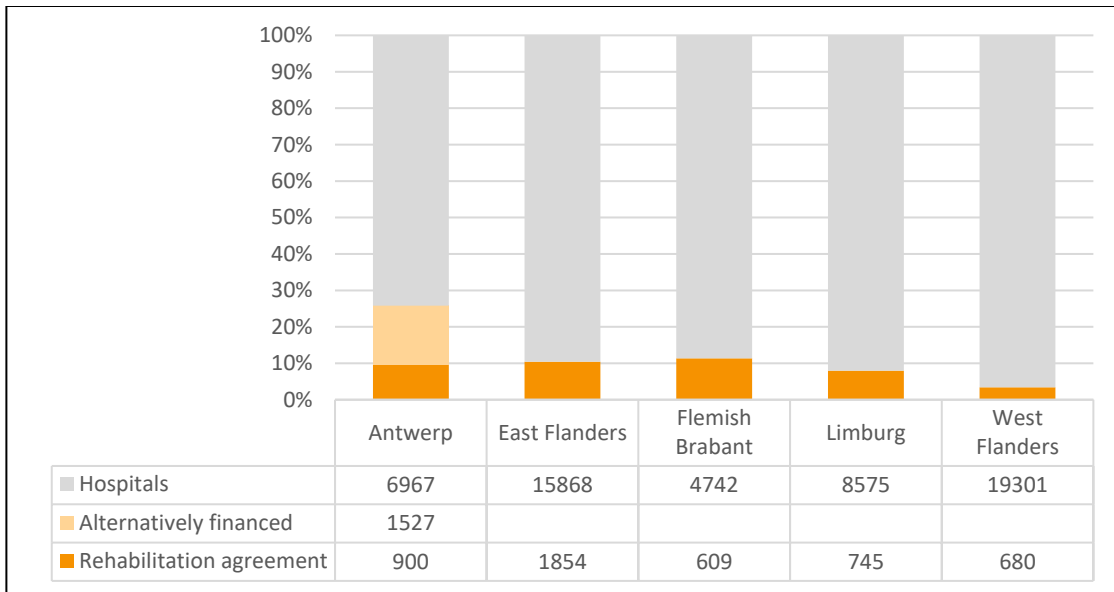


Figure 5.17 Total number and proportion of new in-patient addiction treatment episodes by type of facility and by province between 2015 and 2019 (Sciensano, TDI aggregated data).

Both figures above show that the total numbers of newly started episodes in ambulatory and in-patient addiction treatment programs vary strongly from province to province. In Figure 5.19 new addiction treatment episodes in different services are compared to the population per province. For the Centers for Mental Health Care, data from the CGG Brussels were not included.

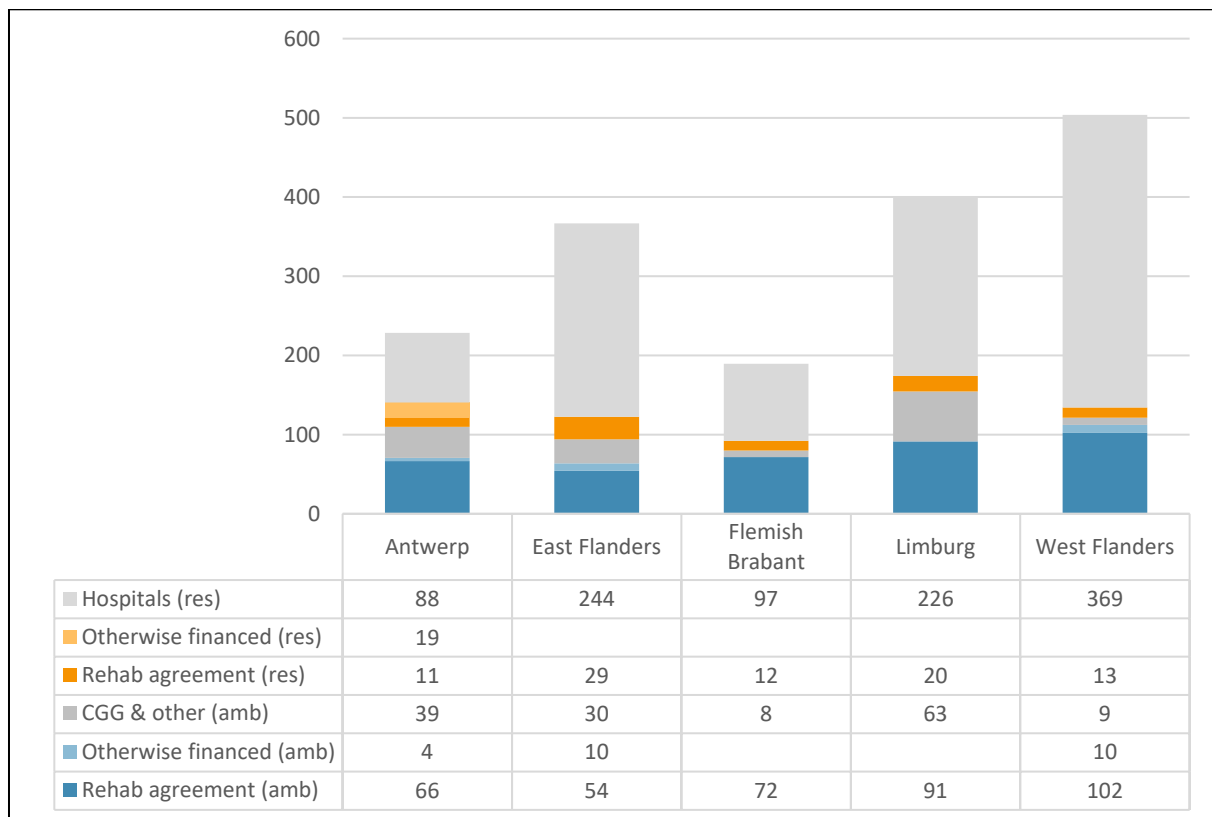


Figure 5.18 Mean number of newly started addiction treatment episodes per 100.000 inhabitants (12 years or more) per year between 2015 and 2019, by program and by province (Sciensano, TDI aggregated data; Population data: Federal Planning Bureau, Statbel).

Ambulatory addiction treatment in all services ranges from 155 new care periods per 100.000 inhabitants per year in Limburg to 121 in West Flanders, 110 in Antwerp, 94 in East Flanders, and 80 in Flemish Brabant. For in-patient treatment in rehabilitation centers and hospitals, the proportion of newly started care episodes per 100.000 inhabitants per year was largest in West Flanders (382), followed by East Flanders (273), Limburg (246), Antwerp (119), and Flemish Brabant (110). Although these numbers show substantial differences in addiction care between provinces, it is likely that they reflect differences in supply rather than or in addition to actual differences in needs. Moreover, addiction treatment programs in Brussels may partly fulfill treatment demand as well, especially in neighboring provinces.

### 3.2.5 Characteristics of service users in the Rehabilitation Centers for Addiction

In this paragraph we describe the clients of the Rehabilitation Centers for Addiction, hereby focusing on socio-economical characteristics (gender, age, income status), treatment antecedents (previous treatment, referring instance), and epidemiological characteristics (problem drugs, primary drug). As in the previous paragraphs of this section, all results refer to newly started episodes, with a small number of these episodes involving the same client.

*Age and gender*

Between 2011 and 2019, approximately 83% of all new treatment episodes in the Rehabilitation Centers for Addiction were provided to male clients. The proportion of female clients was slightly higher in the ambulatory programs (17 to 19%) than in in-patient programs (16%), as shown in Figure 5.20 below.

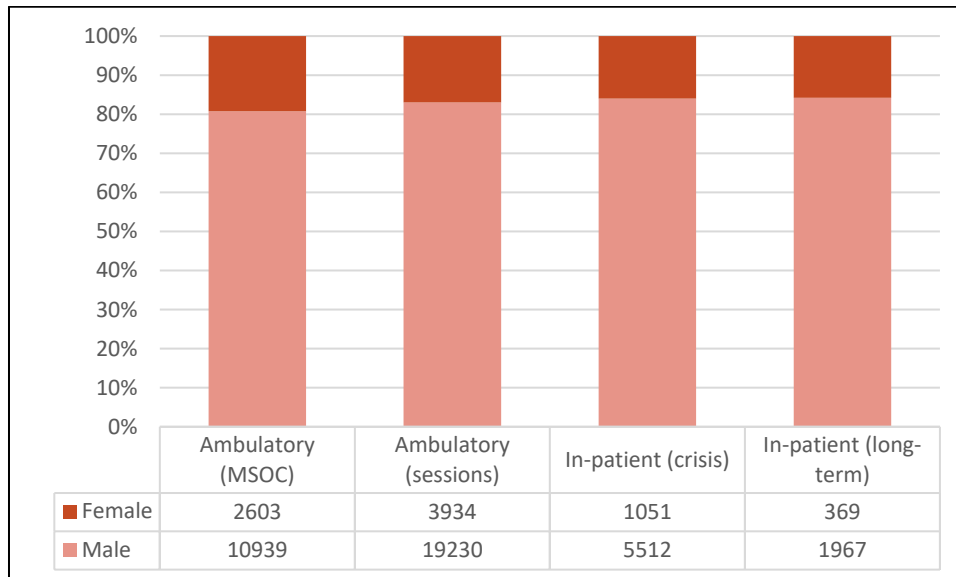


Figure 5.19 Total number and proportion of new episodes for male and female clients in the Rehabilitation Centers for Addiction between 2011 and 2019, by program type (NIHDI/Flemish Government financed programs only; Sciensano, TDI aggregated data).

In ambulatory programs, both the number of episodes for male and female clients increased between 2011 and 2019, but the increase was proportionately larger for female clients (13%) than for male clients (7%) (Figure 5.21).

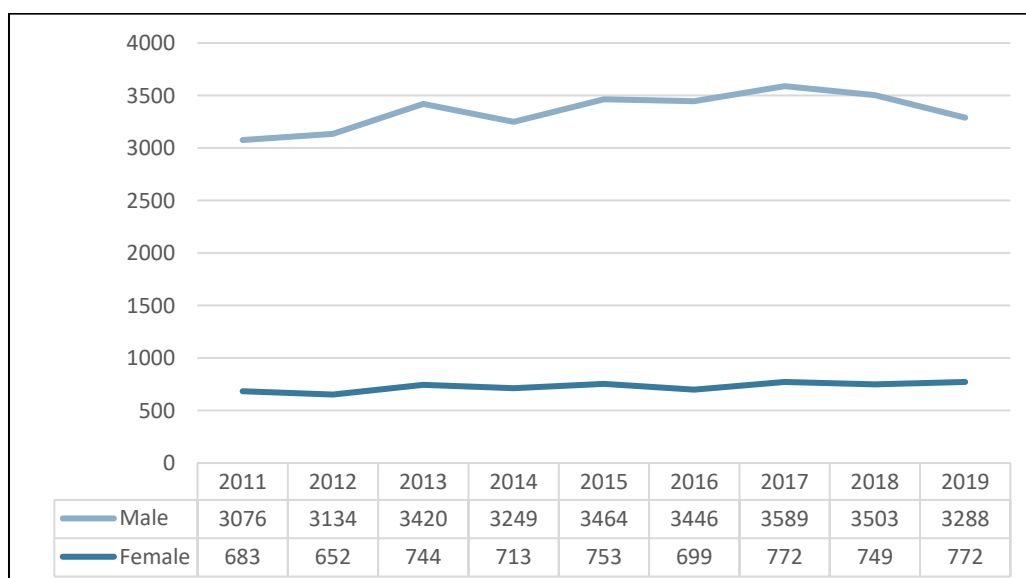


Figure 5.20 Evolution of new ambulatory episodes for male and female clients in the Rehabilitation Centers for Addiction from 2011 to 2019 (NIHDI/Flemish Government financed programs; Sciensano, TDI aggregated data).

For in-patient programs there was a 17% decrease in the number of new episodes involving male clients, as opposed to a 17% increase for female clients. This increase probably reflects recently launched initiatives for women with addiction problems (e.g. modification of the treatment model of therapeutic communities to incorporate empowering gender-sensitive approaches for women, Schamp et al., 2018), rather than changes in needs.

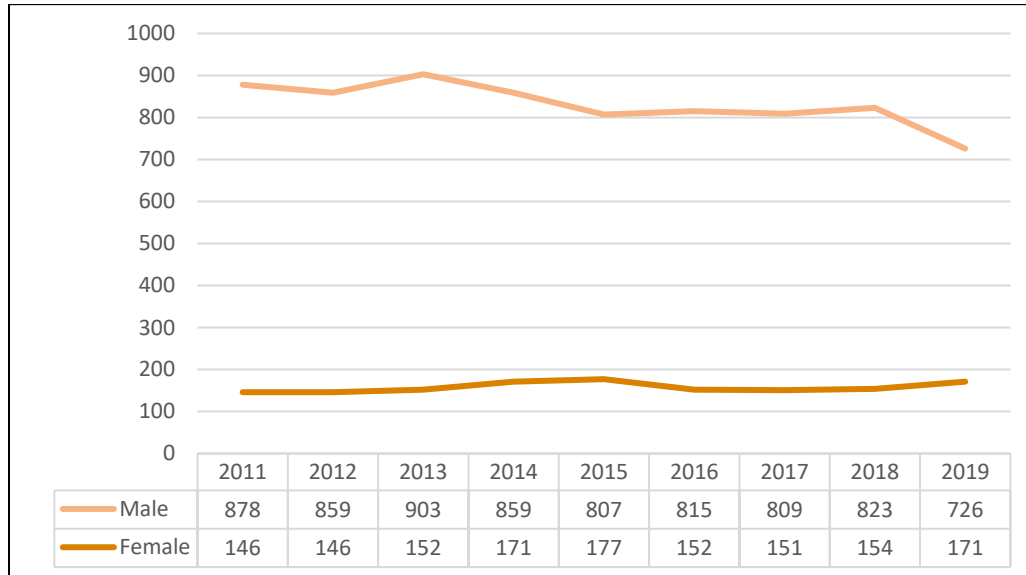


Figure 5.21 Evolution of new in-patient episodes for male and female clients in the Rehabilitation Centers for Addiction from 2011 to 2019 (NIHDI/Flemish Government financed programs; Sciensano, TDI aggregated data).

The vast majority of all new episodes in the Centers for Rehabilitation of Addicts were started for relatively young clients, with less than 7% of episodes involving clients older than 45 and less than 1% involving clients over 60 years. In the ambulatory MSOC, the proportion of new episodes for older clients was relatively high, when compared to other program types. More than 10% of episodes were started for clients over 45 and almost 40% for clients over 35, whereas in the other programs, the latter proportion was about 20 to 25%. This means that more than three out of four episodes were started for clients under 35 in ambulatory sessions programs, in-patient crisis programs and long-term in-patient programs. The proportion of episodes for clients under 25 varied between one fourth (ambulatory MSOC and in-patient crisis programs) and one third (ambulatory sessions and long-term in-patient programs) of all newly started episodes.

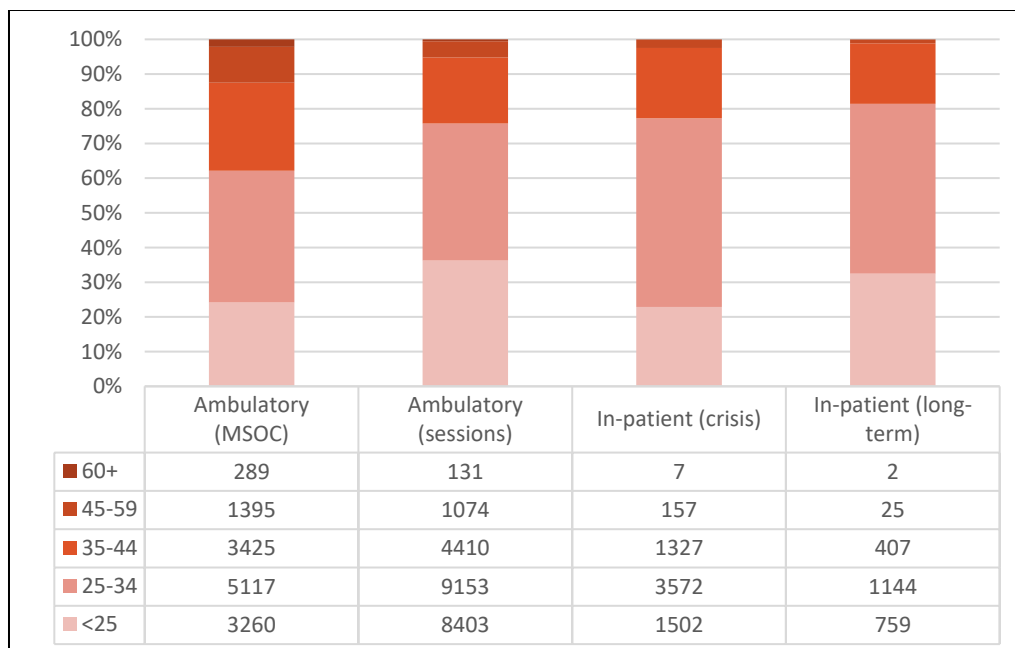


Figure 5.22 Total number and proportion of new episodes per age category in the Rehabilitation Centers for Addiction between 2011 and 2019, by program type (NIHDI/Flemish Government financed programs only; Sciensano, TDI aggregated data).

When focusing on the evolution of new episodes per age category, a slight ageing effect seems to emerge in ambulatory as well as in-patient programs. The number and proportion of episodes started for clients under 35 decreased between 2011 and 2019, especially in the youngest age category. At the same time, gradually more episodes were started for clients in the age group from 35 to 44 in all settings, and for clients in the age groups from 45 to 59 and over 60, particularly in ambulatory programs.

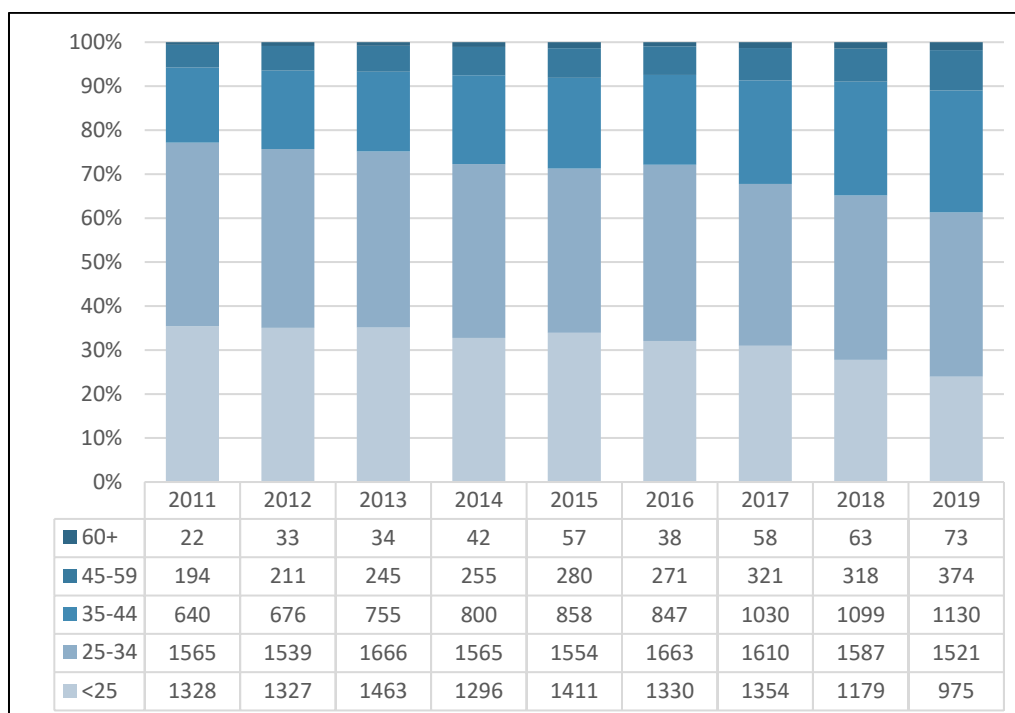


Figure 5.23 Evolution of the proportion of new ambulatory episodes per age category in the Rehabilitation Centers for Addiction from 2011 to 2019 (NIHDI/Flemish Government financed programs; Sciensano, TDI aggregated data)



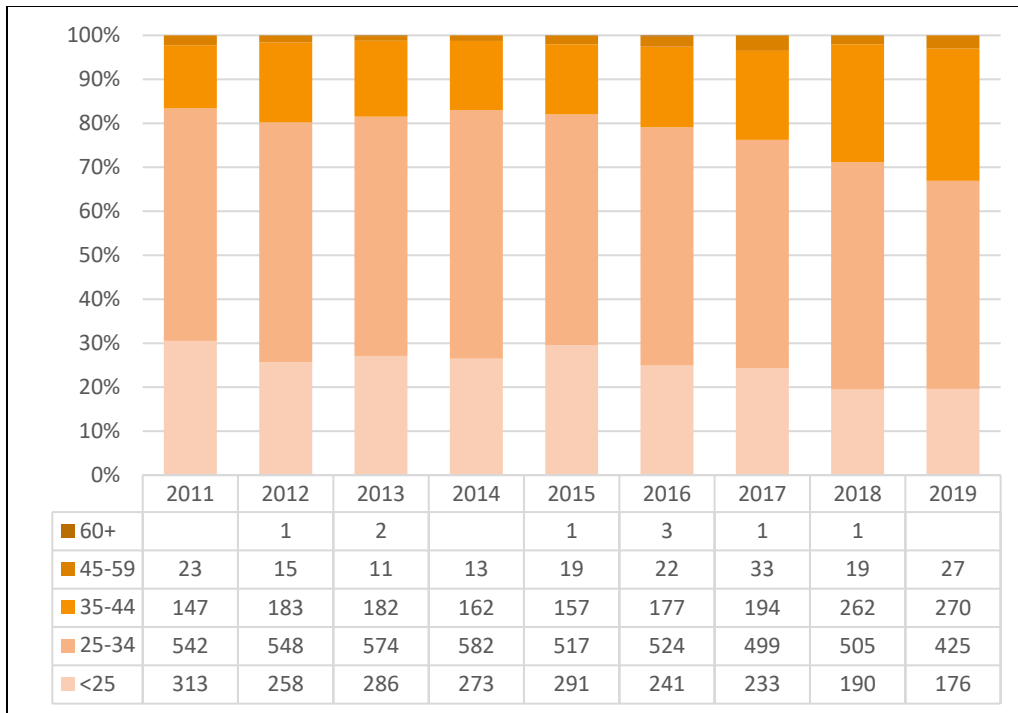


Figure 5.24 Evolution of the proportion of new in-patient episodes per age category in the Rehabilitation Centers for Addiction from 2011 to 2019 (NIHDI/Flemish Government financed programs; Sciensano, TDI aggregated data).

Figure 5.26 below relates age categories to gender, showing that female clients were slightly more represented in the age group between 25 and 34. For the other age categories, the ratio of both sexes varied little in ambulatory programs, whereas in in-patient programs the proportion of female clients seemed to decrease above 45, with no female clients above 60 starting new episodes between 2011 and 2019.

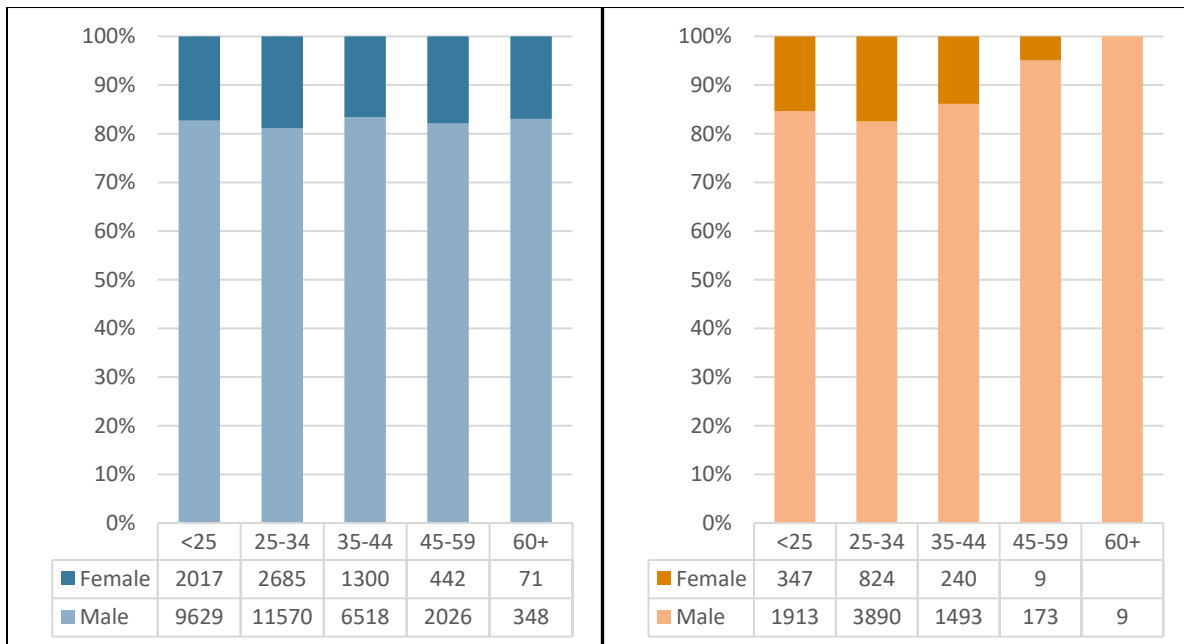


Figure 5.25 Total number and proportion of new ambulatory and in-patient episodes for male and female clients per age category in the Rehabilitation Centers for Addiction between 2011 and 2019 (NIHDI/Flemish Government financed programs only; Sciensano, TDI aggregated data).

*Income status*

Figure 5.27 shows the registered income status per program type in the Rehabilitation Centers for Addiction. As registration seemed to alter between 2014 and 2015 (also see Figure 5.28), data were limited to the last five years. The majority of care episodes started in the Rehabilitation Centers for Addiction involved clients with no income or a replacement income, particularly an unemployment benefit, living wage, or sickness or disability benefit. In ambulatory programs, 30 to 40% of new care episodes were started for clients receiving a salary, whereas this percentage lowered to a mere 13% in in-patient crisis programs and 5% in long-term residential programs.

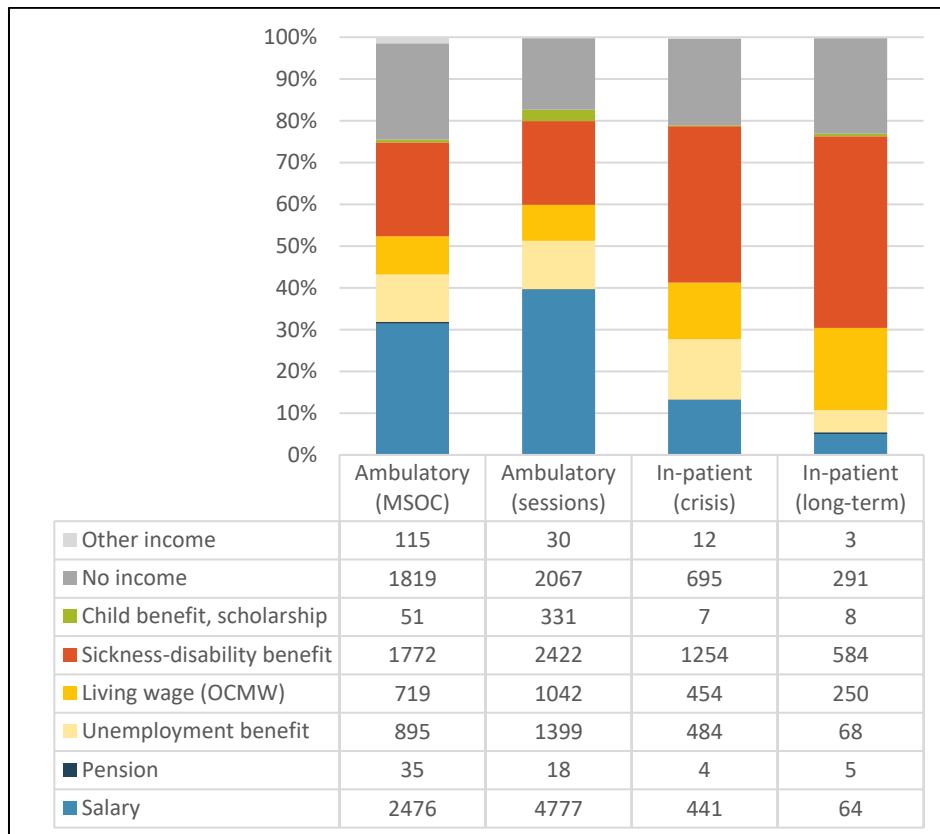


Figure 5.26 Total number and proportion of new episodes by client income status and per program type in the Rehabilitation Centers for Addiction between 2015 and 2019 (NIHDI/Flemish Government financed programs only; Sciensano, TDI aggregated data).

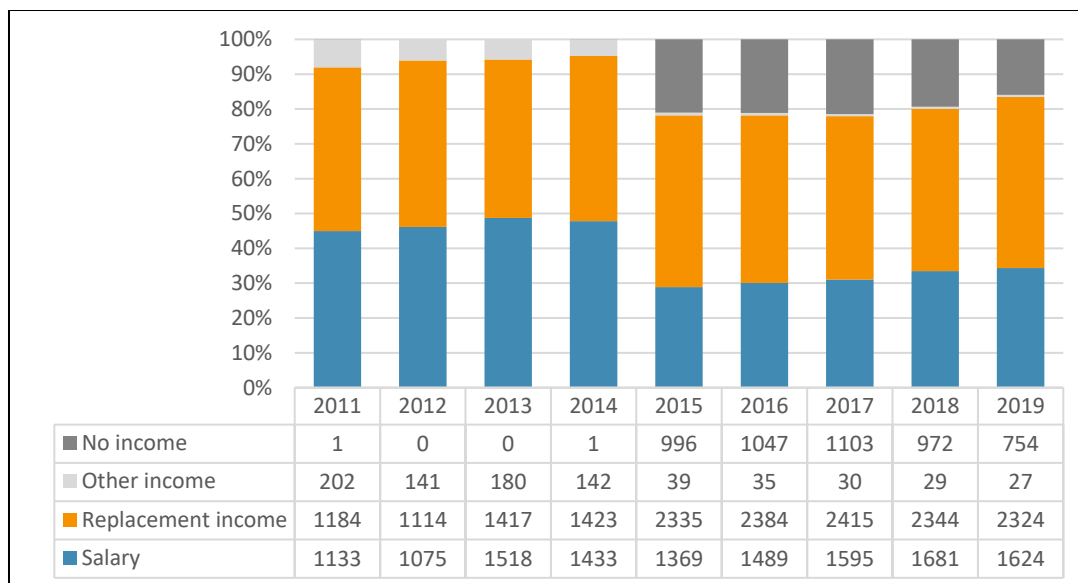


Figure 5.27 Evolution of the proportion of new episodes by client income status in the Rehabilitation Centers for Addiction from 2011 to 2019 (NIHDI/Flemish Government financed programs; Sciensano, TDI aggregated data).

When considering the period from 2011 to 2014 on the one hand and from 2015 onwards on the other hand, in both registration periods the proportion of care episodes for clients receiving a salary increased somewhat (from 45 to 48% and from 29 to 34%, respectively). At the same time, the proportion of care episodes for clients registered as receiving any type of replacement income remained quite stable (around 47% in the first period and around 48% in the second period), whereas the no income group became relatively smaller between 2015 and 2019 (from 21% to 16%).

*Referrer and previous treatment*

In addition to socio-economic variables, the TDI-register contains information concerning treatment antecedents, such as the referral instance and previous addiction treatment.

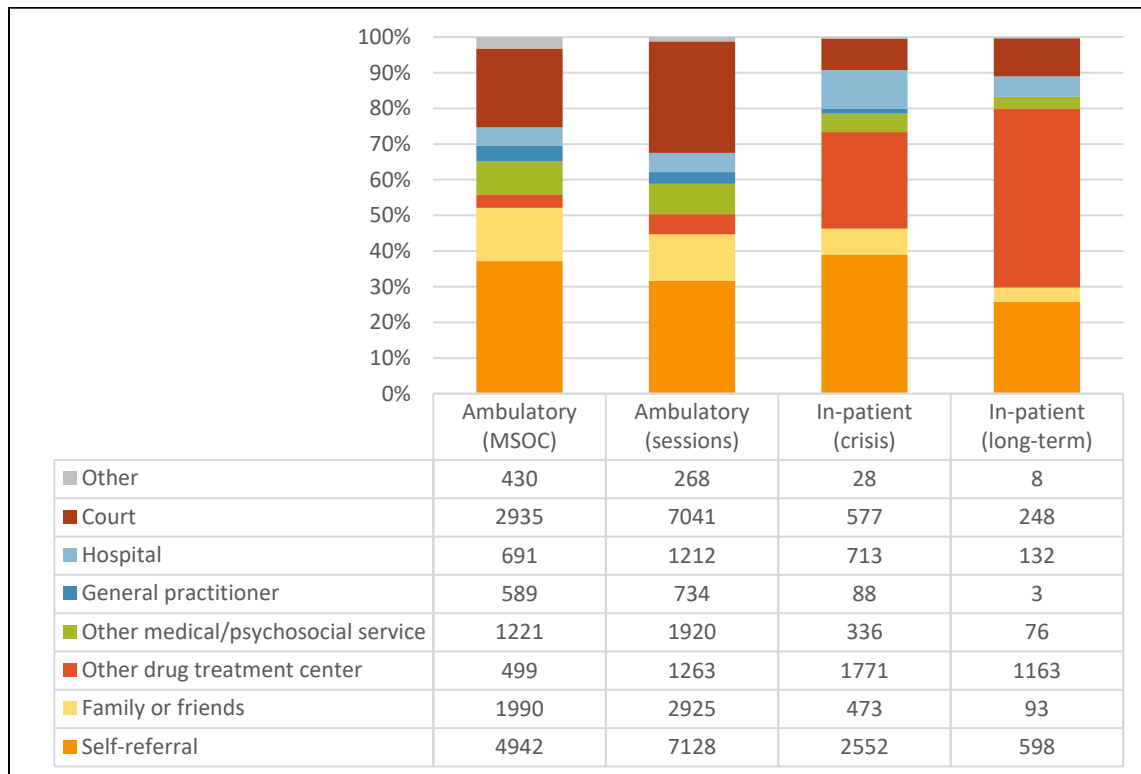


Figure 5.28 Total number and proportion of new episodes by referring instance and per program type in the Rehabilitation Centers for Addiction between 2011 and 2019 (NIHDI/Flemish Government financed programs only; Sciensano, TDI aggregated data).

Between 2011 and 2019, 40 to 50% of new care episodes in ambulatory and in-patient crisis programs were started following self-referral or referral by family or friends. In ambulatory programs, referral by the court was frequent as well, whereas for in-patient treatment clients were more often referred by other drug treatment centers. Around 20% of new care episodes in ambulatory rehabilitation centers involved clients referred by hospitals, general practitioners or other medical or psychosocial services. For in-patient programs, the role of the latter two was somewhat smaller, whereas the role of hospitals as referring instance was somewhat more important, especially for crisis treatment.

Figure 5.30 shows that up to 90% of in-patient episodes in the Rehabilitation Centers for Addiction were started for clients who had previous addiction treatment, whereas this was the case for less than 60% of ambulatory episodes, suggesting that most first-time treatments took place in ambulatory programs. Reported previous treatment refers to addiction treatment in various services which may or may not be included in the TDI-register (e.g. primary care services), seeing that more than half of all clients were never before registered in the TDI-register (Antoine, 2019), while only one third of care episodes involved first-time clients according to the previous treatment variable.

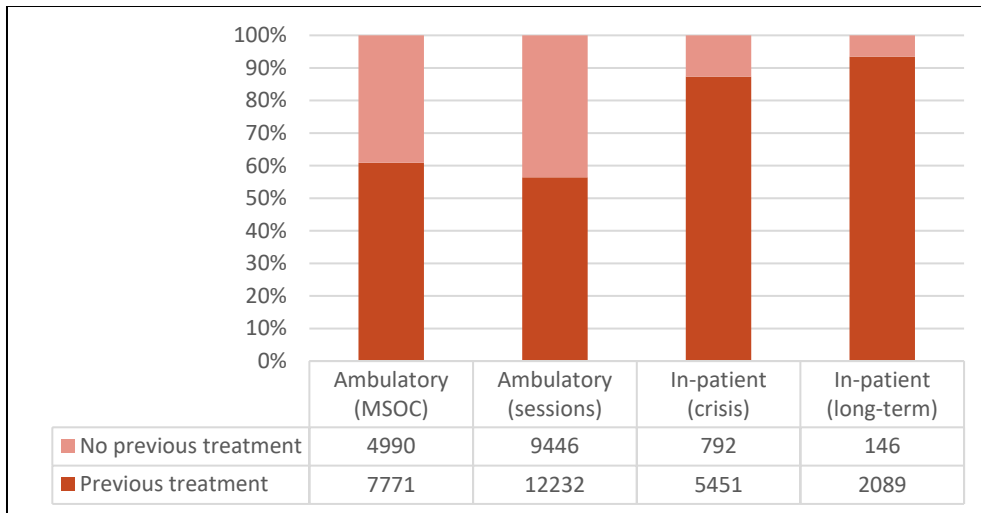


Figure 5.29 Total number and proportion of new episodes for previously or not previously treated clients in the Rehabilitation Centers for Addiction between 2011 and 2019, by program type (NIHDI/Flemish Government financed programs only; Sciensano, TDI aggregated data).

In Figures 5.31 and 5.32 below, the evolution of the number of newly started episodes in function of previous treatment is presented. Both figures show that registration improved considerably from 2013 onwards. For ambulatory programs, the number and proportion of new episodes for previously treated clients increased, whereas for in-patient programs there seemed to be a slight decrease. This means that first-time clients became a relatively less important group in ambulatory programs, and a somewhat more important group in in-patient facilities.

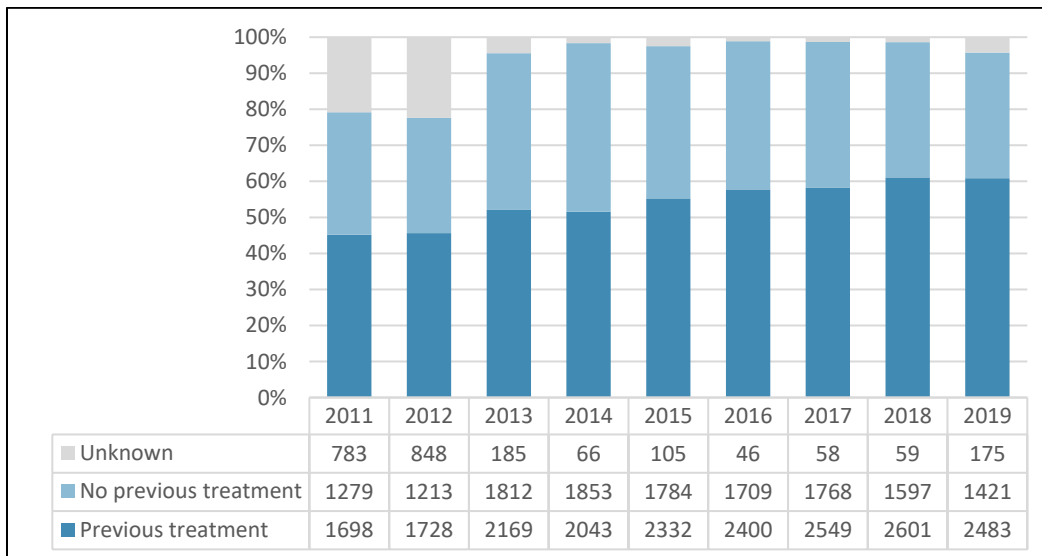


Figure 5.30 Evolution of the number and proportion of new ambulatory episodes started for previously treated or not previously treated clients in the Rehabilitation Centers for Addiction from 2011 to 2019 (NIHDI/Flemish Government financed programs only; Sciensano, TDI aggregated data).

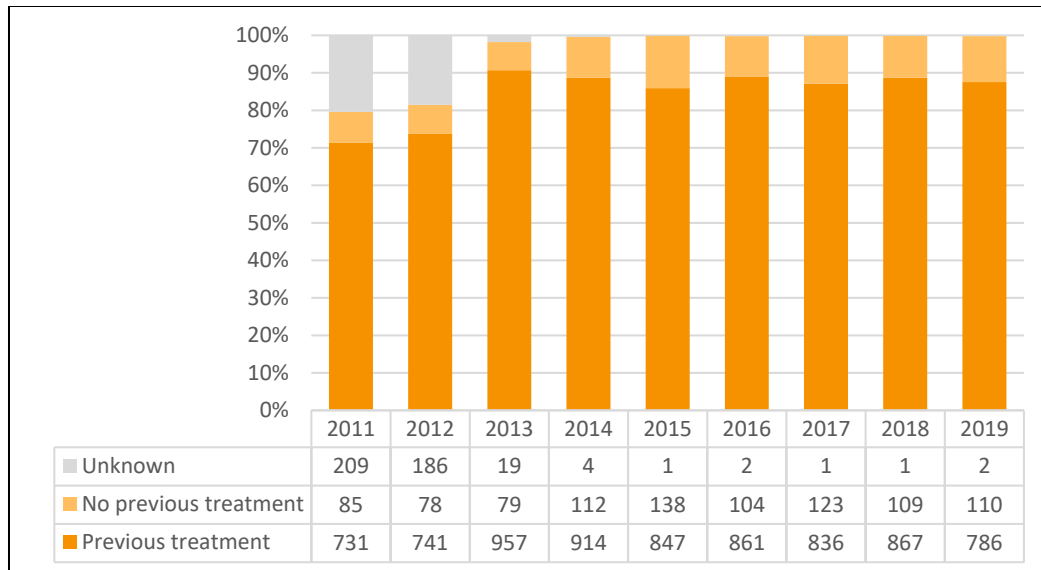


Figure 5.31 Evolution of the number and proportion of new in-patient episodes started for previously treated or not previously treated clients in the Rehabilitation Centers for Addiction from 2011 to 2019 (NIHDI/Flemish Government financed programs only; Sciensano, TDI aggregated data).

*Problematic substances and primary drug*

In the TDI-database, the specific substance used, is registered in two different ways (see Table 5.2). Considering that many clients use different substances, presence or absence of problematic use is indicated for every listed substance, with reliable data available since 2015. However, for the majority of the addiction treatment episodes, the substance causing most problems in the clients’ life can also be identified and is captured by the primary drug variable in the TDI-register.

Figure 5.33 shows the use of different problematic substances as a percentage of the total number of new episodes per program type between 2015 and 2019. With the exception of cannabis in ambulatory sessions programs and opioids in the MSOC, all percentages are higher in in-patient programs, which suggests a larger number of care episodes for polydrug users in these programs than in ambulatory programs.

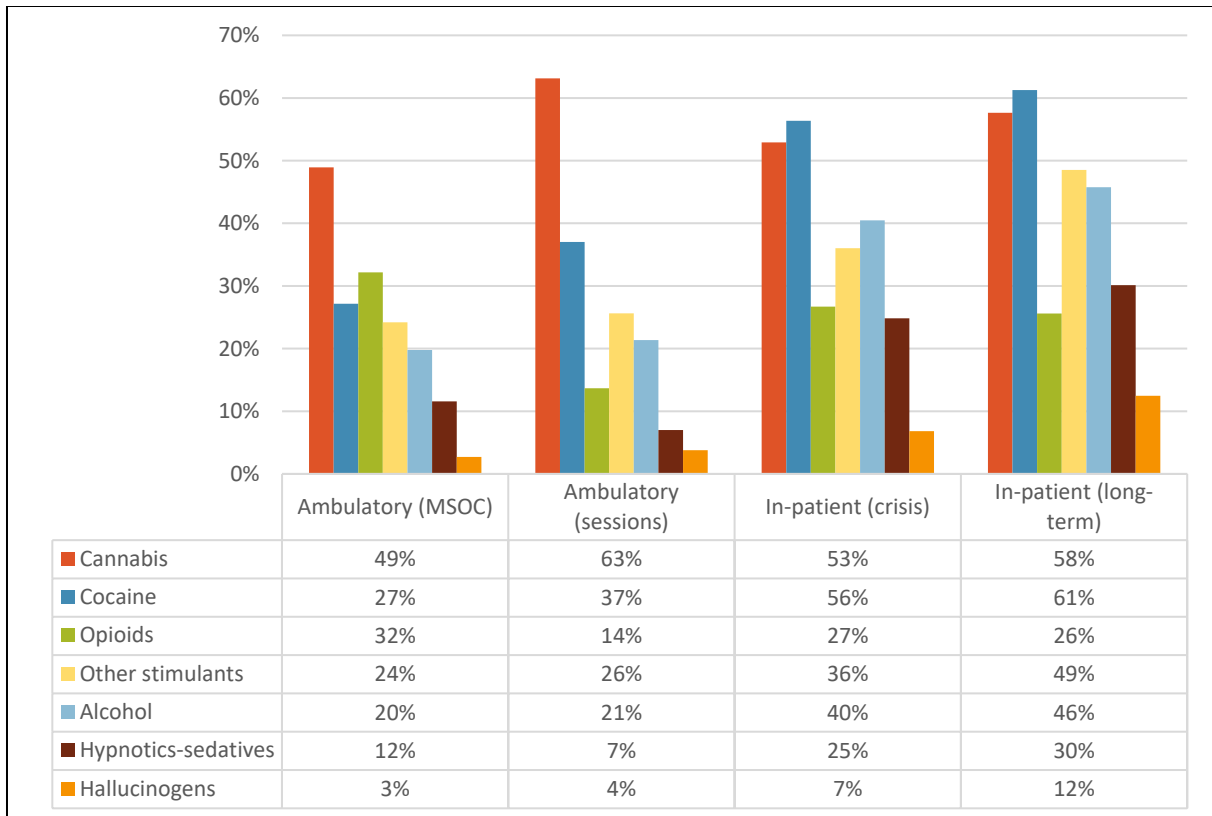


Figure 5.32 Use percentages of problematic substances in new episodes per program type in the Rehabilitation Centers for Addiction between 2015 and 2019 (NIHDI/Flemish Government financed programs only; Sciensano, TDI aggregated data).

Figure 5.34 shows that the number of episodes for clients using cocaine gradually increased between 2015 and 2019, whereas for opioids the reverse was true. Most other substances reached their peak in 2017 and lowered again thereafter, most noticeably so for problematic cannabis use.

The evolution of problematic cocaine use shown in Figure 5.34 reflects the evolution of prevalence percentages in Flanders, Belgium as a whole, and some European countries (Appendix 1, Figures 1.6 and 1.12, also see De Donder & Rosiers, 2020a). Prevalence percentages for opioids on the other hand, rose rather than descended in Belgium between 2013 and 2018 (Appendix 1, Figure 1.8), but data with respect to opioid use are insufficient to draw strong conclusions (De Donder & Möbius, 2020). For (problematic) cannabis use, prevalence percentages also seemed to increase between 2013 and 2018 in Belgium (Appendix 1, Figure 1.4 and Table 1.4) and between 2015 and 2019 in some European countries (Appendix 1, Figure 1.11), with no sign of a recent descending trend as yet (also see De Donder & Van Damme, 2020).

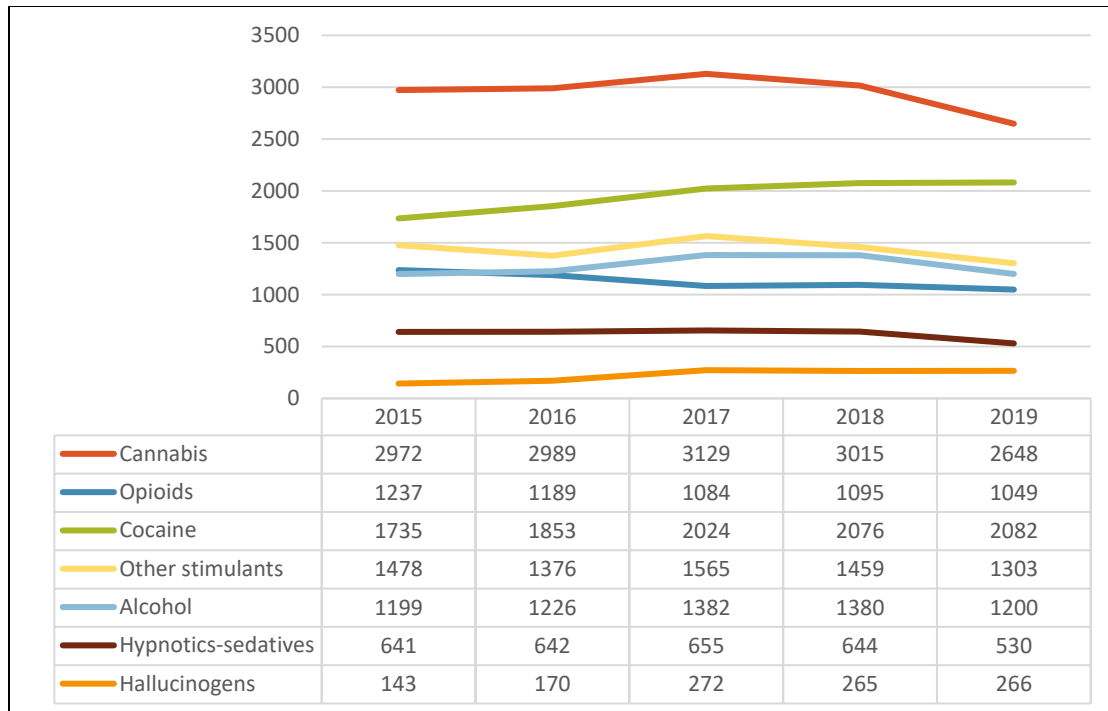


Figure 5.33 Evolution of the number of new episodes per problematic substance in the Rehabilitation Centers for Addiction from 2015 to 2019 (NIHDI/Flemish Government financed programs only; Sciensano, TDI aggregated data).

For most treatment episodes in the TDI-register, the primary substance is identifiable and registered as such, in addition to the registration of all problematic substances. Between 2011 and 2019, more than 40% of new episodes in ambulatory day centers and specialized sessions involved clients with primary cannabis dependence problems (Figure 5.34), whereas in the ambulatory MSOC, episodes for opioid users outnumbered other primary substances. This is not surprising, seeing that opioid substitution treatment forms an important part of MSOC provisions.

New in-patient treatment episodes are predominately started for cocaine, other stimulants, or opioids dependencies: Around 70% of crisis episodes and 65% of long-term episodes involve one of these substance types as primary drug.



It is important to keep in mind though, that the proportions of new episodes per primary substance presented in Figure 5.35 do not necessarily reflect the distribution of all episodes or clients over these substances. This is certainly the case for opioid users having ambulatory substitution treatment, as this type of treatment may take a long time, with relatively few new episodes registered in a given year in comparison to clients in ongoing episodes.

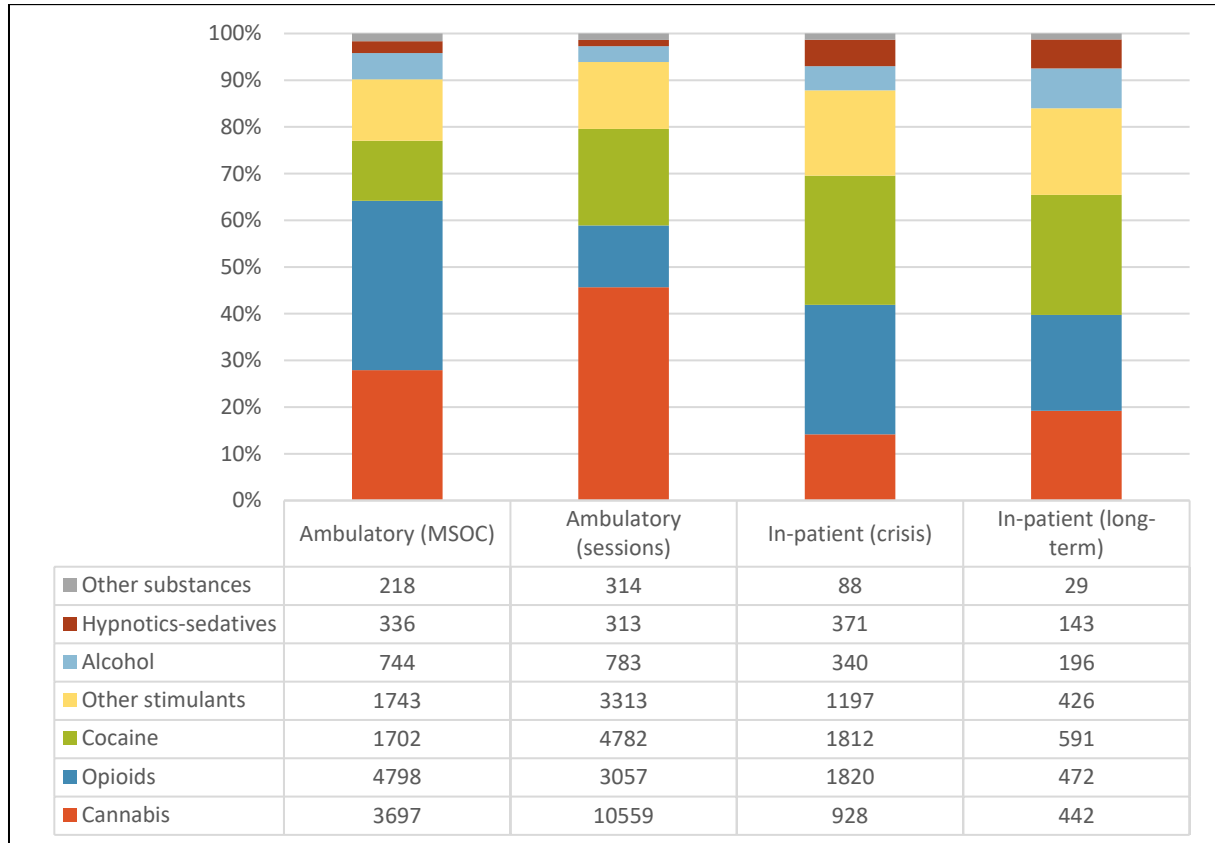


Figure 5.34 Total number and proportion of new episodes per primary drug in the Rehabilitation Centers for Addiction between 2011 and 2019, by program type (NIHDI/Flemish Government financed programs only; Sciensano, TDI aggregated data).

Figure 5.36 below pictures the evolution of new episodes per primary substance. Since 2012, the majority of new episodes were started for users of cannabis as primary substance. According to the umbrella organization of the Rehabilitation Centers for Addiction (VVBV, Van Deun, 2019), cannabis users became a more important client group since the beginning of the new millennium, with numbers slowly stabilizing from 2013 onwards.

The most noticeable time trend in Figure 5.36, however, is the 89% increase of new episodes for clients identified as primary cocaine users between 2011 and 2019, together with a 45% decrease of opioid episodes. The upward evolution of problematic cocaine use, combined with a downward evolution in opioid use shown in Figure 5.33 above, thus becomes even more outspoken when considering the primary drug only. Although cocaine and other stimulant drug use remains rather low in the population as a whole (De Donder & Rosiers, 2020a, 2020b), combining both types of stimulants, leads to around 2000 new episodes started for primary stimulant use since 2017, thereby outnumbering new primary cannabis episodes.

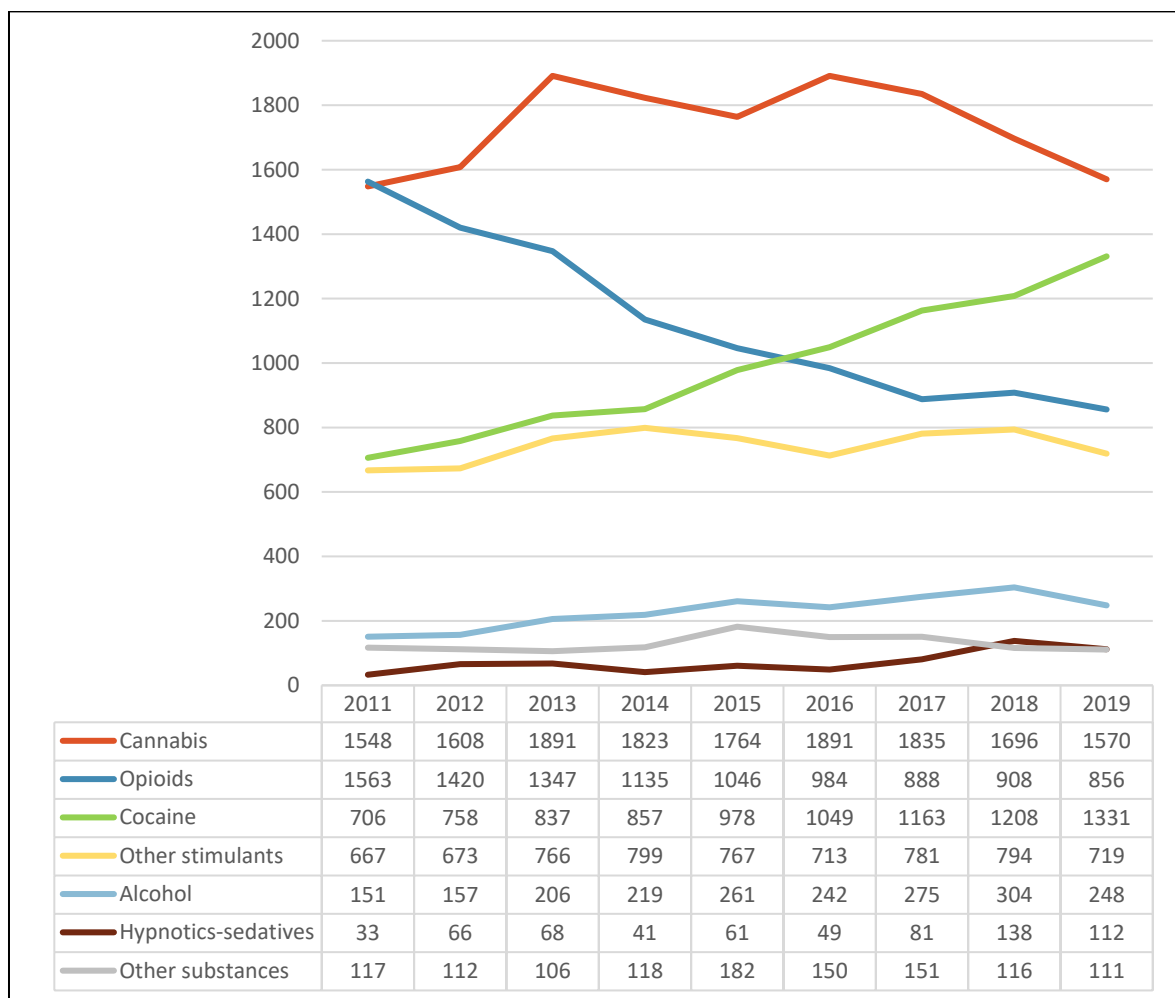


Figure 5.35 Evolution of new episodes in the Rehabilitation Centers for Addiction from 2011 to 2019 by primary drug (NIHDI/Flemish Government financed programs only; Sciensano, TDI aggregated data).

As shown in Figure 5.37, the trends for cocaine and opioid episodes are present in ambulatory as well as in-patient settings, with ambulatory and in-patient cocaine episodes doubling and increasing 52%, respectively from 2011 to 2019, and ambulatory and in-patient episodes for primary opioid users lowering with 40 and 65%, respectively.

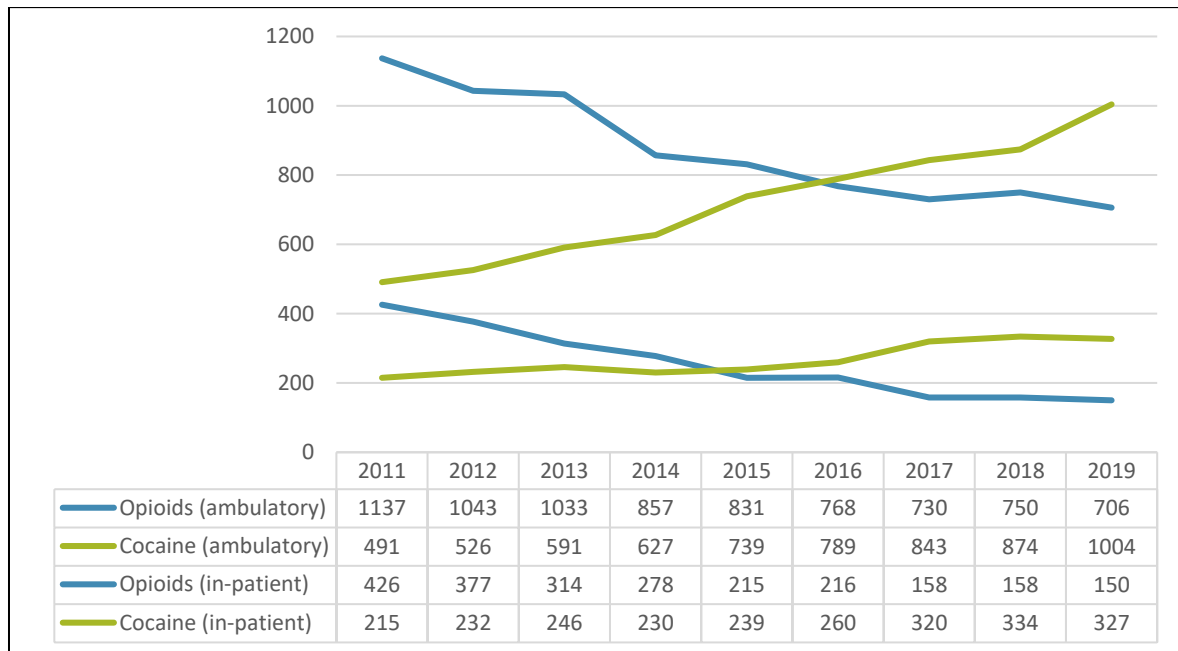


Figure 5.36 Evolution of new ambulatory and in-patient episodes started for cocaine and opioid as primary drug in the Rehabilitation Centers for Addiction from 2011 to 2019 (NIHDI/Flemish Government financed programs only; Sciensano, TDI aggregated data).

Figures 5.38 and 5.39 show the relation between primary drug and program type for ambulatory and in-patient rehabilitation and other addiction treatment programs respectively.

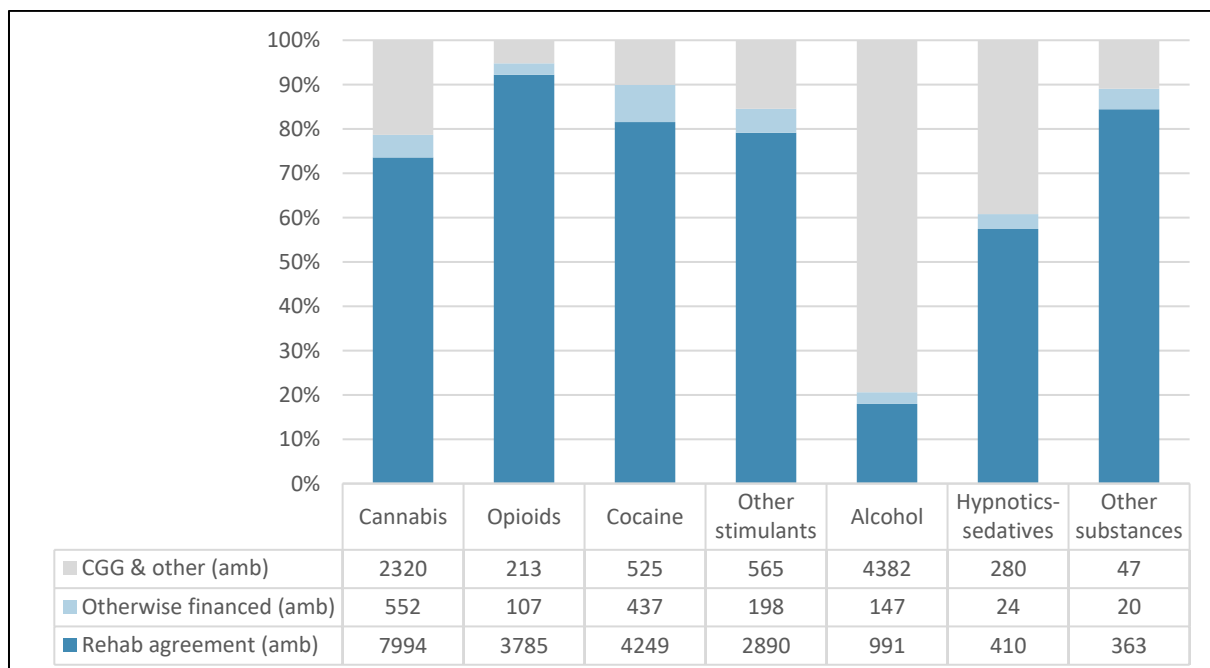


Figure 5.37 Total number and proportion of new ambulatory episodes per primary drug between 2015 and 2019, by addiction treatment program type (Sciensano, TDI aggregated data).

Primary opioids, cocaine, cannabis, other stimulants and other substance users in ambulatory programs are treated in the Rehabilitation Centers for Addiction in more than 80% of all registered new care episodes. The Centers for Mental Health Care mostly treat primary alcohol users (around 80%) and clients addicted to hypnotics or sedatives (around 40% of new care episodes).

In in-patient programs, primary alcohol users most often end up in hospital, whereas primary illicit drug users are treated in the rehabilitation centers in 10 to 20% (hypnotics or sedatives and cannabis), more than 30% (stimulants) or up to 40% (cocaine and opioids) of care episodes.

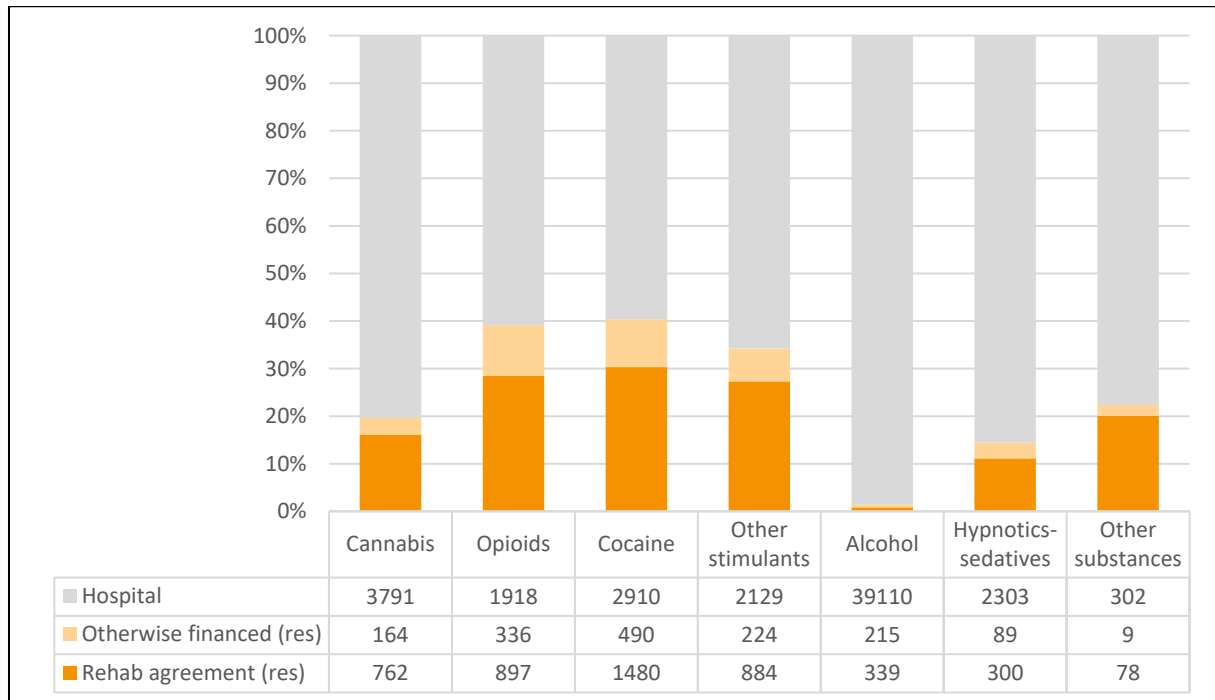


Figure 5.38 Total number and proportion of new in-patient episodes per primary drug between 2015 and 2019, by addiction treatment program type (Sciensano, TDI aggregated data).

The choice of a specific treatment program is not only dependent on the primary problem substance, but may be the result of several interacting factors. For example, addiction to hypnotics and sedatives is more common in women, who often seek treatment in the Centers for Mental Health Care or in hospitals. Schamp et al. (2018) mentions different reasons for this observation, such as the frequent occurrence of comorbid mental problems with hypnotics and sedatives addiction, in addition to the barriers felt by women when confronted with the predominately male client population in the Rehabilitation Centers for Addiction.

In general, the primary substance variable covaries with most sociodemographic and treatment variables in the TDI-register (Antoine, 2019). For the Rehabilitation Centers for Addiction, this translates into the following picture for the relation with gender (Figure 5.40), age (Figure 5.41), and previous treatment (Figure 5.42).

For all primary substances, male clients make up at least three quarters of the client population. Between 2011 and 2019, the proportion of new care episodes for women was highest for primary stimulants and hypnotics or sedatives use (up to 25%) and lowest for primary cannabis and cocaine use (around 15%).

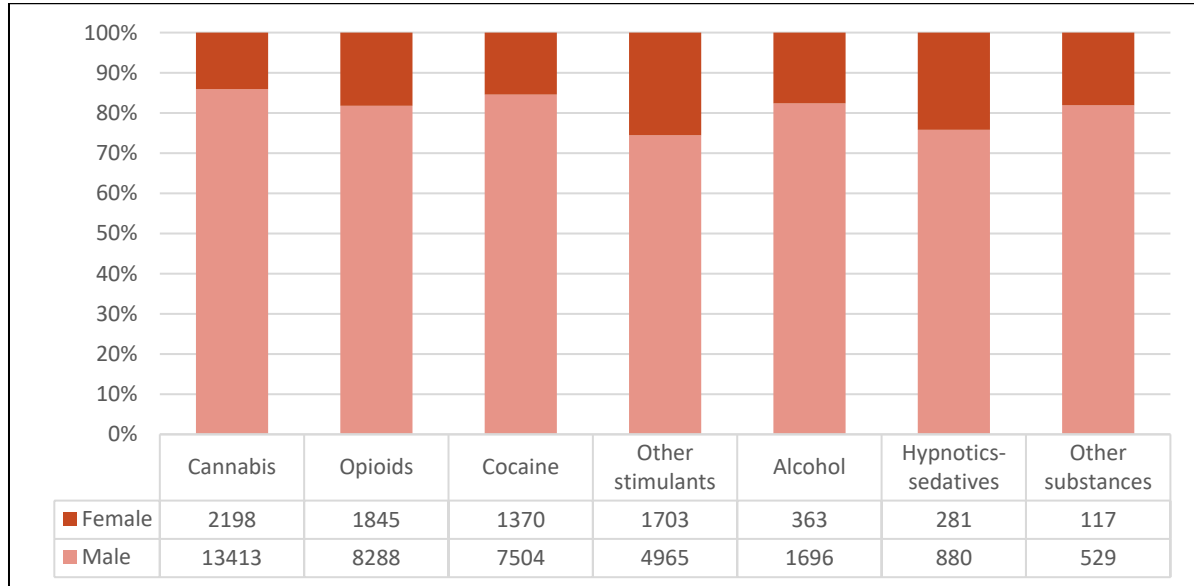


Figure 5.39 Total number and proportion of new episodes for male and female clients per primary drug in the Rehabilitation Centers for Addiction from 2011 to 2019 (NIHDI/Flemish Government financed programs only; Sciensano, TDI aggregated data).

Care episodes for primary cannabis use were started for a generally younger client population, with more than half of these episodes involving clients under 25 years. For most other primary drugs, the client group between 25 and 34 years was the largest group, but treatment for primary opioid and alcohol use was also started in more than 40% of new care episodes for users over 35 years.

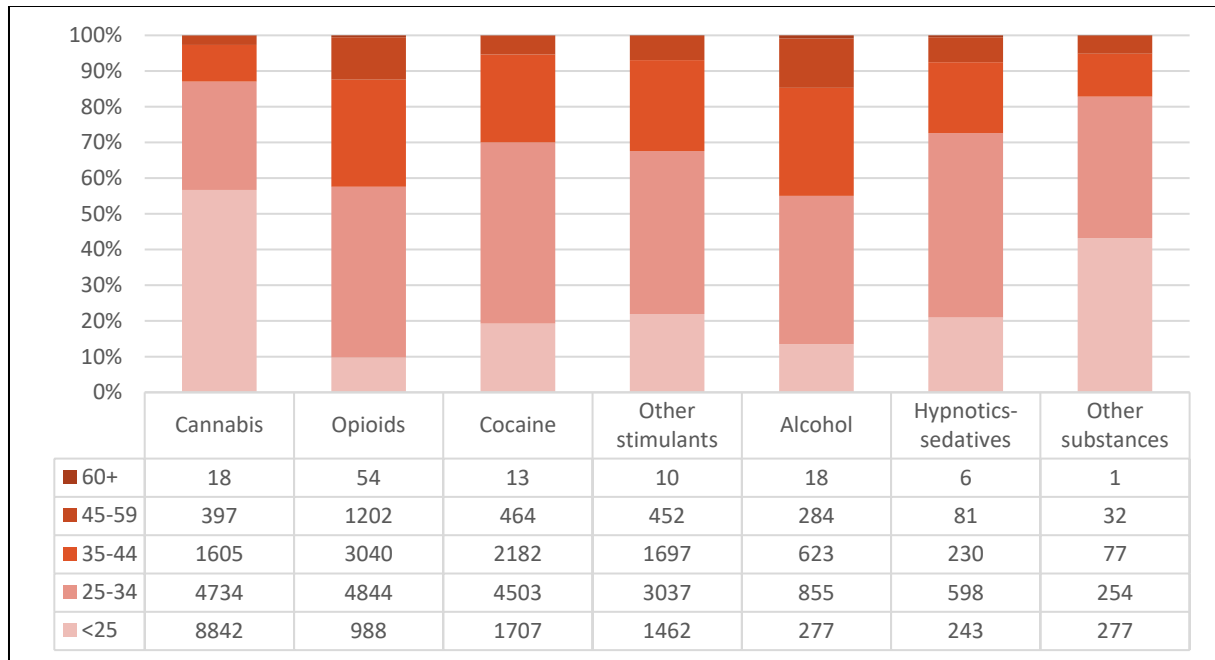


Figure 5.40 Total number and proportion of new episodes per age category by primary drug in the Rehabilitation Centers for Addiction from 2011 to 2019 (NIHDI/Flemish Government financed programs only; Sciensano, TDI aggregated data).

In more than 90% of new care episodes for primary opioid use and more than 80% of new care episodes for primary hypnotics or sedatives use, clients had been treated for addiction previously. For cannabis on the contrary, more than half of the new care periods involved first-time care seekers, with the other listed substances falling in between these percentages.

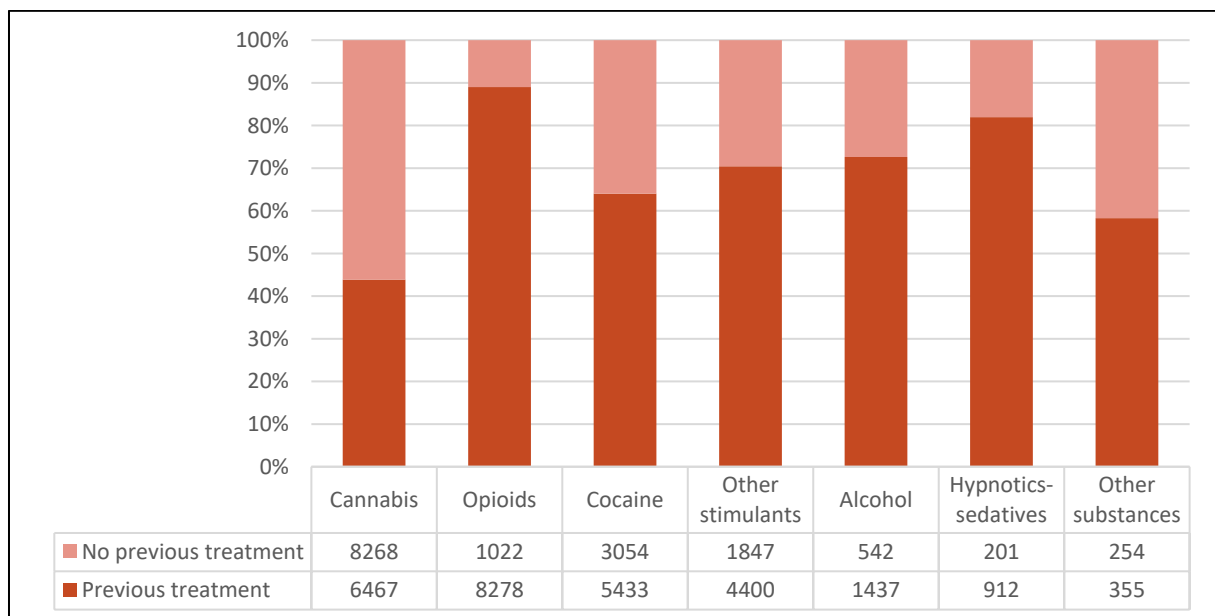


Figure 5.41 Total number and proportion of new episodes for previously or not previously treated clients per primary drug in the Rehabilitation Centers for Addiction from 2011 to 2019 (NIHDI/Flemish Government financed programs only; Sciensano, TDI aggregated data).

In Figures 5.43 and 5.44, regional differences in the proportion of new episodes per primary drug are shown for ambulatory and in-patient rehabilitation programs respectively. For some substances, these proportions varied substantially between 2011 and 2019 (e.g. opioids), whereas for others differences between provinces were limited (e.g. cocaine in ambulatory programs). Most noticeably, primary alcohol and hypnotics or sedatives use was treated more frequently in Limburg and less frequently in West Flanders than in the other provinces, especially in in-patient programs. This varied picture may be the result of several factors, such as the availability of alternative supply, regional practice differences in referral, etc. Nevertheless, alternative supply for ambulatory treatment seems ample in both provinces when compared to some of the other provinces, as the number of (new) care periods in the Centers for Mental Health Care in comparison to the population and the proportion of these care periods for addiction treatment suggest (see Figures 2.16, 2.17, 2.37, and 2.38 in Chapter 2). Given the fact that addiction treatment mainly involves clients with primary alcohol addiction in the Centers for Mental Health Care (see Figure 5.38), these results seem to suggest a greater need for alcohol addiction treatment in Limburg, or a greater shortage in supply in other provinces.

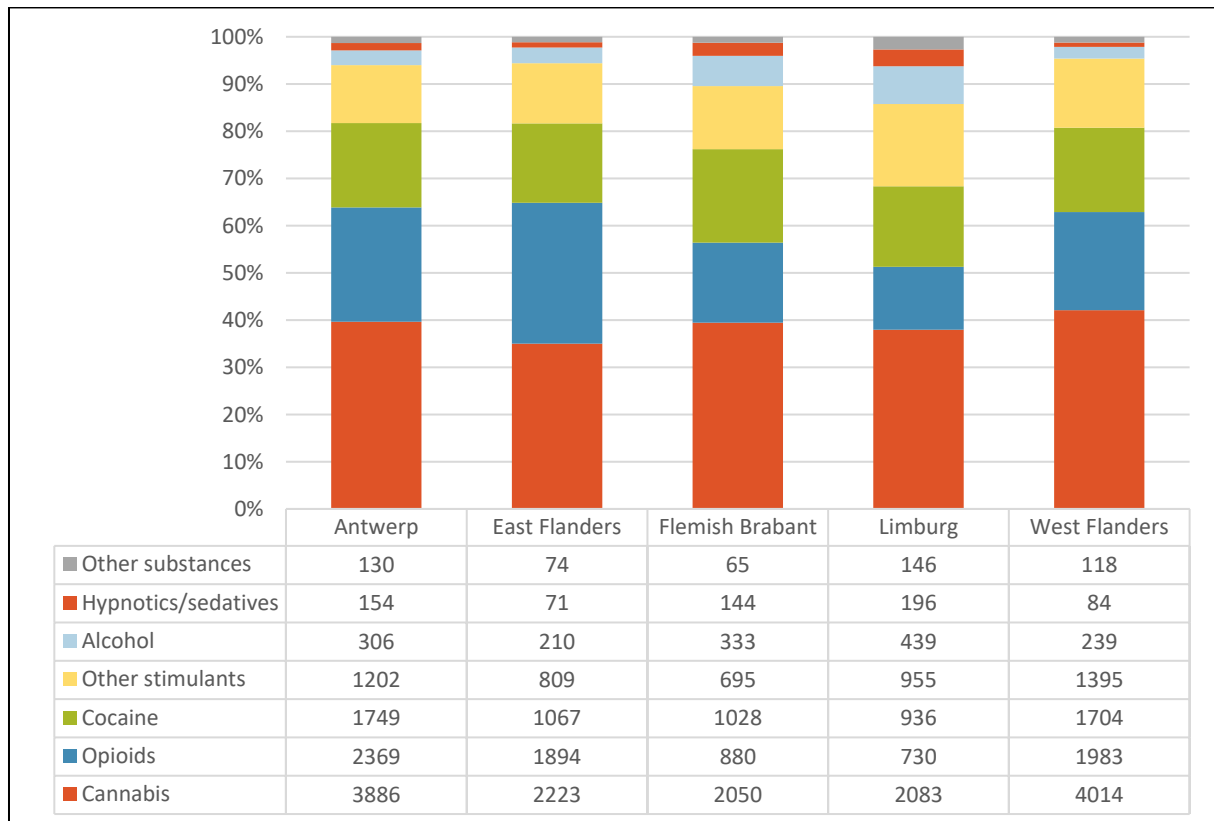


Figure 5.42 Total number and proportion of new episodes per primary drug in ambulatory Rehabilitation Centers for Addiction between 2011 and 2019, by province (NIHDI/Flemish Government financed programs only; Sciensano, TDI aggregated data).

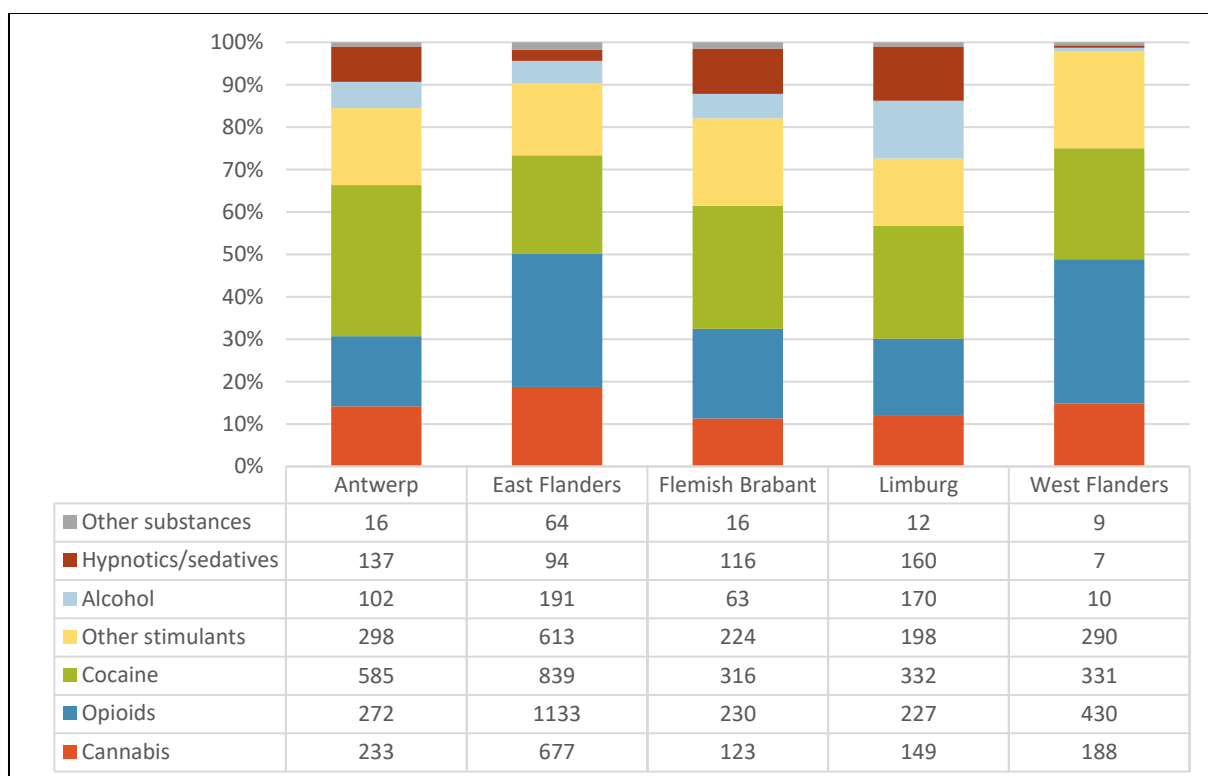


Figure 5.43 Total number and proportion of new episodes per primary drug in in-patient Rehabilitation Centers for Addiction between 2011 and 2019, by province (NIHDI/Flemish Government financed programs only; Sciensano, TDI aggregated data).

### 3.3 Description of costs in the Rehabilitation Centers for Addiction

Apart from a general overview of the total costs per nomenclature code (see paragraph 3.1 of this section) per year, provided by the National Institute for Health and Disability Insurance, a comprehensive electronic database with cost data for the Rehabilitation Centers for Addiction was not available for this project. Therefore, we limit our description of costs to two figures, showing the evolution of total costs for ambulatory services (sessions or rehabilitation weeks) and in-patient stay-days (Figure 5.45) and the evolution of calculated costs per case (Figure 5.46).

From 2008 to 2017, total costs for services in the Rehabilitation Centers for Addiction (including regularizations) augmented with 31%. This increase was relatively stronger for ambulatory services (40%) than for in-patient services (26%), mirroring the somewhat stronger increase in the number of ambulatory than in-patient provisions (see Figures 5.1 and 5.2).



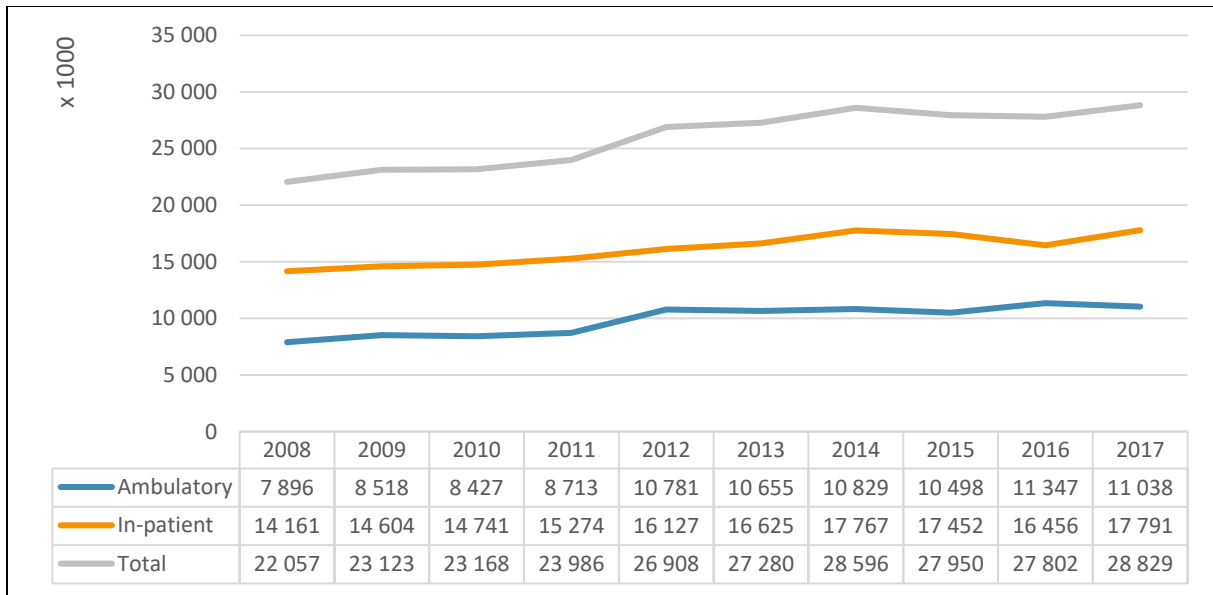


Figure 5.44 Evolution of total costs of ambulatory and in-patient rehabilitation services provided by the Rehabilitation Centers for Addiction from 2008 to 2017, including catch-up fees (NIHDI health insurance data).

In Figure 5.46 a rough approximation of the evolution of the average cost per delivered service is shown. Total costs were divided by the total number of cases, separately for services within or outside normal 90% billing capacity. Cases with nomenclature codes for regularizations and the associated catch-up costs were not considered.

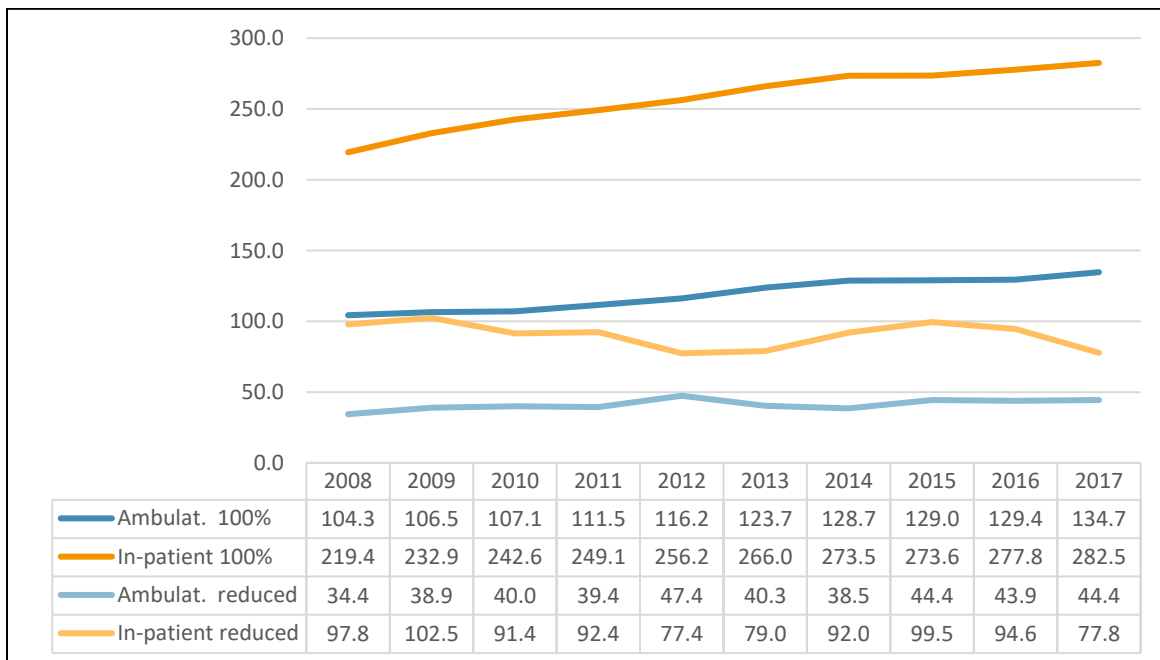


Figure 5.45 Evolution of costs per case of ambulatory and in-patient rehabilitation services provided by the Rehabilitation Centers for Addiction from 2008 to 2017, within or outside normal 90% billing capacity (NIHDI health insurance data).

The figure shows that the 100% rate cost per service increased with 29% between 2008 and 2017 for ambulatory as well as in-patient services. For services exceeding the 90% normal billing capacity, costs per case were fluctuating more for in-patient than for ambulatory services. As the total costs for these services

are the result of the number of rehabilitation centers exceeding their normal billing capacity, as well as of the number of services per rehabilitation center billed at different reduced rates (50% or 25%), it is difficult to draw conclusions from this.

#### **4 Projection of future needs, use and costs in the Rehabilitation Centers for Addiction**

The data presented in Section 3 of this chapter are not sufficient to construct a full explanatory, let alone predictive model for service use and associated costs in the Rehabilitation Centers for Addiction. Even when using the original individual records TDI-database instead of the aggregated data presented in this report, essential information to determine actual use in the Rehabilitation Centers for Addiction would still be lacking. For example, the database does not include data for ongoing treatment episodes in addition to newly started episodes. Neither does it include information regarding treatment duration or the number of delivered services per treatment episode.

Moreover, the Rehabilitation Centers for Addiction are probably another example of restricted supply and insufficient capacity, making future projections based on current use unreliable, as was argued in the introductory chapter of this report. This suggestion is corroborated by the data reported in Section 3, with the aggregated NIHDI service use data and the new episodes TDI-data both showing limited evolution in the overall use of the Rehabilitation Centers for Addiction between 2008 and 2019 (see Figures 5.1, 5.4 and 5.5 in Section 3 of this chapter).

This is not surprising, given that the maximum capacity of the programs in the Rehabilitation Centers for Addiction, financed by the federal and later the Flemish Government, was laid down in the conventions with NIHDI and confirmed in the rehabilitation agreements with the Flemish Agency for Care and Health, without providing a mechanism for adaptation to possible trends in demand. As a result, capacity hardly changed in the past years and capacity shortages were sometimes compensated by establishing alternatively financed programs within existing centers.

In addition, most rehabilitation centers seem to operate near maximum capacity. Although waiting list registration data are not available for the Rehabilitation Centers for Addiction, anecdotal evidence and questionnaire data suggest that waiting times to intake can be long. In a 2019 newspaper article (De Standaard), a spokesperson of an in-patient center indicated occupancy rates regularly exceeding 100% in recent years, leading to an average of four to five weeks waiting time for new clients in need of detoxification or follow-up care in a long-term residential program, or even resulting in temporary waiting list closure. A slightly less negative picture emerges in the waiting time report based on a study involving 1600 people seeking mental health care (SGGG & UA, 2020). In this study sample, 25 care seekers received care in the Rehabilitation Centers for Addiction, 12% of which within one week, 28% within two weeks, 64% within one month, and 92% within three months. However, the remaining two people (8%) had to wait between three and six months and an additional 20 people applied for care, but were not yet helped, with 15% of them still on the waiting list and one person (5%) confronted with an application stop.

Despite the limitations of the data pertaining to service use in the Rehabilitation Centers for Addiction, the description presented in Section 3 of this chapter draws attention to several important factors associated with service use that should be incorporated in any explanatory use or cost model. These factors can be considered as a first set of building blocks and include client variables (e.g. gender, age, income, primary substance) and treatment characteristics (e.g. referrer, previous treatment), interacting with each other

and with supply factors, manifest in the unequal regional spread of rehabilitation capacity and the use of other addiction treatment services.

However, to the extent that capacity regulations rather than the distribution of needs determine supply, any prediction model for service use in the Rehabilitation Centers for Addiction will be incomplete and should incorporate needs data, collected independently of current service use. In the introductory chapter of this report, we already suggested the approach of using population prevalence data to assess needs in the context of restricted supply. However, the summary of prevalence data in Appendix 1 concerning substance-related disorders and substance use shows that complete yearly time series for substance use in the entire Flemish population are not available. Measures that do provide yearly data are limited to specific groups (e.g. secondary school students) or specific regions (e.g. waste water analysis studies). Moreover, substance abuse or dependencies are measured in terms of use, which may provide a good estimate for hard drugs (e.g. opioids), but not so much for other substances, such as cannabis or alcohol. Problematic use in addition to use was only measured since 2018 for these two substances. Finally, what is mostly missing, is an association of prevalence data with service use. In other words, which part of the group of people using or abusing illicit or other substances needs the specialized rehabilitation care programs offered in the Rehabilitation Centers for Addiction, instead of other services providing addiction treatment, ranging from the general practitioner to the Centers for Mental Health Care or Hospital care.

#### **4.1 Prediction models for service use in the Rehabilitation Centers for Addiction**

Notwithstanding the shortcomings, the substance use (prevalence) data summarized in Appendix 1 show some important trends that reflect the trends in service use in the Rehabilitation Centers for Addiction described in Section 3. Two observations stand out: The rise of stimulant use (including cocaine) and regional differences in substance use within Flanders, suggesting that the uneven regional spread of addiction treatment facilities may not solely be supply-driven. In the regressions on the aggregated new care episodes TDI-data for the Rehabilitation Centers for Addiction presented in Appendix 5, an attempt is made to include these and other observations described in Section 3 of this chapter in a few simple projection models. However, as we noted in Chapter 2 describing the regressions models for the Centers for Mental Health Care, any observed regional effects (of province dummies) are difficult to interpret using aggregated datasets per center, given the interaction between the capacity of individual centers, the number of other centers in the province, and actual regional differences in care need.

Again, in a first step, we simply add year dummies to establish time trends in addition to regional effects in models predicting all new care episodes and new care episodes per problematic or primary drug. In a second step, estimates of the population in Flanders with problematic drug use are added, using the international meta-analysis estimate for substance-related disorder (Steel et al., 2014) and HIS-prevalence estimates for problematic use of specific substances, including cocaine, other stimulants, opioids, cannabis, alcohol, and poly drug use (see Appendix 1 for further details). Given that only two years of measurement were available (2013 and 2018), datasets are very small when using the HIS-based estimates, especially when considering ambulatory and in-patient programs separately. It is therefore not surprising that observed effects were few.

As expected from the description of service use in Section 3 of this chapter, no significant effects were observed for the year dummies in the models using the total number of new episodes per center as a dependent variable (see Appendix 5). In other words, there is no evolution in these totals, as was the case for the other service types described in this report. Given this lack of evolution, it is not surprising that the

inclusion of the prevalence-based Flemish population estimates instead of the time dummies has no effect in most regressions either. When evolution in care episodes is apparent, as for cocaine and stimulant use, significant effects are sometimes observed (e.g. model 6a and model 7a), but due to the HIS-prevalence estimates limited to only two years, these results cannot be considered reliable.

The regression analyses presented in Appendix 5 are thus not very useful for constructing projection models, but again, they clearly illustrate the problem with restricted supply mentioned in the introductory chapter. When hardly any evolution is observed in the past, despite prevalence-based estimates clearly showing a rising trend, it is not possible to make projections for the future.

## Chapter 6

### Other psychosocial and physical rehabilitation centers

In addition to the Centers for Ambulatory Rehabilitation and the Rehabilitation Centers for Addiction described in Chapter 4 and 5, the Flemish Government is responsible for several other rehabilitation facilities since 2019. Specific modalities with respect to objectives, target group, rehabilitation activities, financing, personnel, administration and registration, etc. are described in separate rehabilitation agreements per center that can be consulted on the website of the Flemish Agency for Care and Health (<https://www.zorg-en-gezondheid.be/revalidatieovereenkomsten>).

These centers are aimed at rehabilitation, psychological wellbeing, and social (re)integration of clients with psychosocial (<https://www.zorg-en-gezondheid.be/psychosociale-revalidatieovereenkomsten>) and physical disorders (<https://www.zorg-en-gezondheid.be/fysieke-revalidatieovereenkomsten>), offering ambulatory and/or in-patient care in different locations throughout Flanders. They include:

- The Psychosocial Rehabilitation Centers for Adults
- The Psychosocial Rehabilitation Centers for Children and Adolescents
- Autism Reference Centers
- Rehabilitation Units for Disturbances in Early Parent-Child Interactions
- Centers for Locomotor and Neurological Rehabilitation
- Rehabilitation Centers for Children with Respiratory and Neurological Disorders
- Centers for Visual Rehabilitation
- Respite Care Units

Seeing that these centers and units were previously under the responsibility of the federal government, health insurance data with respect to delivered services and costs are available at the National Institute for Health and Disability Insurance (NIHDI) and the Inter-Mutualistic Agency. However, the number of clients in the permanent sample (EPS) of the IMA-database we obtained for this research project was extremely small for most services, as Table 6.1 illustrates for the main normal fee nomenclature codes used in 2017. In that year, there were no clients at all in the sample for five out of the eight rehabilitation service types.

Table 6.1 The number of unique clients in the EPS in 2017 for normal fee ambulatory and in-patient rehabilitation pseudo-nomenclature codes, by rehabilitation service type (EPS, Health Insurance data).

Rehabilitation service type	NIHDI-pseudo nomenclature code(s)	Unique clients in EPS
Psychosocial Rehabilitation Centers for Adults	Ambulatory: 772052 In-patient: 772063	4
Psychosocial Rehabilitation Centers for Children and Adolescents	Ambulatory: 772096 In-patient: 772100	0
Autism Reference Centers	Ambulatory: 784571 In-patient: 784582	0
Rehabilitation Units for Disturbances in Early Parent-Child Interactions	Ambulatory: 773371 In-patient: 773382	0
Centers for Locomotor and Neurological Rehabilitation	Ambulatory: 772030, 774690 In-patient: 772041, 774701	11
Rehabilitation Centers for Children with Respiratory and Neurological Disorders	Ambulatory: 772133, 772413 In-patient: 772144, 772424	0
Centers for Visual Rehabilitation	Ambulatory: 771271, 771293 In-patient: 771282, 771304	32
Respite Care Units	In-patient: 776705	0

Due to this lack of data, the rehabilitation services listed above will not be described further in the current report. Instead, we refer to the report of Moors et al. (2021), which provides important insights into care delivery in these and the other mental health care and rehabilitation services under the responsibility of the Flemish Government, based on an extensive consultation round with representatives from the sector.

## Chapter 7

### Conclusion and recommendations for data collection

In this chapter, we briefly summarize some conclusive comments with respect to the availability, accessibility, and quality of service use data (7.1) and the problem of restricted supply in the mental health care and rehabilitation sector (7.2). Furthermore, an attempt is made to listing basic recommendations for future data collection as a means of mapping care needs to predict service use and costs in the coming years (7.3).

#### 1.1 Availability, accessibility, and quality of service use data

Despite the elaborate description of service use in the Centers for Mental Health Care, the Centers for Ambulatory Rehabilitation, and the Rehabilitation Centers for Addiction, the present report mainly shows the limitations of the available registration data for these services, as well as for the Sheltered Living Initiatives and the other rehabilitation facilities under the responsibility of the Flemish Agency for Care and Health.

For the development of service use and cost projection models in elderly care, the permanent sample (EPS) of the health insurance database managed by the Inter-Mutualistic Agency proved very useful (see Part II of this report), but for the description of service use in the mental health care and rehabilitation sector, it is clearly inadequate, mainly due to the limited number of relevant cases in the sample. At the very least, it would have been necessary to request the complete IMA-database for the services described in this report. However, even then information would fall short to paint a complete picture, seeing that services delivered by the Centers for Mental Health Care have never been covered by the health insurance funds and are thus not registered in the IMA-database. In addition, for other services that were part of the federal health insurance system before the Sixth State Reform, nomenclature codes are quite general, so that little detail is available about the conditions that are treated or the actual care activities they refer to.

An exception to this last point are the Centers for Ambulatory Rehabilitation (Chapter 4), with separate problem-specific nomenclature codes for diagnostic and treatment sessions. But even there, as a result of the low number of cases in the EPS and the unavailability of the complete IMA-database for this report, it was necessary to look for other data sources for the description of service use as well. At first sight, a good amount of relevant information seemed to be available in the annual reports sent yearly to the Flemish Agency for People with a Disability (VAPH), albeit not on the individual level, but on the level of the center and in separate documents. Digitalization into a small database, though, showed that a considerable quantity of the data was missing, leading to more or less incomplete time series for all variables. With data quality control lacking as well, it is clear that all reported results have to be interpreted with care and that generalization to service use in all Centers for Ambulatory Rehabilitation is not straightforward. At present, the best information available for describing time trends in service use and costs in the CAR thus remains the complete IMA-database.

Contrary to the Centers for Ambulatory Rehabilitation, the EPS or the full IMA-database are of no use at all for describing service use and costs in the Centers for Mental Health Care. Only a small number of specific services (e.g. psychiatrist consultations or speech therapy) fall under the health insurance system, but these services cannot be distinguished from similar services performed by the same professions outside the

context of the Centers for Mental Health Care. However, the Centers for Mental Health Care use their own specific registration system, which is probably the most comprehensive one in the sector at present. As Chapter 2 of this report shows, many important variables for describing client profiles and (the evolution of) service use in the Centers for Mental Health Care are included in this electronic patient filing system or EPD. Yet, apart from the yearly interactive summary web report published on the website of the Agency for Care and Health, the wealth of information registered in the EPD since 2008 does not seem to have been used much in research projects and little information is available with respect to standardization of the registration and the reliability of the data. For the current report, we obtained a number of aggregated datasets, underlying the separate interactive tables in the published annual web reports. Due to the lack of information regarding the registered variables, though, results are sometimes difficult to interpret. In addition, possibilities for developing projection models are limited using separate aggregated datasets, containing only a small number of variables each. Nevertheless, the descriptive statistics reported in Chapter 2 show the potential of the EPD database, given that the individual level information could be made accessible for research purposes.

Another registration database in the mental health care sector is the Minimal Psychiatric Dataset (MPG), which includes information regarding the Sheltered Living Initiatives in addition to other, mostly in-patient psychiatric facilities (e.g. the Psychiatric Care Homes or PVT). We did not use this dataset for the present research project, but it has been widely used in several other projects describing clients in different psychiatric facilities, including the Sheltered Living Initiatives (e.g. Verniest, et al., 2008).

In both the MPG and EPD registration system, the social security identification number (INSZ) of the client is not or not consistently registered. Consequently, data from both registration systems cannot be coupled with data from other facilities or health insurance data. However, for clients with addiction problems, facilities are encouraged to register the INSZ as part of the requested information for the Treatment Demand Indicator (TDI), even though clients still have the right to refuse and insist on anonymous registration.

For the description of service use in the Rehabilitation Centers for Addiction in Chapter 5 of this report, we used an aggregated dataset derived from the TDI database. Given that important efforts have been made by the federal health institute Sciensano to standardize registration, reliability of the TDI dataset since 2011 is acceptable. However, the mapping of service use and care delivery is not the main objective of the TDI data collection. As a result, many relevant treatment variables are not included and data are restricted to newly started care periods, making the dataset of limited usability for the purposes of this report.

Notwithstanding this, apart from the EPS health insurance data, the TDI is the only dataset we explored containing data from different facilities, including the Centers for Mental Health Care. In addition, registration of the INSZ, makes it theoretically possible to couple different care periods in the care trajectory of clients throughout different facilities. Considering that there is an overlap in target group between the Rehabilitation Centers for Addiction and the Centers for Mental Health Care, registration of a common identification number in both facilities is useful to gain insight into the relation between care need and service use in the mental health care and rehabilitation sector.

A similar overlap in client profile is apparent in other services as well, as is clear from the description of target groups in the different chapters in the present report. People with mental illness receive care in the Centers for Mental Health Care, but are the main target group of the Psychosocial Rehabilitation Centers and the Sheltered Living Initiatives as well. Children and adolescents with developmental disorders and comorbid mental problems may best be helped through cooperation of the Centers for Ambulatory



Rehabilitation and the Mental Health Care Centers in a joint care trajectory (Kimpe et al., 2019), etc. Coupling of data between services is therefore necessary to construct the ideal dataset for describing care use and predicting future trends suggested in the introductory chapter, with rows distinguishing needs groups and columns representing different mental health care and rehabilitation services.

However, the use of a common identification number is not enough to achieve this. In addition, it is crucial that important client and treatment variables identifying needs groups and predicting service use are consistently registered in a standardized way throughout the sector. With the introduction of BelRAI in the mental health care and rehabilitation sector (Van Horebeek, et al., 2021), the first steps in implementing a uniform comprehensive assessment instrument with the potential to provide such a dataset has been made. Besides its main focus of mapping care needs as a key element in the realization of well-coordinated, continued care for every client, the registered information can form the basis for quality management, care planning, and financing at the level of organizations, networks, or governments. With the Flemish Government Decision of 30 November 2018 to implement the decree of 18 May 2018 regarding the Flemish Social Protection (Vlaamse overheid, 2018), the implementation of BelRAI as the foundation for a care need based Flemish financing system (the so-called person-following financing) became a priority target. In the recent report of Moors et al. (2021), important steps have been taken to realize this target by developing a uniform conceptual framework for the person-following financing system, based on extensive input from all the care sectors involved, including the mental health care and rehabilitation sector.

## **1.2 The problem of restricted supply**

In addition to the problem of data availability, a more fundamental issue arises when describing service use in the mental health care and rehabilitation sector, as was already mentioned in the introductory chapter. For most of these services, capacity regulations lead to restricted supply and insufficient coverage of care needs in some or all Flemish provinces. Waiting lists are long and increasing, leading to clients ending up using services that are not entirely suited to their needs or potential clients not being treated at all in a sector where stigma and insufficient knowledge of care offer already hinders access to the appropriate help.

In this context, service use data are not sufficiently informative of needs, and future projections solely based on observations about past use, may be very misleading as an indicator of coming trends. It is therefore necessary to expand our method to projecting future needs by incorporating population prevalence data as a means of assessing mental health care or rehabilitation needs independently from actual service use. The prevalence information summarized in Appendix 1, though, showed that Flemish prevalence data are insufficient at present. With four to five-year gaps and operationalizations changing in between measurements in the Belgian Health Interview Survey (HIS), complete time series for the Flemish population are not available. In addition, regional differences within Flanders cannot be established, as sample sizes per province are mostly too small and not representative. It is also noteworthy that the prevalence of certain conditions is probably underestimated. Demarest et al. (2012) explicitly mention people with problematic illicit substance use, which are difficult to reach and therefore underrepresented in the HIS sample, especially when marginalized (e.g. homeless persons, detainees) or when using heavily.

Finally, even when reliable and complete time series for the prevalence of mental health problems, developmental disabilities, and other relevant conditions were available, additional information is needed to build a complete service use model, including information with regard to the connection between problem (e.g. severity, co-morbidities, etc.) and appropriate service, as the specific care offered by the

specialized services described in this report is not necessarily indicated for all people reporting that problem. Therefore, data with respect to client profiles from all facilities in the care trajectory of clients would be useful, including data from general practitioners and other referring instances. Although some general practice data are available in Flanders, their usefulness for projecting future mental health care and rehabilitation needs is limited at present. An example is the integrated computerized morbidity registration network Intego (Truyers et al., 2014; <https://intego.be/>), routinely collecting data from over 90 general practitioners in Flanders since 1994. The Intego database contains good quality data and is considered representative for the Flemish population regarding gender and age. However, participating general practitioners are unequally distributed across Flanders, further referral information is not included, and registered diagnoses on the general practice level may not be sufficiently differentiated to distinguish clients in need of the specialized services described in this report. Moreover, many people with specialized mental health care or rehabilitation needs are referred by services in sectors other than the health care sector, including education, welfare, and justice, or they have not yet found their way to the care they need. Information from these sectors, as well as data with respect to (socio-economical) characteristics (e.g. income, social surroundings, etc.) distinguishing people seeking help from people with unmet care needs, could prove insightful as well.

### **1.3 Recommendations for future data collection**

Reality caught up with this research project in the sense that the implementation of BelRAI as the basis for care planning and financing in the mental health care and rehabilitation sector is well underway, thereby providing a uniform system of data collection and an answer to many of the problems with the available data in the sector. Nevertheless, the final roll-out will still take a considerable number of years, with even more years added before time series cover a sufficiently long period to estimate service use trends.

When formulating recommendations, it is thus necessary to take into account BelRAI as the foundation of future data collection on the one hand, without losing the wealth of information from the past on the other hand.

In a first step, the results in the present report can help relate (the evolution in) client profiles to (the evolution of) service characteristics, thereby determining crucial client as well as treatment variables that should be included in BelRAI or any system of data collection used in the mental health care and rehabilitation sector.

Second, given the problem of restricted supply outlined in Paragraph 7.2 above, the development of models for describing and predicting service use requires additional internal and external information, ideally including:

- Internal waiting time and waiting list data, registered continuously and in a uniform way throughout the mental health care and rehabilitation sector.
- External information regarding the entrance gates to the specialized mental health care and rehabilitation services, with the possibility of coupling data on the client level through the use of the INSZ code by means of a Thrusted Third-Party system.
- Reliable and sufficiently frequently collected external prevalence data for the developmental, psychosocial, and physical health problems with a need for specialized mental health care and psychosocial rehabilitation in the Flemish population. Whilst prevalence data are preferably collected in the general population, independently of health care service use, it would be informative

to include service use questions for all health care facilities in the surveys used, among which the Flemish mental health care and rehabilitation services. By doing so, it becomes possible to connect characteristics of the surveyed conditions and disorders (e.g. severity, comorbidities, etc.) to specific service use. In addition, it would be helpful to apply the same definitions for determining the prevalence of disorders in the general population as for the registration of diagnostic information in the mental health care and rehabilitation services. Finally, all relevant socio-demographic variables determining distinct client profiles or needs groups in the mental health care and rehabilitation services, should also be included, with attention paid to possible regional differences in the prevalence of certain problems as well, making it necessary to ensure representative sampling, at least at the provincial level.

Meanwhile, given the long trajectory ahead for implementing BelRAI, the existing databases described in this report can provide information to mapping the evolution in service use in the near future as well. Especially the EPD system in the Centers for Mental Health Care contains extensive and detailed information on the individual client and care period level. It is however necessary to enhance the usability of the EPD-data by improving standardization and data-quality control and making the database more accessible. This is not only important at present, but may also help prolong time series to map evolutions in the future, especially when data-coupling on the client level can be realized, e.g. through consistent registration of a common identification code (the INSZ).

For the other mental health care and rehabilitation services described in this report, the IMA-database probably remains the most important data source for past service use information. However, it is necessary to make use of the complete dataset, given the low number of cases in the permanent sample (EPS) requested for this research project. Especially for the Centers for Ambulatory Rehabilitation, it would be worthwhile to explore the IMA-dataset, considering the use of diagnosis-specific nomenclature codes for billing treatment sessions. In addition, for the Rehabilitation Centers for Addiction, coupling with the TDI-database can be realized through the INSZ, as was done in a Sciensano research project (De Ridder et al., 2015), thereby linking the services billed under the quite general nomenclature codes in the IMA-dataset with relevant variables in the TDI-register (e.g. problematic substances).

At present, financing of the services that transferred to the Flemish government after the Sixth State Reform, is basically still structured in much the same way as it was under the responsibility of NIHDI, even if codes for billing services have changed. This means that, for now and in the near future, it is possible and therefore advisable to continue the registration in a similar fashion so as to produce time series that connect seamlessly to the federal data collected in the IMA-database.



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## Part III - Appendix 1

### Prevalence of mental health problems and developmental disorders

Appendix 1 summarizes international and Belgian population prevalence data with respect to mental health problems and developmental disabilities as a means of assessing the need for mental health care and rehabilitation. Therefore, the aim of this summary is not to give an exhaustive overview, but to provide an estimate of needs in the Flemish population, that can be incorporated into a model for predicting future use of the services described in the report.

In Section 1, we focus on assessing the prevalence of mental disorders (including substance abuse and dependence) in order to estimate the population with a potential need for care in the Centers for Mental Health Care and the Rehabilitation Centers for Addicts. Section 2 assesses the prevalence of developmental disorders in children and adolescents, who constitute the main target group in the Centers for Ambulatory Rehabilitation.

In both sections, we first provide an overview of prevalence percentages from international meta-analyses, followed by data from the Belgian Health Interview Survey or other data sources. Finally, we describe different approaches for estimating the Flemish population targeted by the services mentioned above, with prevalence percentages applied to demographic data.

#### 1 Prevalence of mental health problems and mental illness

##### 1.1 International meta-analyses

In 2014, Steel et al. reported a pooled 12-month period prevalence estimate of common mental disorder of 17,6% for adults, based on a meta-analysis of 155 surveys, conducted in 59 countries between 1980 and 2013. Table 1.1 summarizes the gender-specific prevalence estimates for mental disorder in general and for the most common specific mental disorders, resulting from this meta-analysis.

Table 1.1 Twelve-month period gender-specific prevalence estimates for any common mental disorder and specific mental disorders in adults.

<i>Steel et al. (2014)</i>	Prevalence adults	Prevalence men	Prevalence women
<b>Any common mental disorder</b>	<b>17,6%</b>	<b>14,7%</b>	<b>19,7%</b>
Mood disorder	5,4%	4,0%	7,3%
Anxiety disorder	6,7%	4,3%	8,7%
Substance-related disorder	3,8%	7,5%	2,0%

In addition to gender differences, Steel et al. (2014) observed time effects and regional variations. Studies conducted during the 1990s returned higher pooled prevalence estimates (21,8%) than studies conducted after 2000 (14,7%), but the covarying effect of the diagnostic nomenclature method used, makes it difficult to draw conclusions from this. In high-income countries the overall prevalence estimate

was 17,5%, with a higher estimate for English-speaking countries (19,0%) than for other European (17,1%), and especially Asian countries (11,5%).

For children and adolescents, Polanczyk et al. (2015) conducted a meta-analysis, including 41 studies from 27 countries, published between 1985 and 2012. They found a worldwide pooled prevalence estimate for mental disorders of 13,4%, with no evidence for estimates varying significantly as a function of the geographic location of the studies or year of data collection.

Table 1.2 Prevalence estimates for any mental disorder and specific mental disorders in children and adolescents.

<i>Polanczyk et al. (2015)</i>	Prevalence
<b>Any mental disorder</b>	<b>13,4%</b>
Any depressive disorder	2,6%
Any anxiety disorder	6,5%
Any disruptive disorder	5,7%

## 1.2 Belgian Health Interview Survey

### 1.2.1 Overall measures of mental health problems and mental illness

In the Belgian Health Interview Survey (HIS), the prevalence of mental health problems and probable mental illness are estimated on the basis of 12 self-report items (General Health Questionnaire GHQ-12) measuring psychological well-being in the past weeks (Gisle et al., 2018). The threshold of the probable mental illness indicator corresponds with presumed psychopathology and identifies people in need of professional treatment. Figure 1.1 shows the evolution of the probable mental illness indicator in Flanders in comparison with Belgium as a whole and the other regions. The HIS-percentages in the figure were obtained from the HIS Interactive Analysis (HISIA) website (Drieskens et al., 1997-2018) and are weighted percentages, with weighting factors adjusting for differences between survey sample and population in terms of distributions by age, gender, household size, and province.

The Belgian prevalence estimates are in line with the results of the international meta-analysis conducted by Steel et al. (2014), with an estimate of 17,2% in the late 1990s and lowering percentages in the years following 2000. In 2013 and 2018, however, estimates increased again to more than 17%. Notwithstanding this, prevalence estimates in Flanders were markedly lower than in the other Belgian regions in all years, suggesting regional differences even within rather restricted areas.

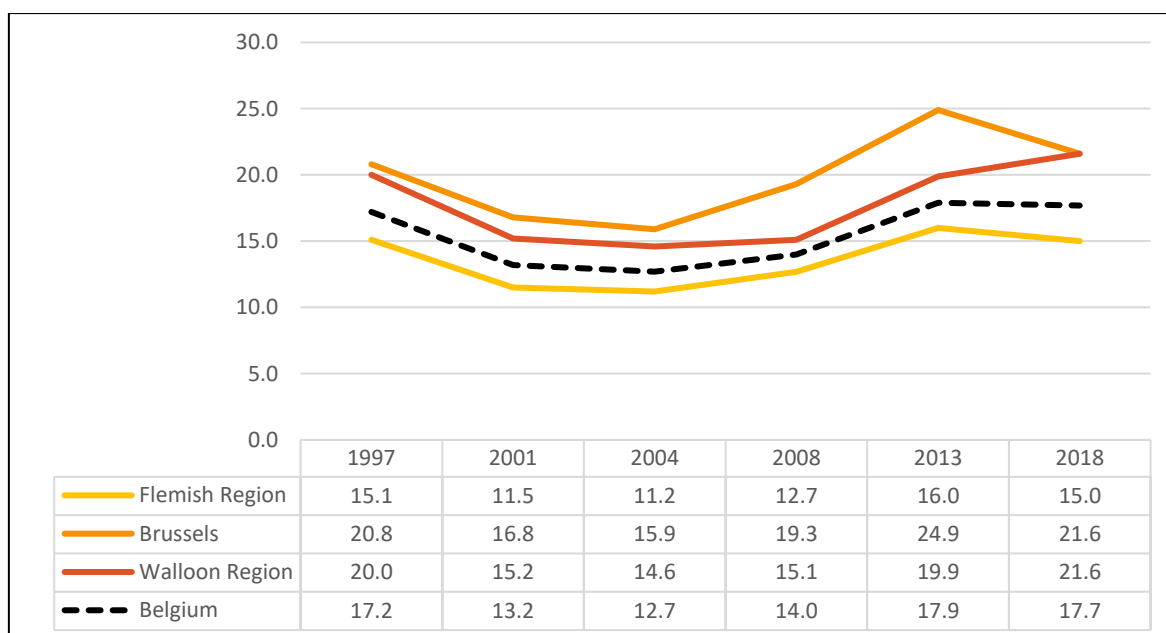


Figure 1.1 Evolution of the percentage of the Belgian population aged 15 years and over with probable mental disorder, by region (HISIA, indicator WB\_3).

A comparison between six European countries in the ESEMeD/MHEDEA-project funded by the EU-Commission and conducted between 2001 and 2003 (EPREMED Consortium, 2008) corroborates this suggestion with 12-month prevalence estimates for any mental disorder ranging from 8,4%, 9,3%, and 10,9% in Italy, Spain, and Germany, respectively to 13,4% and 18,3% in the Netherlands and France, with the 12,7% Belgian estimate falling in between. For the Netherlands, the NEMESIS-2 study (de Graaf et al., 2010) led to a higher 18,0% prevalence estimate for any mental disorder between 2007 and 2009 than the earlier ESEMeD project, which suggests an even stronger increase than in Belgium.

In 2018, the Strengths and Difficulties Questionnaire (SDQ) was included in the Belgian Health Interview Survey as a measure of the mental health of children and adolescents between 2 and 18 years. The resulting percentages of children and adolescents with borderline or probable mental disorder (emotional problem, behavioral problem, or ADHD) in Flanders as compared to the other regions are shown in Table 1.3 below.

Table 1.3 The percentage of the Belgian children and adolescent population (2 to 18 years) with borderline or probable mental disorder, by region (Indicator CH\_18)

<i>Gisle et al., 2020</i>	Borderline	Probable
Flemish Region	6,4%	7,5%
Brussels	5,8%	6,9%
Walloon Region	6,5%	11,0%
<b>Belgium</b>	<b>6,4%</b>	<b>8,7%</b>

The Belgian Health Interview Survey estimate for probable mental disorder in children and adolescents is markedly lower than the estimate for any mental disorder in children and adolescents by Polanczyk et al. (2015). However, when including both borderline and probable mental disorder, the added percentage for Belgium as a whole is higher (15%), with the estimate for Flanders and Brussels (13,9% and 12,7%) approaching the international meta-analysis estimate of 13,4%.

## 1.2.2 Specific mental disorders

### *Mood and anxiety disorders*

In addition to the probable mental disorder indicator described above, the Belgian Health Interview Survey includes questions for specific mental disorders, such as mood disorders and anxiety disorders. Figures 1.2 and 1.3 show the evolution of the period prevalence of both disorders in Belgium and the Belgian regions. Differences between 2018 and earlier years have to be interpreted with caution, though, as a result of methodological changes under the impulse of Eurostat for better international comparison within Europe and beyond (Gisle et al., 2018). From 2001 to 2013, the Symptom Checklist (SCL-90R,10) was used for measuring mood and anxiety disorder, whereas in 2018 mood disorder was measured with the Patient Health Questionnaire (PHQ, 11) and anxiety disorder with the Generalized Anxiety Disorder scale (GAD-7, 12), which are both translated in several languages and validated in different cultures.

The HIS-prevalence percentages for any mood disorder (major or other) lowered from 2001 to 2004 and mounted again between 2004 and 2013 in all regions. In every year, prevalence percentages were estimated higher in Brussels and the Walloon Region than in Flanders. The newly introduced questionnaire in 2018 led to a 6,4% prevalence percentage in Flanders, which is closer to the international meta-analysis estimate of 5,4% than the higher earlier year percentages. Contrary to the Flemish Region percentages, the 2018 percentages for Belgium as a whole and for the other regions were higher than the 2001 and 2004 percentages. In 2018, the HIS also provided a measure for major depressive disorder, which amounted to 4,8% for Belgium, 3,2% for the Flemish Region, 6,2% for Brussels, and 7,4% for the Walloon Region.

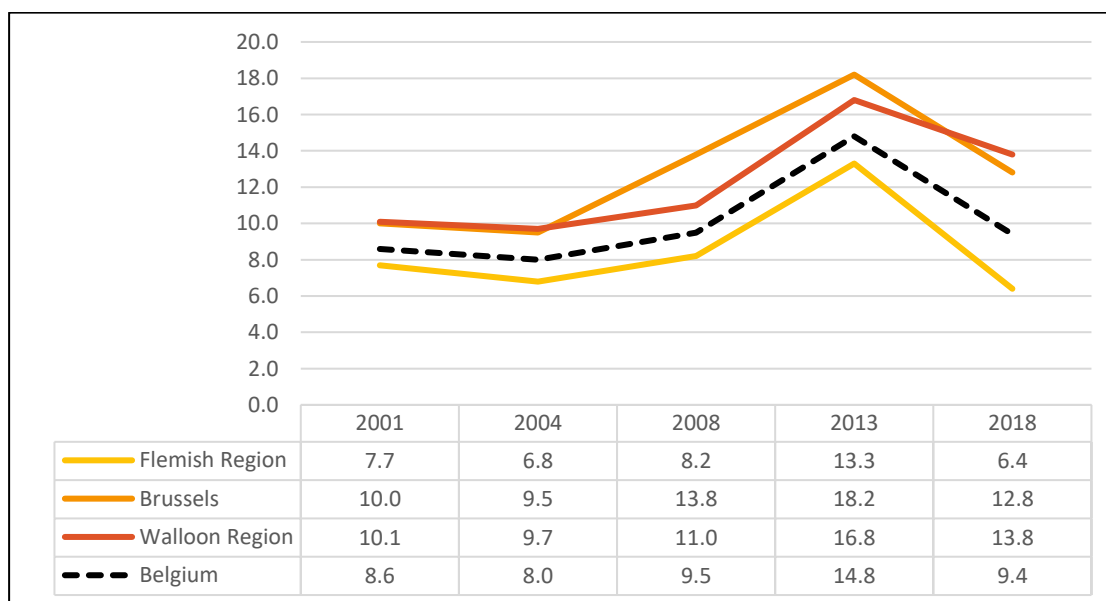


Figure 1.2 Evolution of the percentage of the Belgian population aged 15 years and over with any mood disorder, by region (HISIA, indicator AD\_6).

The generalized anxiety HIS-prevalence percentages for Belgium as a whole are comparable to the international meta-analysis estimate of 6,7% in the first three years of measurement, but the Flemish Region estimates were lower than in the other regions. In 2013, the observed prevalence percentages mounted markedly in the whole of Belgium and in 2018 the newly introduced questionnaire led to a

slightly lower percentage in Flanders, but to even higher percentages in Brussels and especially the Walloon Region.

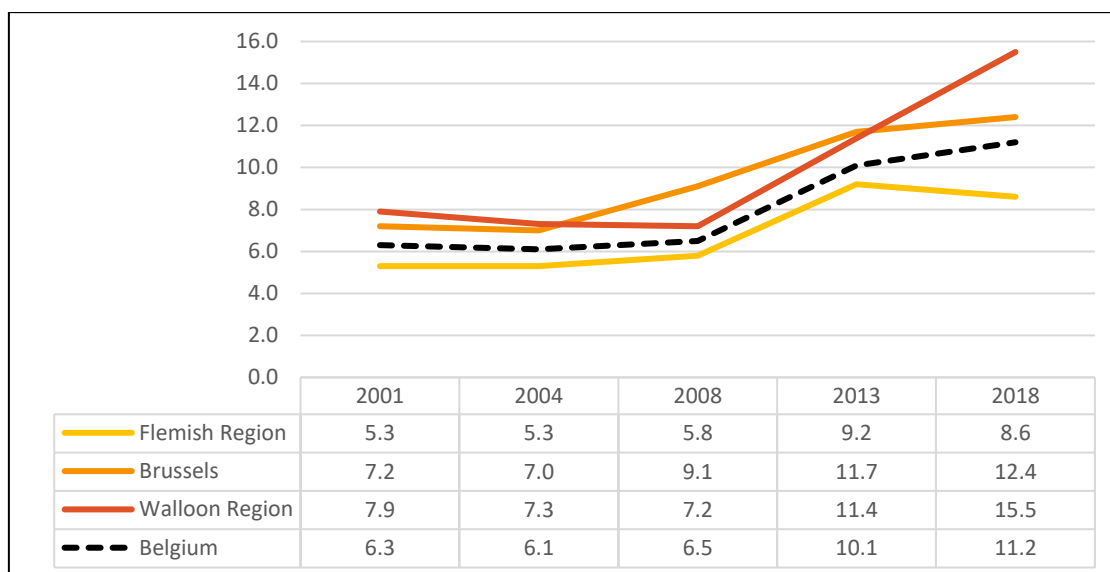


Figure 1.3 Evolution of percentage of the Belgian population aged 15 years and over with generalized anxiety disorder, by region (HISIA, indicator AD\_1).

The regional differences shown in both figures above, are also apparent when comparing Belgium with surrounding countries. In the six European countries of the ESEMeD/MHEDEA-project prevalence estimates for mood disorder ranged from 3,3% in Germany to 6,5% in France, with a reported estimate of 5,3% for Belgium (EPREMED Consortium, 2008), which was markedly lower than the reported HIS-percentages. Prevalence estimates for anxiety disorder were highest in France as well (13,1%) and lowest in Italy (6,0%), with Belgium again falling in between with a higher percentage than the HIS-percentages in 2001 and 2004 (7,6%). The NEMESIS-2 study in the Netherlands (de Graaf et al., 2010) returned a 6,1% prevalence estimate for any mood disorder and a 10,1% prevalence estimate for any anxiety disorder, as compared to 5,1% and 8,6% respectively in the ESEMeD/MHEDEA-project.

#### *Substance-related disorders and addiction*

The Belgian Health Interview Survey doesn't provide an overall indicator for substance-related disorders or addiction, but measures the use of several individual substances, including cannabis, cocaine, other stimulants (amphetamines and ecstasy), opioids, and alcohol. Additional indicators, based on combined measures include the use of drugs other than cannabis or the use of different substances by the same individual (polydrug use).

HIS-percentages of cannabis use are presented in Figure 1.4. In Flanders and Brussels, percentages were lowest in 2013, with a strong increase between 2013 and 2018, whereas in the Walloon Region there was a gradually increasing trend from 2004 to 2018. Cannabis use was markedly higher in Brussels than in the Flemish and Walloon Region.

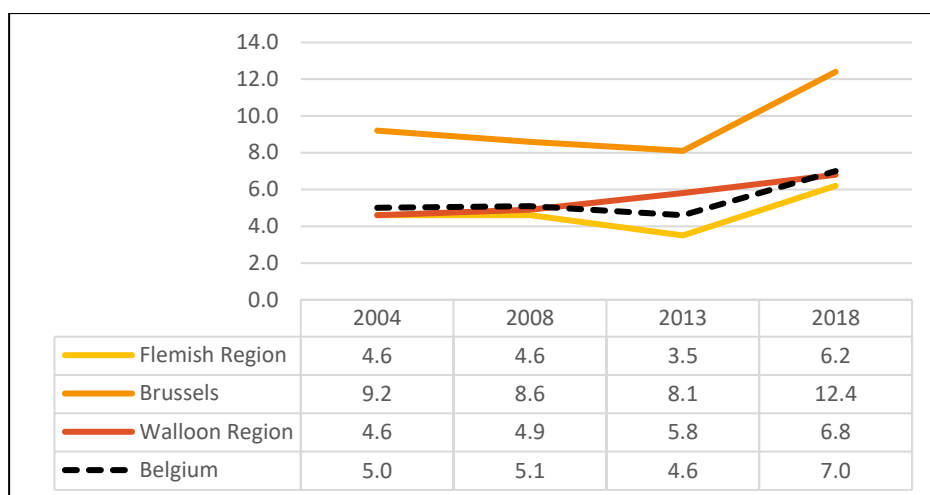


Figure 1.4 Evolution of the percentage of the Belgian population aged 15 to 64 years that took cannabis in the past 12 months, by region (HISIA, indicator ID03\_2)

Since 2018, a new measure indicating problematic cannabis use was added to the Health Interview Survey. Table 1.4 shows the ratio between use and problematic use observed in 2018 (between 43% and 47%, depending on the region), applied to the use percentages of the previous years as an estimate for problematic use.

Table 1.4 Estimated evolution of the percentage of the Belgian population aged 15 to 64 years with problematic cannabis use in the past 12 months, by region (based on HISIA 2018 indicator ID04\_2 and indicator ID03\_2)

<i>Drieskens et al. (2004-18)</i>	2004	2008	2013	2018
Flemish Region	2,0%	2,0%	1,5%	2,7%
Brussels	4,3%	4,0%	3,8%	5,8%
Walloon Region	2,0%	2,1%	2,5%	2,9%
<b>Belgium</b>	2,2%	2,3%	2,0%	3,1%

The use of illegal drugs other than cannabis showed a similar trend than cannabis use, with the highest percentages observed in 2018. Again, percentages were higher overall in Brussels.

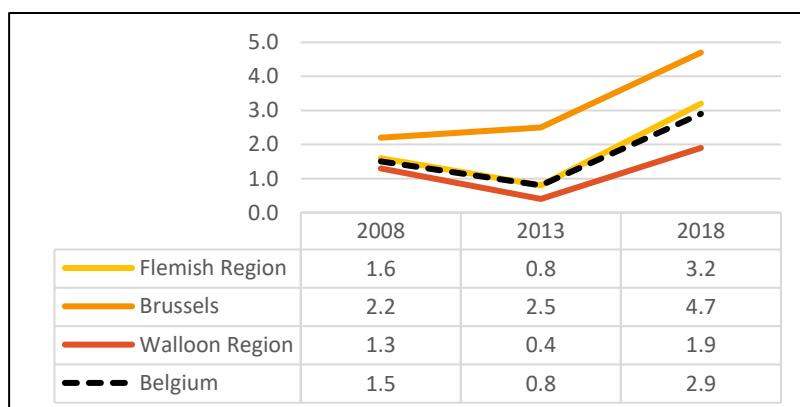


Figure 1.5 Evolution of the percentage of the Belgian population aged 15 to 64 years that took illegal drugs other than cannabis in the past 12 months, by region (HISIA, indicator ID07\_2)

Figures 1.6, 1.7, and 1.8 show the evolution of cocaine use, the use of other stimulant drugs (amphetamines or ecstasy), and the use of heroin or other non-prescribed opioids. For both cocaine and other stimulants, there was a drop in 2013 followed by an increase in Flanders and the Walloon Region and a gradual increase between 2008 and 2018 in Brussels, with Brussels showing the highest percentages overall. For opioids, a different picture emerges, with the Flemish and Walloon Region showing higher percentages than Brussels, especially in 2018.

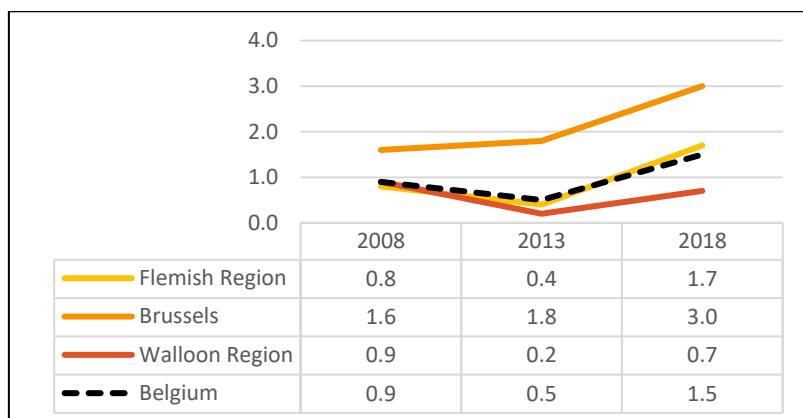


Figure 1.6 Evolution of the percentage of the Belgian population aged 15 to 64 years that took cocaine in the past 12 months, by region (HISIA, indicator ID07\_2)

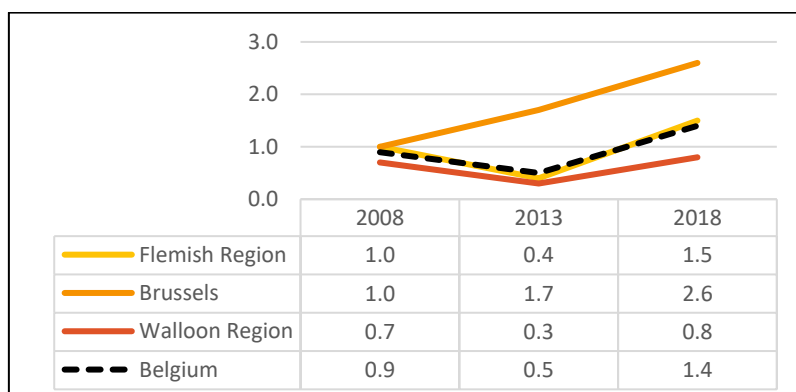


Figure 1.7 Evolution of the percentage of the Belgian population aged 15 to 64 years that took amphetamines or ecstasy in the past 12 months, by region (HISIA, indicator ID07\_30)

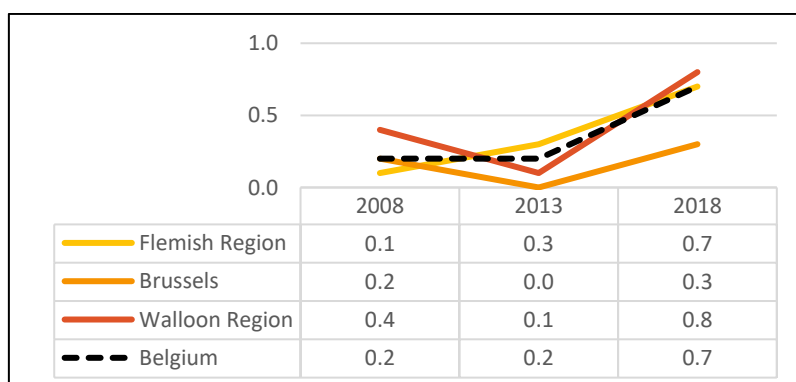


Figure 1.8 Evolution of the percentage of the Belgian population aged 15 to 64 years that took heroin or non-prescribed opioids in the past 12 months, by region (HISIA, indicator ID07\_7)

The evolution of the use of different individual drugs is reflected in the use of multiple drugs by the same individual, as shown in Figure 1.9 below. Again, the highest percentages were observed in 2018 for all regions and in Brussels in all years. In Flanders and the Walloon Region, there was a noticeable decrease between 2008 and 2013, followed by a strong increase between 2013 and 2018.

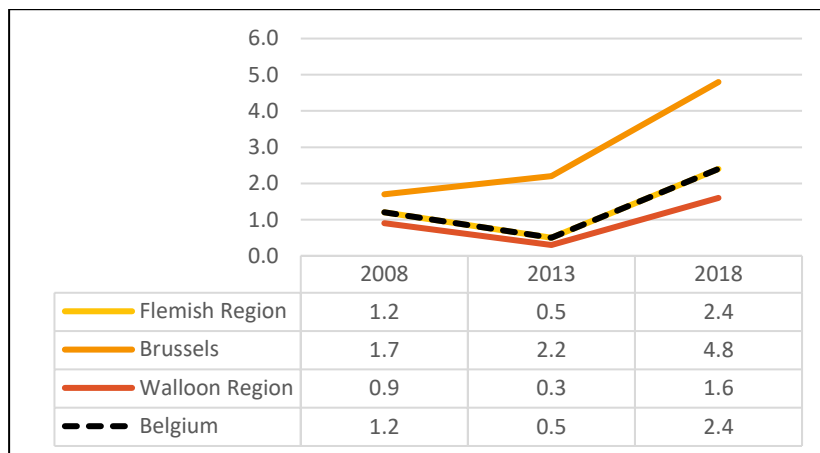


Figure 1.9 Evolution of the percentage of the Belgian population aged 15 to 64 years with polydrug use in the past 12 months, by region (HISIA, indicator ID\_1)

Differences in illegal drug use between the Flemish and Walloon Regions on the one hand and Brussels on the other hand may largely be explained by the degree of urbanization in these respective regions. However, when comparing countries, substantial differences are observed throughout Europe as well, with prevalence percentages varying from less than 4% (Cyprus, Hungary, Lithuania, and Greece) to more than 10% (Spain, the Netherlands, Czechia, Croatia, France, and Italy).

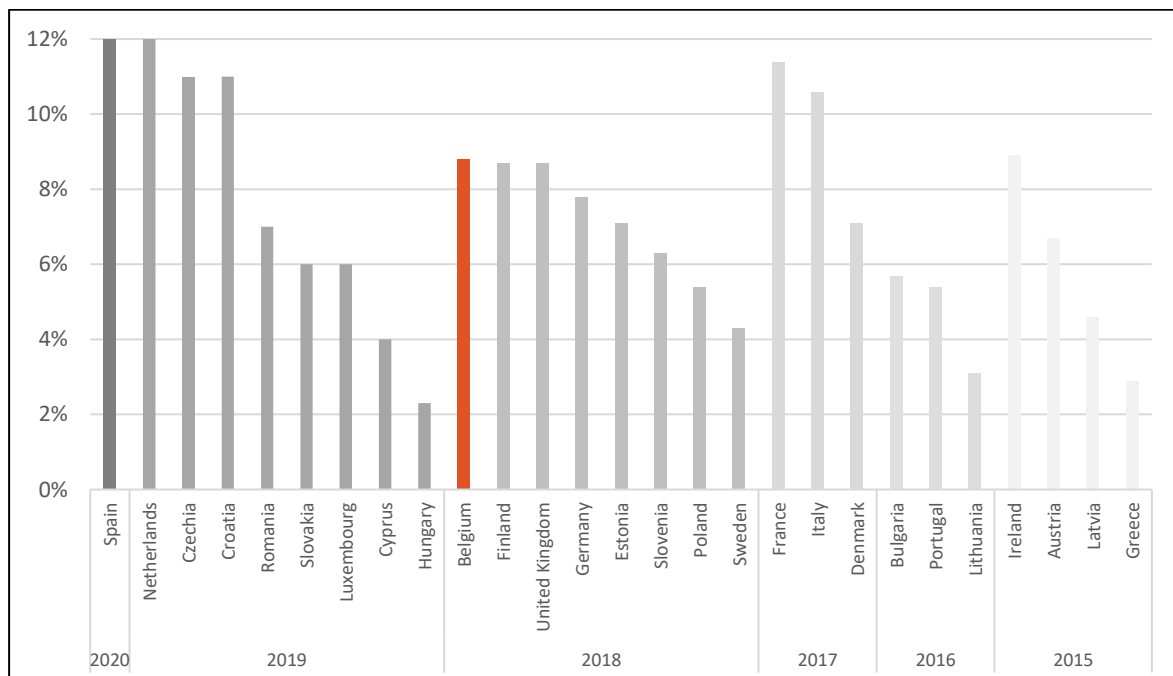


Figure 1.10 Comparison of the most recent 12-month prevalence percentages of illicit drug use in the population aged 15 to 64 years old in Europe (EMCDDA)



Figure 1.11 and 1.12 below show 12-month prevalence percentages for cannabis use and cocaine use in four European countries with more or less complete time series. Although most countries show fluctuating trends, later estimates are generally higher than earlier estimates.

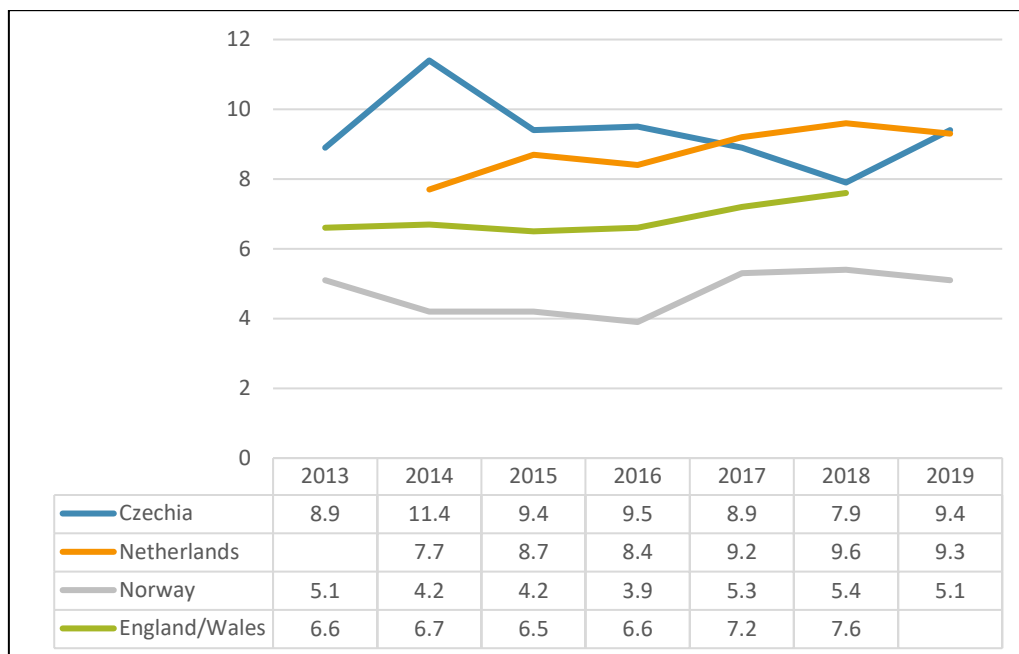


Figure 1.11 Evolution of the 12-month prevalence percentage for cannabis use in four European countries from 2013 to 2019 (EMCDDA)

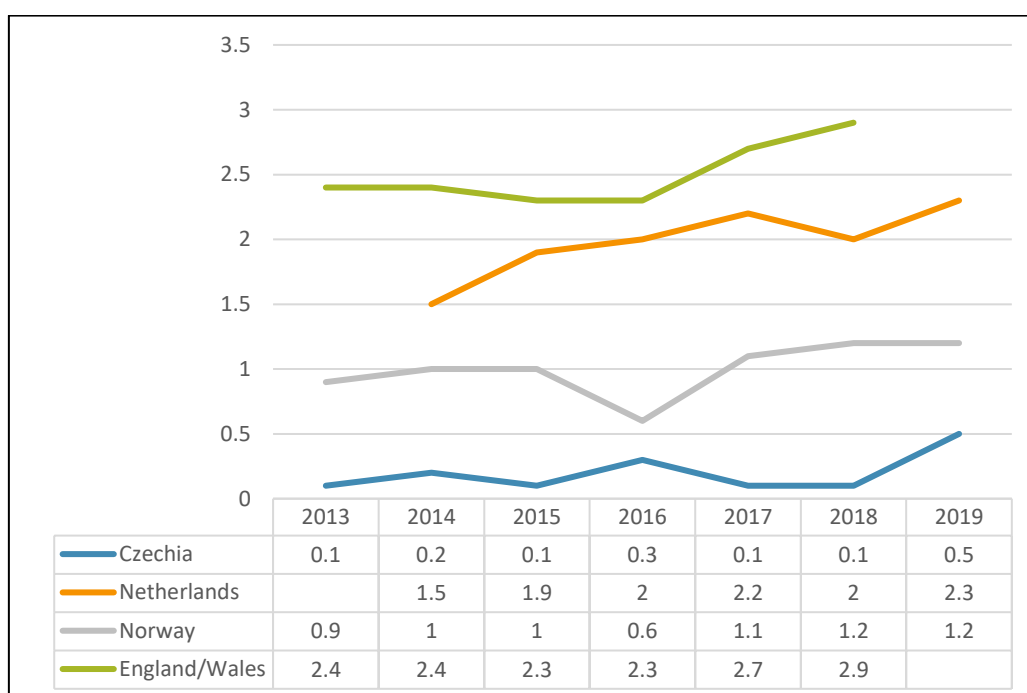


Figure 1.12 Evolution of the 12-month prevalence percentage for cocaine use in four European countries from 2013 to 2019 (EMCDDA)

For alcohol use, several measures are available in the Health Interview Survey since 1997. However, a problematic alcohol use indicator, based on the CAGE screening test is available only for 2018. Figure 1.13, 1.14, and 1.15 show the evolution of the percentage of alcohol drinkers, daily alcohol drinkers, and

excessive weekly alcohol drinkers (defined as more than 14 glasses for women or 21 glasses for men). In all three figures, percentages were lower in 2018 than in 2013 (with the exception of daily drinking in Brussels). However, for the daily drinking indicator there was an increase before 2013 in the Flemish and Walloon Region, while the excessive drinking indicator seemed to follow a previously established downward trend.

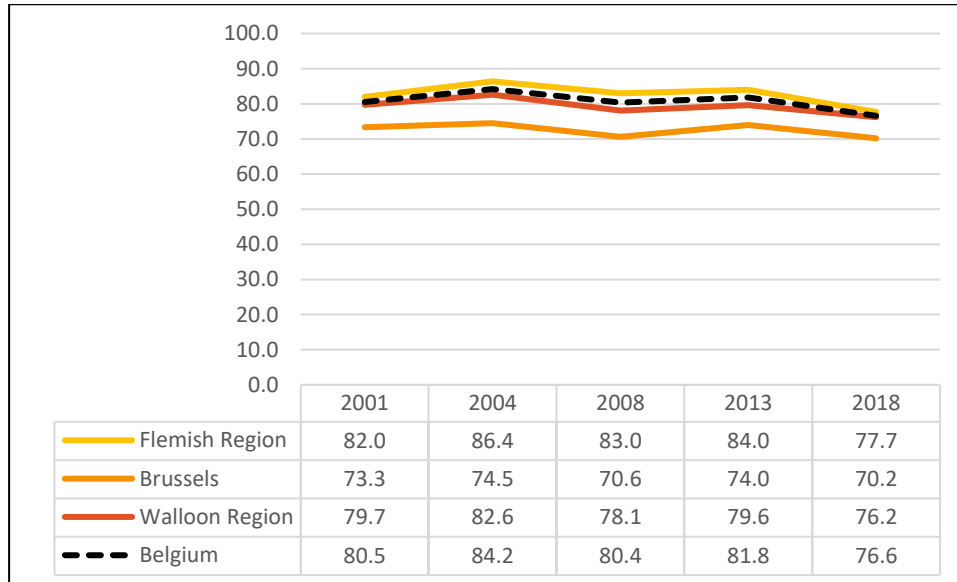


Figure 1.13 Evolution of the percentage of the Belgian population aged 15 or that drank alcohol in the past 12 months, by region (HISIA, indicator AL01\_1)

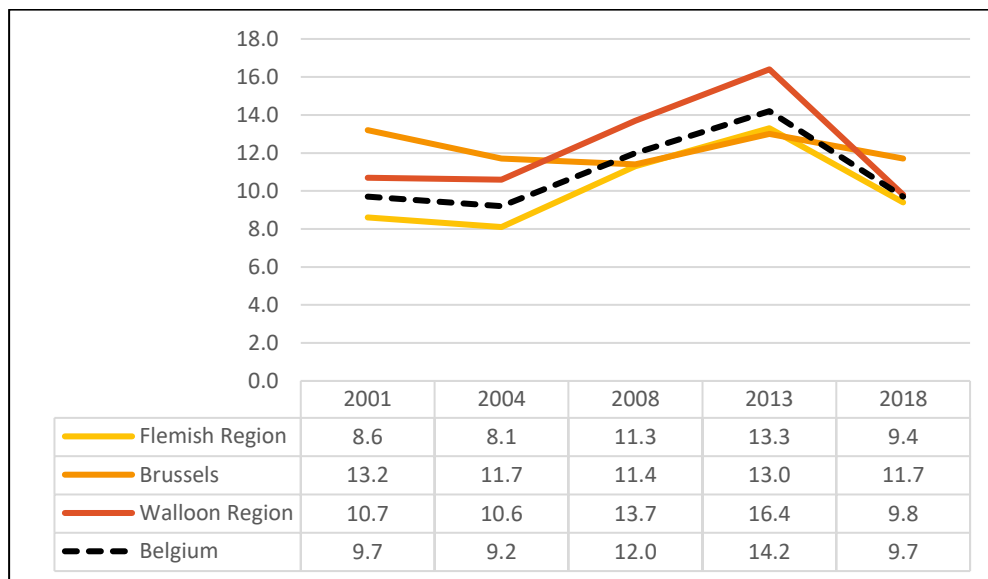


Figure 1.14 Evolution of the percentage of the Belgian population aged 15 or over with daily alcohol use in the past 12 months, by region (HISIA, indicator AL01\_3)

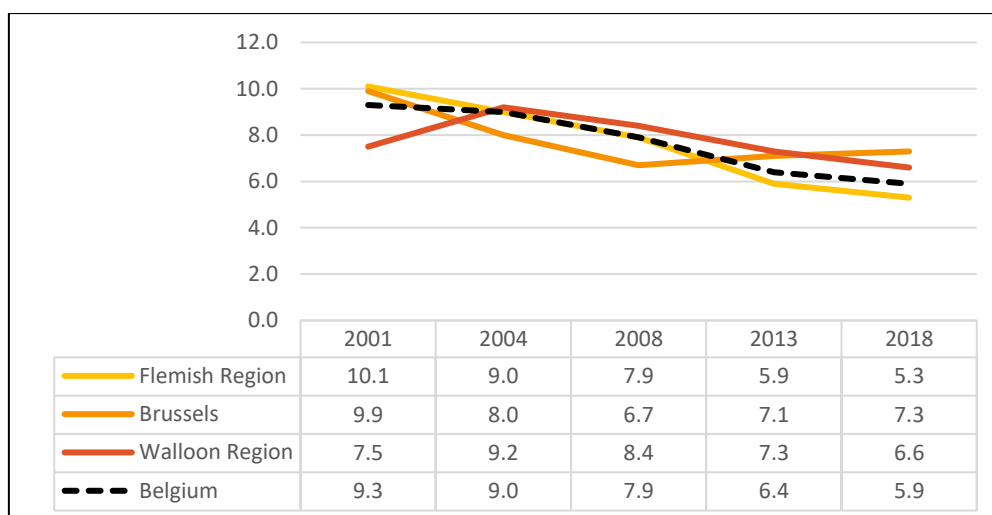


Figure 1.15 Evolution of the percentage of the Belgian population aged 15 or over with excessive weekly alcohol consumption, by region (HISIA, indicator AL05\_4)

The problematic alcohol use indicator in 2018 led to a prevalence percentage of 7% for Belgium, 6,3% for Flanders and 8,1% for Brussels and the Walloon Region. In Table 1.5 the ratio between past 12-month problematic use and use in general in 2018 (ranging from 8% in Flanders to 12% in Brussels) was applied to the use percentages of previous years as an approximation for problematic use. This leads to a rather stable trend with an estimated maximum of 7,7% problem users in Belgium in 2004.

Table 1.5 Estimated evolution of the percentage of the Belgian population aged 15 or over with problematic alcohol use in the past 12 months, by region (based on HISIA 2018 indicator AL\_2 and general alcohol use indicator AL01\_1)

<i>Drieskens et al. (2004-18)</i>	2001	2004	2008	2013	2018
Flemish Region	6,6%	7,0%	6,7%	6,8%	6,3%
Brussels	8,5%	8,6%	8,1%	8,5%	8,1%
Walloon Region	8,5%	8,8%	8,3%	8,5%	8,1%
<b>Belgium</b>	7,4%	7,7%	7,3%	7,5%	7,0%

The problematic alcohol use estimates in the table above are considerably higher than the psychopathological alcohol disorder (abuse and dependence) prevalence percentages reported in the ESEMed/MHEDEA project (EPREMED, 2008), which vary from 0,2% and 0,7% in Italy and Spain, to 1,1% and 1,3% in Germany and France, and to 1,8% and 1,9% in Belgium and the Netherlands. In the latter country, the prevalence of substance-related disorders (alcohol or illicit drug abuse and dependence) for adults between 18 and 64 years old, was estimated at 5,6% in the NEMESIS-2 study between 2007 and 2009 (de Graaf, 2010), which is higher than the international meta-analysis estimate of 3,8% for substance-related disorders.

### **1.3 Estimating the Flemish population with potential need for care in the Centers for Mental Health Care**

As a caution, it is important to mention that all estimates presented below should be interpreted as a coarse measure of care need. After all, not all of the mental health problems and mental disorders covered by prevalence percentages are eligible for treatment in the specialized care facilities described in the report. For people with rather short-lived minor complaints, primary care is more appropriate, while people with very serious or acute mental health problems or disabilities may be treated in psychiatric hospitals.

#### *Adult population*

Based on the results reported above, two approaches for estimating the Flemish population with mental disorders and a potential need of mental health care are used. All estimates are calculated for the three age target groups in the Centers for Mental Health Care: children and adolescents (under 18), adults (18 to 59), and elderly people (60 or older). Data are applied to population numbers from 2008 to 2019, since these are the years for which service use data from the Electronic Patient File database are available.

As a first approach, the prevalence percentages resulting from the international meta-analysis (Steel et al., 2014) for common mental disorders are applied to the Flemish population data made available by the Belgian Federal Planning Bureau. Hereby, the same constant gender-specific percentages (see Table 1.1.) are applied to both the adult (18 to 59 years) and elderly (60 or older) target groups in every year between 2008 and 2019. Consequently, the yearly increase in the resulting estimates per age group and per gender are solely determined by demographic evolutions in the Flemish population. For common mental disorders in general, this approach leads to the estimates shown in Figure 1.16 below, with a larger number of estimated women with common mental disorder and a stronger increasing trend in elderly people.

As a second approach, the National Health Interview Survey prevalence percentages for probable mental illness are applied to the Flemish population data from 2008, 2013, and 2018. On the HIS Interactive Analysis website, all indicators can be calculated per province, age category, gender, education level, income level, degree of urbanization, and household composition (Drieksens, et al., HIS Belgium, 1997-2018). Table 1.6 shows the percentages per age group (adult and elderly) and per gender, with the resulting estimates for these groups in the Flemish population. In this approach, the increase over time is not only determined by the demographic evolution in the Flemish population, but also by the estimated evolution in the prevalence of probable mental disorder per age group and per gender.

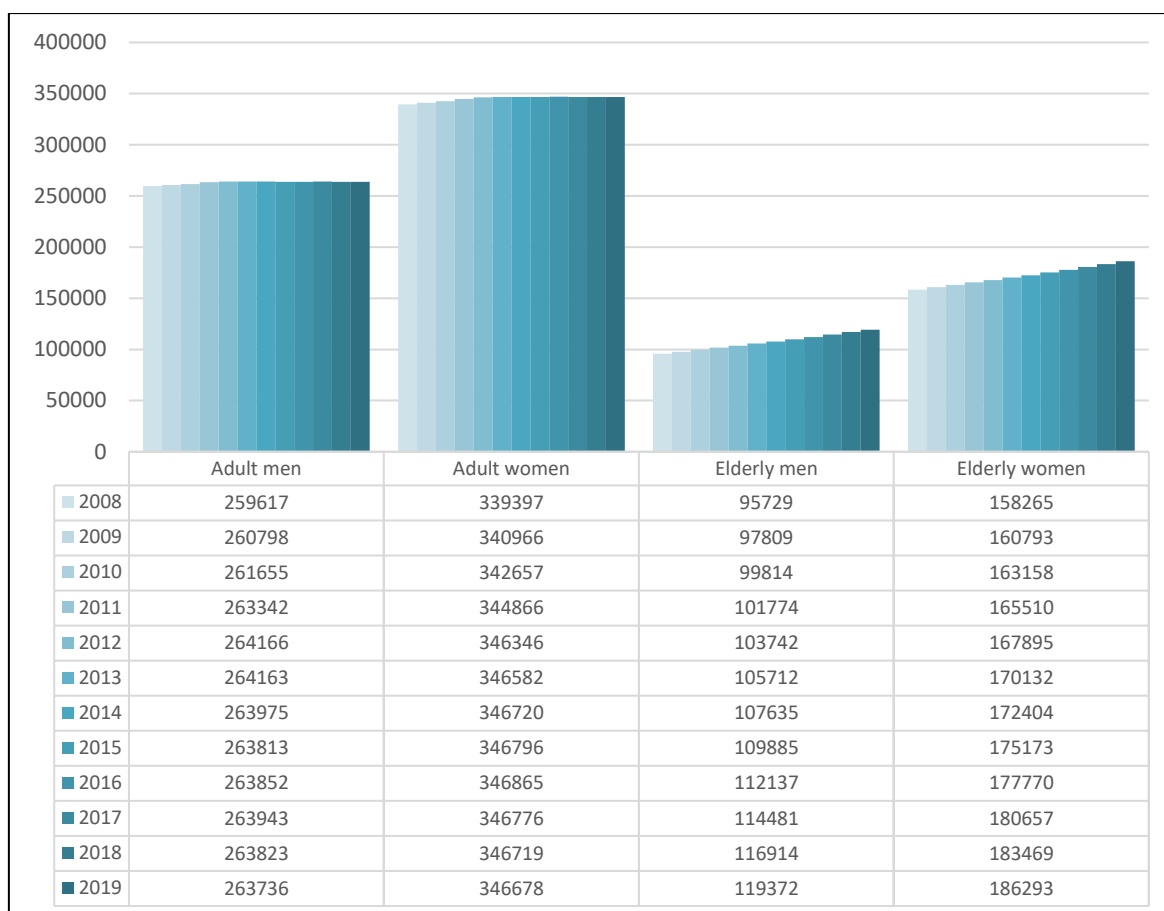


Figure 1.16 Estimated adult (18 to 59 years) and elderly (60 or older) Flemish population with common mental disorder between 2008 and 2019, based on constant gender-specific prevalence percentages (International meta-analysis, Steel et al. 2014) and the demographic evolution of the population in Flanders (Federal Planning Bureau, Statbel).

Table 1.6 Age group and gender-specific prevalence percentages for probable mental disorder (HISIA 2008, 2013, 2018) and estimated adult and elderly people with probable mental disorder in Flanders, based on the prevalence percentages and population data (Federal Planning Bureau, Statbel).

	Prevalence percentages			Estimated Flemish population		
	2008	2013	2018	2008	2013	2018
Adult men (18-59 yrs)	10,2	13,7	13,3	180143	246193	238697
Adult women (18-59 yrs)	15,1	18,8	18,8	260147	330748	330879
Elderly men (60 or older)	10,1	14,9	10,3	65773	107150	81920
Elderly women (60 or older)	15,1	16,7	16,3	121308	144223	151805

Figure 1.17 compares estimates for adults and elderly people from both approaches. The HIS-estimate is generally lower than the meta-analysis estimate. According to the HIS-estimate, there was a stronger increase in the Flemish adult population with probable mental illness between 2008 and 2013 than would be predicted by a constant prevalence percentage applied to population data. For 2018, the estimates lower again (especially for men, as Table 1.6 shows), but still amount to 29% more adults and 25% more elderly people in 2018 than in 2008, whereas the estimate based on the constant gender-specific meta-analysis prevalence percentage only shows 2% more adults and 18% more elderly people.

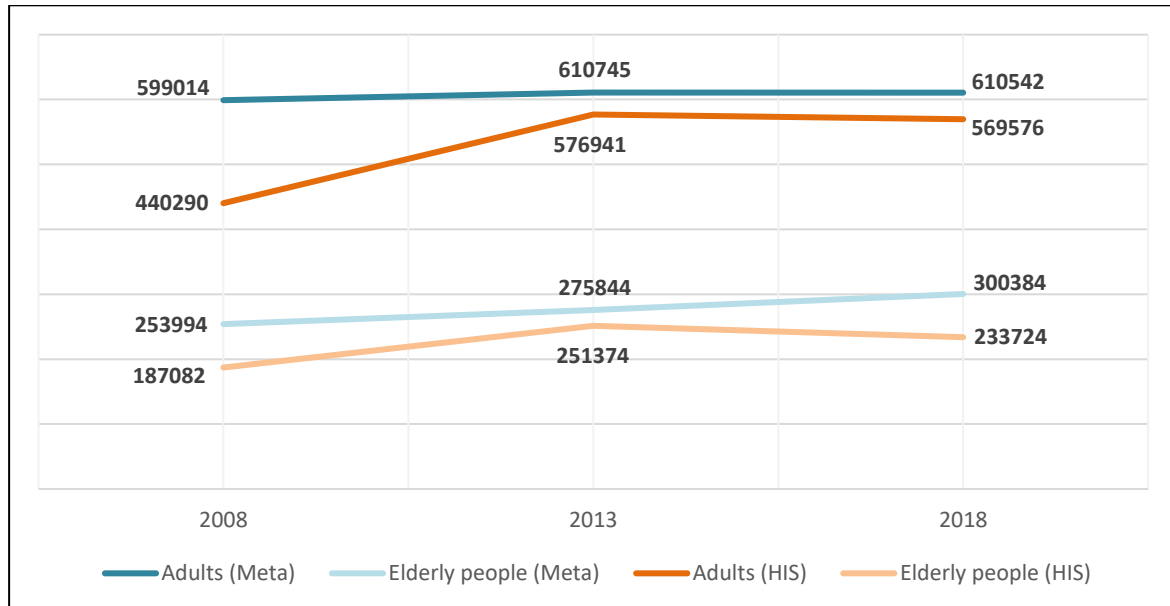


Figure 1.17 Comparison of the estimated adult and elderly population with mental disorders in Flanders, based on international meta-analysis data (Steel et al., 2014) and the Belgian Health Interview Survey (HISIA, 2008, 2013, 2018), and applied to population data (Federal Planning Bureau, Statbel).

Figure 1.18 below shows estimates for adult and elderly men and women with probable mental illness in each Flemish province, based on the same age group and gender-specific HIS-prevalence percentages used above, but applied to population numbers per province. The estimated probable mental illness increased since 2008 in all groups and in all provinces.

On the HISIA website, the age group and gender-specific HIS-percentages can further be calculated by province into province-specific prevalence percentages. In Figure 1.19, these percentages are applied to the population per province. For adults, the resulting estimates show a comparable picture to Figure 1.18, with mounting numbers of adult men and women with probable mental disorder in all provinces. Estimates based on the gender and province-specific prevalence percentages differ the most from the estimates based on gender-specific percentages only for men and women in East Flanders and for women in Limburg. In the case of Limburg, sample sizes were very small, especially in 2018, making the prevalence percentages less reliable. As sample sizes for elderly people were even smaller and probably not representative, estimates based on age group, gender, and province-specific prevalence percentages were considered too unreliable to use as an estimate of probable mental illness in the Flemish provinces.

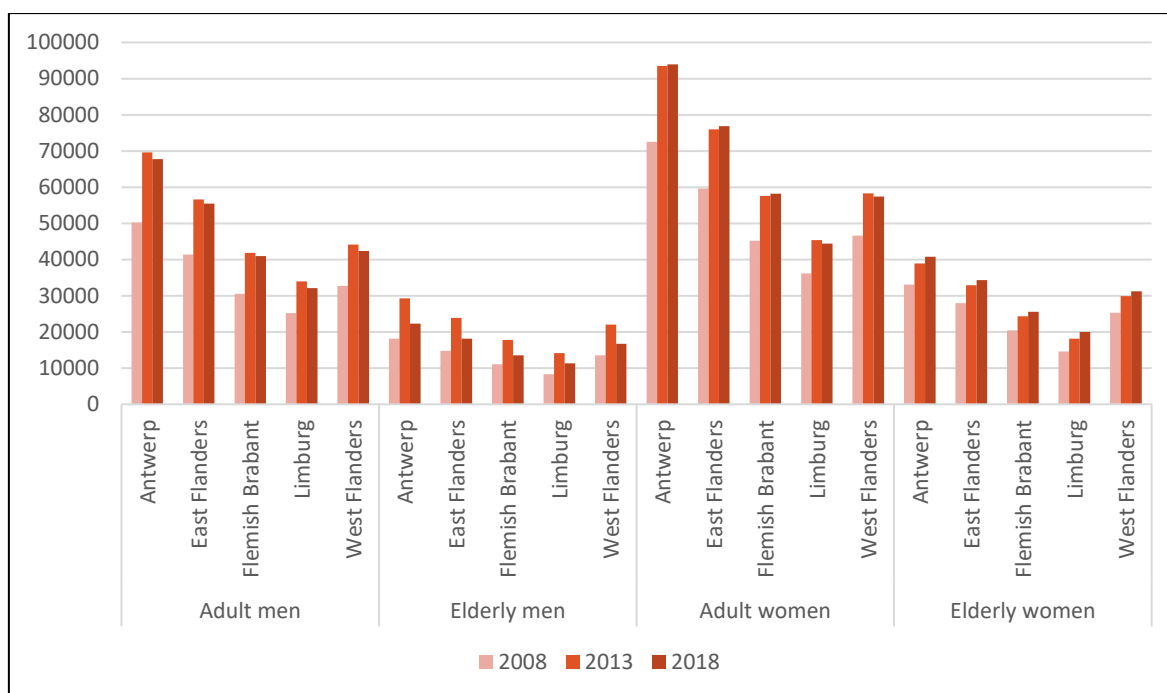


Figure 1.18 Estimated number of adult and elderly men and women with probable mental illness in the Flemish provinces, based on age group and gender-specific prevalence percentages (HISIA, 2008, 2013, 2018) applied to the population per province (Federal Planning Bureau, Statbel).

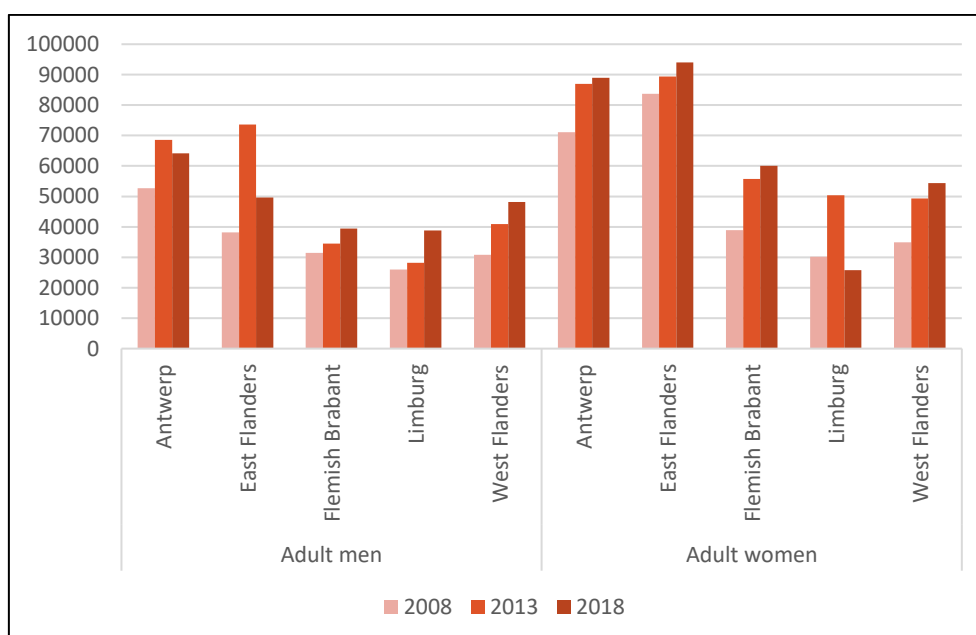


Figure 1.19 Estimated number of adult men and women with probable mental illness in the Flemish provinces, based on age group, gender- and province-specific prevalence percentages (HISIA, 2008, 2013, 2018) applied to the population per province (Federal Planning Bureau, Statbel).

For the specific common mental disorders mentioned above, the same approaches are used, with a gender-specific constant prevalence percentage applied to Flemish population numbers of all years between 2008 and 2019 (Figure 1.20) and the age group and gender-specific HIS prevalence percentages

applied to the Flemish population in 2008, 2013, and 2018 in Table 1.7 (mood and anxiety disorders) and Table 1.8 (problematic alcohol and substance use).

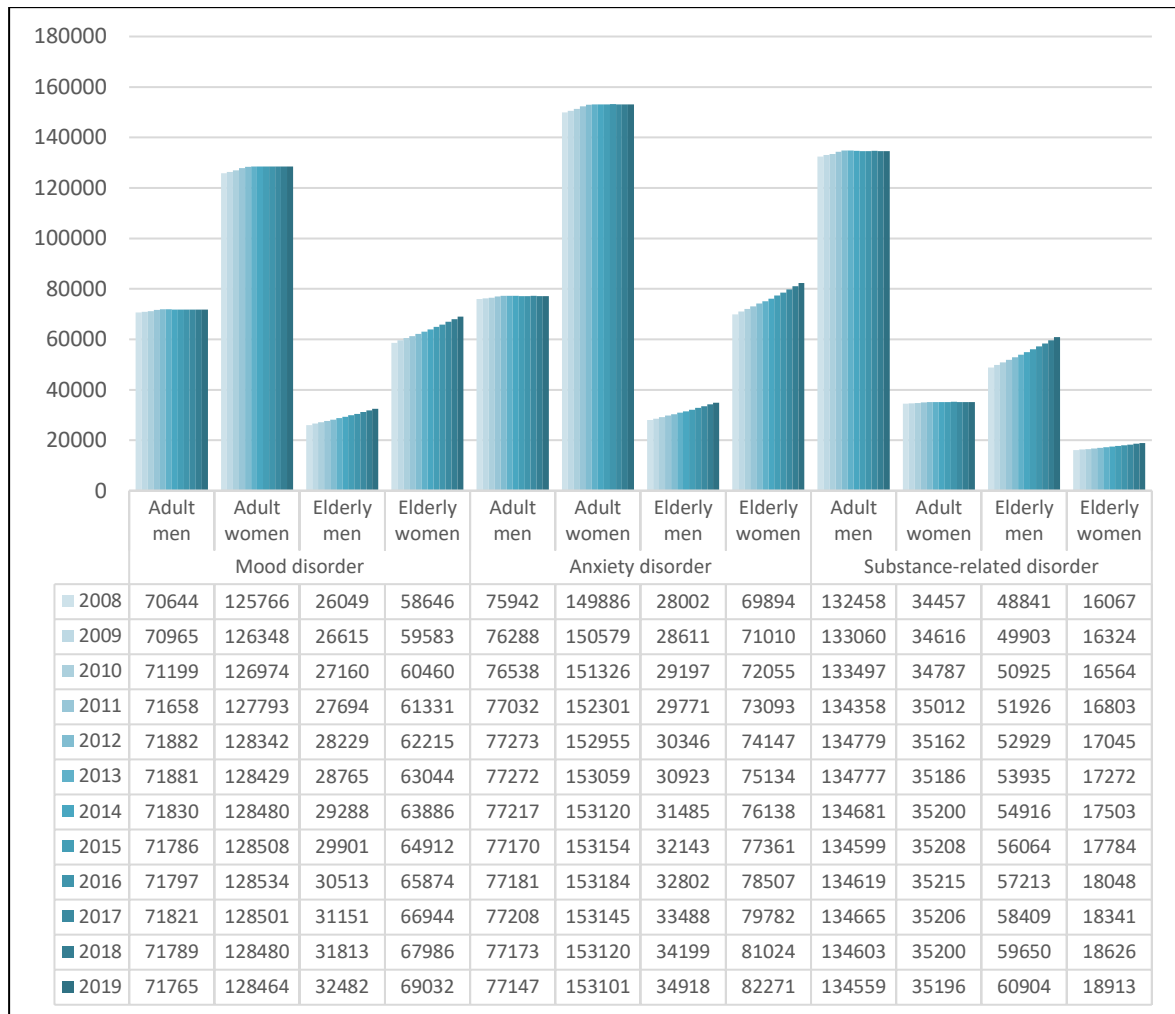


Figure 1.20 Estimated adult (18 to 59 years) and elderly (60 or older) Flemish population with mood disorder, anxiety disorder, or substance-related disorder between 2008 and 2019, based on constant gender-specific prevalence percentages (International meta-analysis, Steel et al. 2014) and the demographic evolution of the population in Flanders (Federal Planning Bureau, Statbel).



Table 1.7 Age group and gender-specific prevalence percentages for mood disorder and anxiety disorder (HISIA 2008, 2013, 2018) and estimated adult and elderly people with mood disorder and anxiety disorder in Flanders, based on the prevalence percentages and population data (Federal Planning Bureau, Statbel).

		Prevalence percentages			Estimated Flemish population		
		2008	2013	2018	2008	2013	2018
Mood disorder	Adult men	2,9	9,0	6,3	51217	161732	113067
	Adult women	10,5	15,6	7,7	180897	274451	135520
	Elderly men	9,8	13,9	5,2	63819	99959	41357
	Elderly women	14,7	15,3	6,2	118096	132133	57742
Anxiety disorder	Adult men	2,7	5,6	7,3	47685	100634	131014
	Adult women	7,3	11,5	12,8	125766	202320	225279
	Elderly men	6,0	6,7	4,2	39073	48182	33404
	Elderly women	10,3	12,9	8,4	82748	111406	78231

Table 1.8 Gender-specific prevalence percentages for problematic alcohol use in adults and elderly people and problematic cannabis use, and other illegal drug use in adults (HISIA 2008, 2013, 2018) and estimated population with substance use problems in Flanders, based on the prevalence percentages and population data (Federal Planning Bureau, Statbel).

		Prevalence percentages*			Estimated Flemish population		
		2008	2013	2018	2008	2013	2018
Problematic alcohol use	Adult men	11,5	11,9	11,2	203102	213846	201008
	Adult women	4,7	4,8	4,4	80973	84446	77440
	Elderly men	3,1	3,1	3,0	20188	22293	23860
	Elderly women	3,2	3,1	2,9	25708	26772	27008
Problematic cannabis use	Adult men	3,9	2,5	5,6	68878	44926	100504
	Adult women	0,5	0,3	0,6	8614	5278	10560
Other illicit drug use	Adult men	2,9	1,3	6,0	51217	23361	107683
	Adult women	0,7	0,5	1,3	12060	8797	22880
All substances	Adult men				323197	282133	409195
	Adult women				101647	98521	110880

\*For problematic alcohol use percentages for 2008 and 2013 were estimated based on the application of the 2018 ratio between use and problematic use on the use percentages.

*Children and adolescents*

In Figure 1.21, the prevalence percentages for any mental disorder, any mood disorder, any anxiety disorder, and any disruptive disorder, resulting from the 2015 meta-analysis by Polanczyk and others, are applied to the total number of children and adolescents in Flanders. The same constant percentage is thus used for both boys and girls in all years, resulting in an increase solely determined by the demographic evolution in the population under 18 in Flanders.

When comparing this approach with the 2018 HIS gender-specific prevalence percentages for any mental disorder in children and adolescents (Table 1.9), the estimates for that year are higher for boys and lower for girls in the former than in the latter approach.

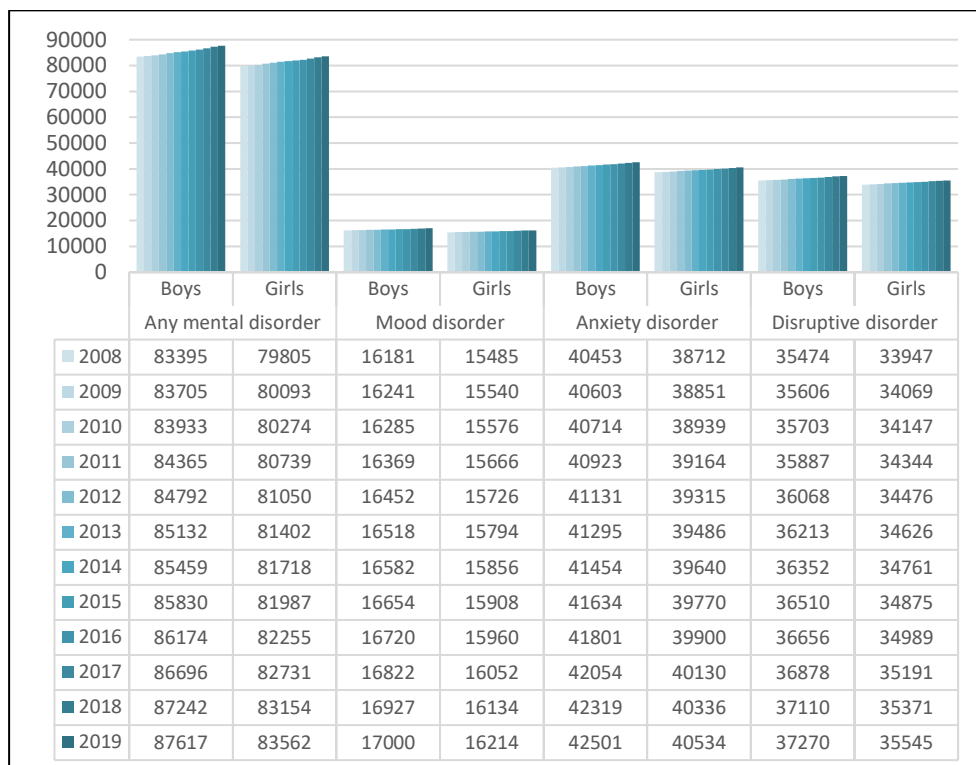


Figure 1.21 Estimated number of children and adolescents with any mental disorder, mood disorder, anxiety disorder, or disruptive disorder in Flanders between 2008 and 2019, based on constant gender-specific prevalence percentages (International meta-analysis, Polanczyk et al., 2015) and the demographic evolution of the Flemish population (Federal Planning Bureau, Statbel).

Table 1.9 Gender-specific prevalence percentages for any mental disorder (borderline or probable) in children and adolescents (HISIA, 2018) and estimated children and adolescent population with any mental disorder in Flanders, based on the prevalence percentages and population data (Federal Planning Bureau, Statbel).

	Prevalence percentage	Estimated Flemish population
Boys (0-17 yrs)	14,7	95705
Girls (0-17 yrs)	13,2	81913

#### 1.4 Estimating the Flemish population with potential need for care in the Rehabilitation Centers for Addicts

The estimates for the Flemish population with potential need for care in the Rehabilitation Centers for Addicts are calculated for the ages between 15 and 64, as the HIS prevalence data for substance use are limited to this age range, which also encompasses most clients with addiction problems in the Rehabilitation Centers for Addicts. Data are applied to population numbers from 2011 to 2019, since these are the years for which the Treatment Demand Indicator service use data are available.

When applying the gender-specific prevalence percentage for substance-related disorders found in the meta-analysis of Steel and others (2014) to the Flemish population as a constant percentage, the evolution of the estimated number of men and women between 15 and 64 years with substance-related disorders is solely determined by the demographic evolution, which should have led to the gradual increase shown in Figure 1.22, with almost four times as many men than women suffering from substance-related disorder.

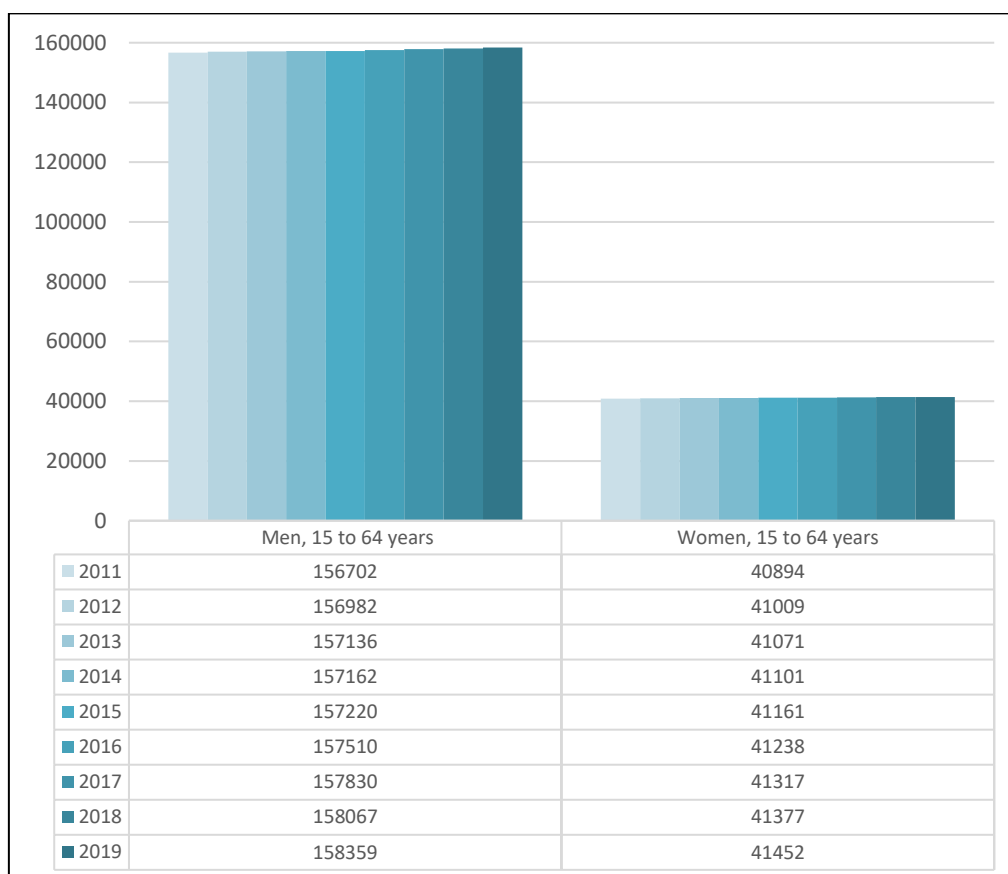


Figure 1.22 Estimated number of men and women between 15 and 64 years with substance-related disorder in Flanders between 2011 and 2019, based on constant gender-specific prevalence percentages (International meta-analysis, Steel et al., 2014) and the demographic evolution of the Flemish population (Federal Planning Bureau, Statbel).

Tables 1.10 to 1.16 below show age group and gender-specific HIS prevalence percentages pertaining to the use of different substances in 2008, 2013, and 2018, including problematic cannabis use, illicit drug use other than cannabis, cocaine use, stimulant use other than cocaine, heroin or other non-prescribed opioids use, and polydrug use. The 2013 and 2018 prevalence percentages in each table are

applied to the Flemish population in 2013 and 2018, which are the only two years for which rehabilitation service use data were available as well.

Table 1.10 Age category and gender-specific prevalence percentages for problematic alcohol use in men and women (HISIA, 2008, 2013, 2018) and estimated men and women with problematic alcohol use in Flanders in 2013 and 2018, based on the prevalence percentages and population data (Federal Planning Bureau, Statbel).

Problematic alcohol use		Prevalence percentages			Estimated Flemish population	
		2008	2013	2018	2013	2018
Men	15-24	17,4	17,9	16,5	67398	60735
	25-34	10,6	10,7	10,6	42409	42889
	35-44	8,4	8,6	8,4	36477	35166
	45-54	10,1	10,7	9,6	52097	45362
	55-64	7,8	8,2	7,5	33194	33276
	All ages				231575	217429
Women	15-24	9,0	9,0	7,1	32995	25071
	25-34	2,9	3,2	2,9	12616	11628
	35-44	4,3	4,1	4,0	17143	16542
	45-54	6,1	6,1	5,2	29099	23932
	55-64	7,6	7,4	7,1	30075	31309
	All ages				121928	108482
Total	All ages				353503	325911

*\*For problematic alcohol use percentages for 2008 and 2013 were estimated based on the application of the 2018 ratio between use and problematic use on the use percentages.*

Table 1.11 Age category and gender-specific prevalence percentages for problematic cannabis use in men and women (HISIA, 2008, 2013, 2018) and estimated men and women with problematic cannabis use in Flanders in 2013 and 2018, based on the prevalence percentages and population data (Federal Planning Bureau, Statbel).

Problematic cannabis use		Prevalence percentages			Estimated Flemish population	
		2008	2013	2018	2013	2018
Men	15-24	4,5	3,2	4,8	12210	17668
	25-34	9,1	5,0	9,8	19795	39652
	35-44	2,6	2,4	9,2	10314	38515
	45-54	0,0	0,8	0,9	4098	4253
	55-64	2,2	0,6	0,9	2617	3993
	All ages				49035	104082
Women	15-24	0,7	0,9	0,9	3342	3178
	25-34	0,9	0,7	1,0	2592	4010
	35-44	0,6	0,0	0,7	0	2895
	45-54	0,1	0,2	0,5	1128	2301
	55-64	0,0	0,1	0,2	405	882
	All ages				7467	13266
Total	All ages				56501	117347

*\*For problematic cannabis use percentages for 2008 and 2013 were estimated based on the application of the 2018 ratio between use and problematic use on the use percentages.*

Table 1.12 Age category and gender-specific prevalence percentages for problematic illicit drug use other than cannabis in men and women (HISIA, 2008, 2013, 2018) and estimated men and women using illicit drugs other than cannabis in Flanders in 2013 and 2018, based on the prevalence percentages and population data (Federal Planning Bureau, Statbel).

Illicit drugs other than cannabis		Prevalence percentages			Estimated Flemish population	
		2008	2013	2018	2013	2018
Men	15-24	5,9	1,5	5,3	5653	19509
	25-34	6,7	4,0	12,0	15893	48554
	35-44	1,6	0,4	8,8	1704	36841
	45-54	0,0	0,3	0,6	1463	2835
	55-64	0,0	0,4	0,0	1628	0
	All ages				26342	107739
Women	15-24	0,0	1,2	2,2	4377	7768
	25-34	1,8	1,4	1,0	5501	4010
	35-44	1,0	0,0	1,2	0	4963
	45-54	0,0	0,0	1,5	0	6904
	55-64	0,0	0,0	0,9	0	3969
	All ages				9878	27613
Total	All ages				36220	135351

Table 1.13 Age category and gender-specific prevalence percentages for cocaine use in men and women (HISIA, 2008, 2013, 2018) and estimated men and women using cocaine in Flanders in 2013 and 2018, based on the prevalence percentages and population data (Federal Planning Bureau, Statbel).

Cocaine		Prevalence percentages			Estimated Flemish population	
		2008	2013	2018	2013	2018
Men	15-24	3,2	1,5	2,9	5653	10675
	25-34	4,1	1,0	8,3	3973	33583
	35-44	0,3	0,4	4,3	1704	18002
	45-54	0,0	0,3	0,2	1463	945
	55-64	0,0	0,4	0,0	1628	0
	All ages				14422	63204
Women	15-24	0,0	0,0	0,7	0	2472
	25-34	0,5	1,1	1,0	4322	4010
	35-44	0,5	0,0	0,2	0	827
	45-54	0,0	0,0	0,0	0	0
	55-64	0,0	0,0	0,0	0	0
	All ages				4322	7309
Total	All ages				18744	70513

Table 1.14 Age category and gender-specific prevalence percentages for stimulant use other than cocaine (amphetamines and ecstasy) in men and women (HISIA, 2008, 2013, 2018) and estimated men and women using other stimulants in Flanders in 2013 and 2018, based on the prevalence percentages and population data (Federal Planning Bureau, Statbel).

Other stimulants		Prevalence percentages			Estimated Flemish population	
		2008	2013	2018	2013	2018
Men	15-24	4,6	1,1	2,3	4146	8466
	25-34	3,3	0,9	6,9	3576	27918
	35-44	1,4	0,4	3,6	1704	15071
	45-54	0,0	0,3	0,2	1463	945
	55-64	0,0	0,0	0,0	0	0
	All ages				10889	52401
Women	15-24	0,0	1,2	0,9	4377	3178
	25-34	1,0	0,7	1,0	2750	4010
	35-44	0,4	0,0	1,1	0	4549
	45-54	0,0	0,0	0,0	0	0
	55-64	0,0	0,0	0,0	0	0
	All ages				7127	11737
Total	All ages				18016	64137



Table 1.15 Age category and gender-specific prevalence percentages for heroin or other non-prescribed opioids use in men and women (HISIA, 2008, 2013, 2018) and estimated men and women using heroin or other non-prescribed opioids in Flanders in 2013 and 2018, based on the prevalence percentages and population data (Federal Planning Bureau, Statbel).

Non-prescribed opioids		Prevalence percentages			Estimated Flemish population	
		2008	2013	2018	2013	2018
Men	15-24	0,3	0,0	0,0	0	0
	25-34	0,0	1,9	1,4	7549	5665
	35-44	0,2	0,2	2,0	852	8373
	45-54	0,0	0,0	0,0	0	0
	55-64	0,0	0,0	0,0	0	0
	All ages				8401	14038
Women	15-24	0,0	0,0	1,0	0	3531
	25-34	0,5	0,0	0,4	0	1604
	35-44	0,0	0,5	0,0	2087	0
	45-54	0,0	0,0	1,5	0	6904
	55-64	0,0	0,0	0,9	0	3969
	All ages				2087	16007
Total	All ages				10488	30045

Table 1.16 Age category and gender-specific prevalence percentages for polydrug use in men and women (HISIA, 2008, 2013, 2018) and estimated men and women using different drugs in Flanders in 2013 and 2018, based on the prevalence percentages and population data (Federal Planning Bureau, Statbel).

Polydrug use		Prevalence percentages			Estimated Flemish population	
		2008	2013	2018	2013	2018
Men	15-24	5,3	1,5	5,5	5653	20245
	25-34	5,3	1,7	10,5	6755	42484
	35-44	1,3	0,4	7,5	1704	31398
	45-54	0,0	0,3	0,2	1463	945
	55-64	0,0	0,0	0,0	0	0
	All ages				15575	95073
Women	15-24	0,0	0,0	1,4	0	4944
	25-34	1,3	1,3	1,1	5108	4411
	35-44	0,4	0,0	1,2	0	4963
	45-54	0,0	0,0	0,0	0	0
	55-64	0,0	0,0	0,0	0	0
	All ages				5108	14317
Total	All ages				20683	109390

Although the 2013 and 2018 estimates based on the HIS prevalence percentages may give a first indication as to the existence of a downward or an upward trend in the use of different substances, these estimates are clearly insufficient as a basis for mapping the evolution of substance use in Flanders, and therefore, as a means of predicting future addiction treatment demand.

European countries with more complete time series data (e.g. Figure 1.11 and 1.12 for cannabis and cocaine use) are not informative either, as they show first and foremost that drug use percentages differ considerably throughout Europe, a picture corroborated by waste water analysis data revealing distinct geographical and temporal trends of illicit drug use across European cities (EMCDDA, 2021). Even within Belgium and Flanders, regional differences are very likely, as Figure 1.22 shows for waste water cocaine loads in different Flemish locations and Brussels. Although these differences are probably explained in part by differences in socio-demographic characteristics of the measuring sites (e.g. the age distribution of the population, degree of urbanization, etc.), there may be other factors that should be taken into consideration as well (e.g. the location near national borders, leading to greater accessibility of illegal substances).

Despite regional differences and temporal fluctuations, Figure 1.23 suggests a general increasing trend in cocaine use in Flanders, with most study locations showing higher waste water loads in the last year of measurement as compared to the first year. The same rise is observed for stimulant use other than cocaine in Antwerp South, as shown in Figure 1.24.

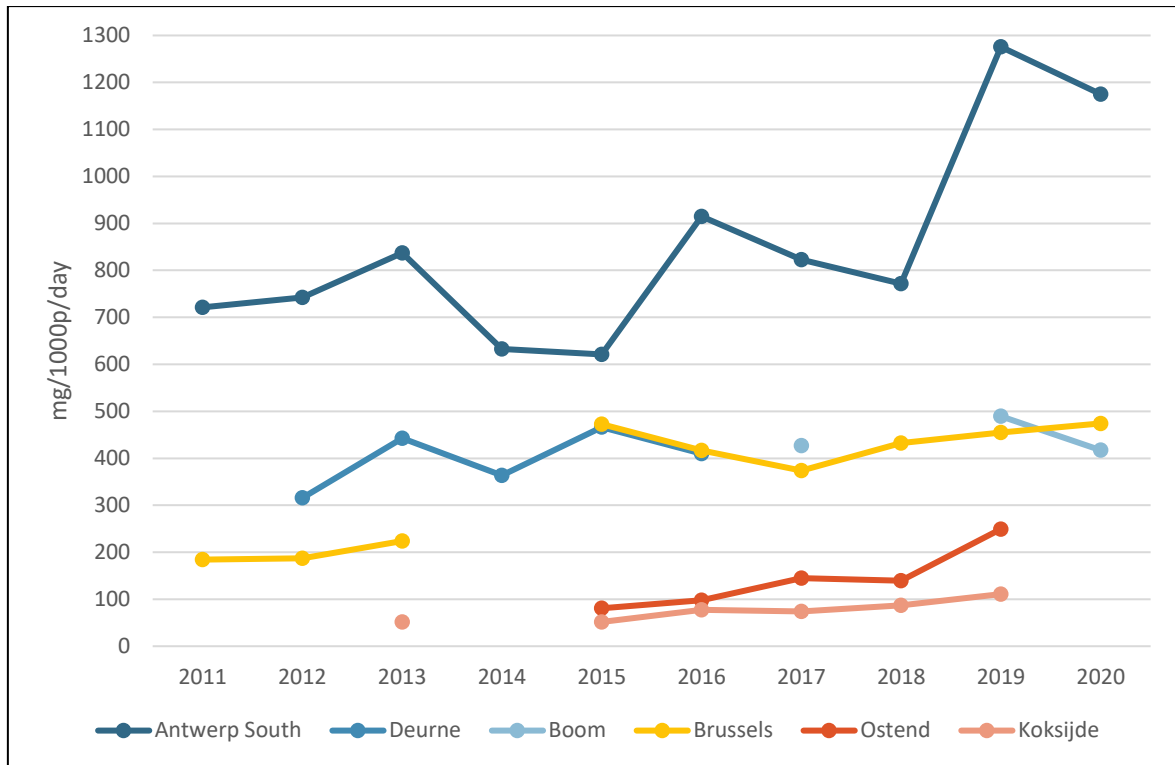


Figure 1.23 Evolution of cocaine loads detected in waste water (in mg per 1000 people per day) in different Flemish locations and Brussels (EMCDDA, 2020).

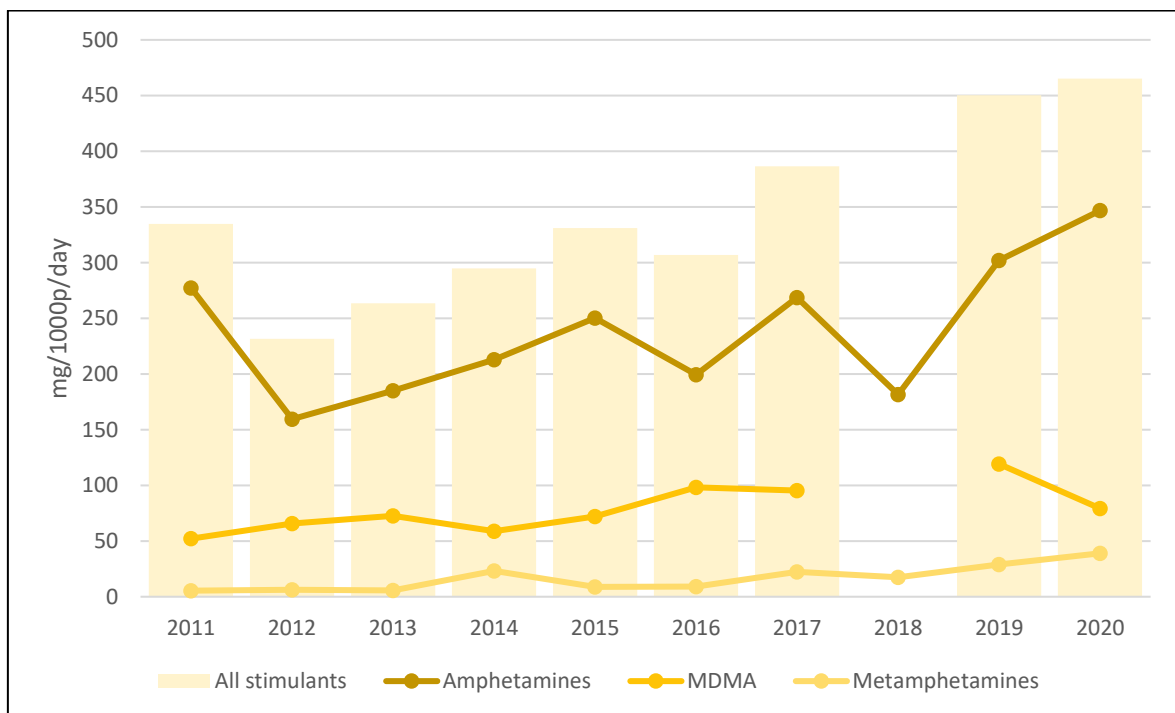


Figure 1.24 Evolution of stimulant loads detected in waste water (in mg per 1000 people per day) in Antwerp South (EMCDDA, 2020).

The waste water analysis data presented in Figures 1.23 and 1.24 thus confirm the increase in cocaine and stimulant use suggested by the 2013 and 2018 HIS data, but cannot be used to calculate prevalence percentages and estimate the number of users in the population.

In addition to the Health Interview Survey, aimed at the entire Belgian population, regular surveys are conducted by the Flemish Center of Expertise for Alcohol and Other Drugs (Vlaams expertisecentrum Alcohol en andere Drugs or VAD) in specific groups and settings. For example, the annual VAD-survey for secondary school students (Rosiers, J. 2020) shows that (regular) alcohol and (regular) cannabis use decreased between school year 2009-2010 to school year 2018-2019. Other VAD-surveys include a survey every four years for higher education students (Van Damme, et al. 2018), and a survey in nightlife settings every two to three years (Rosiers, J. 2019).

## **2 Prevalence of developmental disorders in children and adolescents**

### **2.1 International meta-analyses**

Two of the most common developmental disorders in children and adolescents are Autism Spectrum Disorder (ASD) and Attention Deficit (Hyperactivity) Disorder (ADHD or ADD).

#### *Autism Spectrum Disorder*

MacKay et al. (2016) report a 1,04% prevalence estimate for Autism Spectrum Disorder, based on a final sample from eight high-quality studies (in terms of diagnostic criteria and procedures, sample size, representativeness, statistical analysis, etc.) conducted in four European countries, with no evidence suggesting regional variations. Estimated ASD-prevalence increases with age group, from 0,37% in children of six years or less, to 1,04% between six and twelve years, and 1,14% in children of twelve years or more.

According to an international meta-analysis based on 54 studies, involving a total of more than 13 million participants between 0 and 18 years (Loomes et al., 2017), the male-to-female ratio for Autism Spectrum Disorder is an estimated 3:1, hereby taking into account the diagnostic gender bias with girls meeting ASD criteria at a greater risk of not being diagnosed.

Many other studies have been conducted all over the world, leading to varying estimates for different regions and suggesting a growing population of children with ASD in recent decades. A comprehensive overview by Chiarotti and Venerosi (2020), suggests that these variations can largely be attributed to methodological differences in case detection and definition, with enhanced awareness and changing definitions over time possibly leading to increasing prevalence estimates.

One of the only available time series measuring the prevalence of Autism Spectrum Disorder comes from the Autism and Developmental Disabilities Monitoring (ADDM) Network funded by the Centers for Disease Control and Prevention (CDC/ADDM, 2021). Prevalence is measured every two years across the United States in eight-year-old children, producing estimates mounting from 0,67% (1 in 150 children) in 2000 to 2,30% (1 in 44 children) in 2018 (Figure 1.25). It is not clear however, which factors lie behind the increase, therefore making it difficult to generalize these percentages to other countries. In addition, questions have been raised regarding the reliability of the estimates (Mandell et al., 2014).

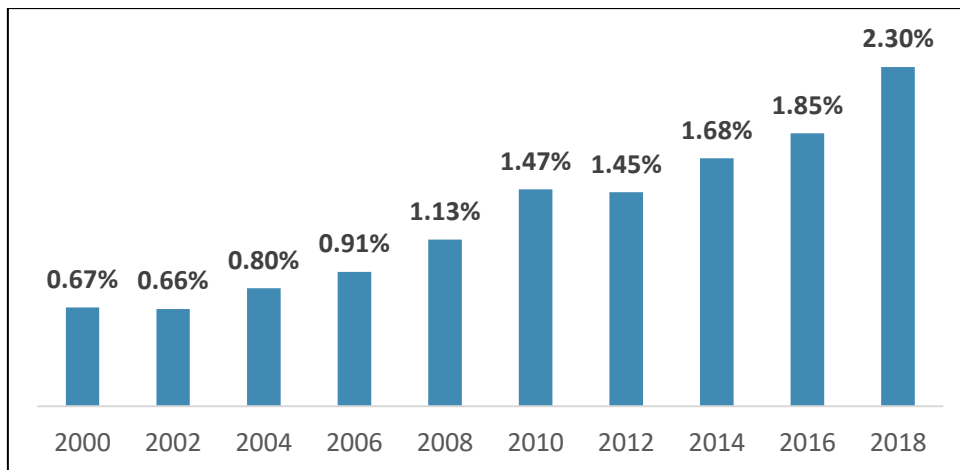


Figure 1.25 Prevalence of Autism Spectrum Disorder in 8-year-olds in the USA (CDC/ADDM, 2021).

#### *Attention Deficit (Hyperactivity) Disorder*

In 2008, Polanczyk et al. published a comprehensive review, including 102 studies conducted across the world. Meta-analysis of the data resulted in a prevalence estimate for ADHD of 5.29%. A 2014 update based on 135 studies led to the conclusion that estimates of ADHD prevalence vary considerably between studies, with variability mainly associated with methodological characteristics of the study, but not so much depending on geographical location and year of study. The authors therefore conclude that there is no evidence to suggest an increase in the number of children meeting the ADHD diagnostic criteria in the past decades (Polanczyk et al., 2014).

Notwithstanding this, data from the USA National Health Interview Survey based on parent-reported ADHD symptoms do suggest rising ADHD prevalence rates in children and adolescents aged four to seventeen years in the past twenty years (Xu et al., 2018), as Figure 1.26 below shows.

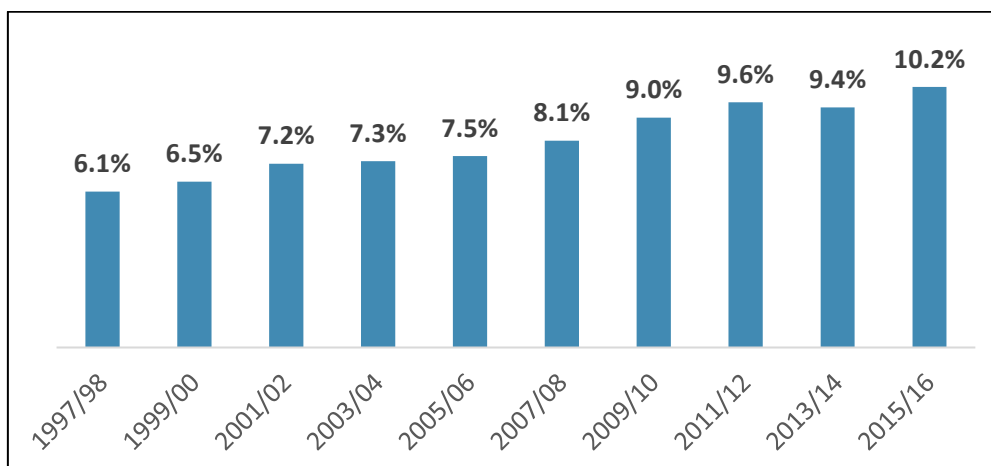


Figure 1.26 Prevalence of ADHD in 4 to 17-year-olds in the USA (Xu et al., 2018).

## 2.2 Belgian Health Interview Survey and other national or European studies

Based on a sample of 6760 primary school children, Geerts & Heyninck (2012) found that 7,5% was diagnosed with at least one developmental disorder, including Autism Spectrum Disorder (1,25%) and ADHD (2,2%).

The Belgian Health Interview Survey does not contain questions to gauge ASD, but the Strengths and Difficulties Questionnaire (SDQ) included in the HIS since 2018 does provide a measure for borderline or probable ADHD (Table 1.17). In principle, prevalence can be calculated per province as well, but resulting percentages are considered unreliable due to small sample sizes.

Table 1.17 The percentage of the Belgian children and adolescent population (2 to 18 years) with borderline or probable ADHD, by gender and by region (Indicator CH\_13)

<i>Gisle et al., 2020</i>	Borderline ADHD			Probable ADHD		
	Boys	Girls	All	Boys	Girls	All
Flemish Region	7,8%	5,1%	6,5%	14,5%	10,8%	12,7%
Brussels	4,9%	5,8%	5,3%	12,8%	6,1%	9,5%
Walloon Region	4,7%	4,9%	4,8%	12,1%	9,4%	10,8%
<b>Belgium</b>	<b>6,4%</b>	<b>5,1%</b>	<b>5,8%</b>	<b>13,5%</b>	<b>9,8%</b>	<b>11,7%</b>

In the Netherlands, health survey data for 2011-2013 are reported by the Central Bureau for Statistics, with estimated prevalence rates for both Autism Spectrum Disorder and hyperactivity each amounting to 2,8% in four to twelve-year-old children. Percentages increased with age group and were markedly higher for boys than for girls, with prevalence for boys estimated at 3,8% (ASD) and 3,6% (hyperactivity), and for girls at 1,7% and 1,9%, respectively (CBS, 2015). Not all of the children reporting ASD are treated in specialized secondary care, e.g. 2,5% of the ten to twelve-year-olds received ASD specialized treatment, as compared to an estimated prevalence of 5,3% in this age group (Houben-van Herten et al., 2014).

Registration data from primary care general practitioners in the Netherlands, reported by the NIVEL institute (Nielen, et al., 2021) show an increasing trend for the diagnosis 'Overactive child/hyperkinetic disorder' between 2016 and 2020, with boys outnumbering girls in every year. Contrary to this, the diagnosis 'Memory, concentration, and orientation disorder' is somewhat more frequent in girls and shows an increase until 2019, followed by a slight decrease in 2020. The reported percentages per primary care diagnosis and gender are shown in Figure 1.27.



Figure 1.27 Prevalence of hyperactivity and attention-deficit diagnoses in primary care in the Netherlands (NIVEL).

Finally, in the NEMESIS-2 self-report study in the Netherlands, 2,9% of 3309 adults between 18 and 44 years indicated having been diagnosed with ADHD in their childhood (Tuithof, et al., 2010).

### 2.3 Estimating care needs of children and adolescents with developmental disorders in Flanders

Seeing that no time series for the prevalence of Autism Spectrum Disorder and ADHD are available for the Flemish population, we use one coarse approach for estimating care needs for children with both types of developmental disorders, based on the two international meta-analysis using diagnostic criteria reported above. In addition, the population for children with ADHD is estimated using the percentages reported by general practitioners in the Netherlands for the primary care diagnoses 'Overactive child/hyperkinetic syndrome' and 'Memory, concentration, and orientation disorders' shown in Figure 1.27 above (Nielen et al., 2021).

The overall prevalence percentages of 1,04% reported for ASD (MacKay et al., 2016) and 5,29 for ADHD (Polanczyk et al., 2008; 2014) are applied to the Flemish population under 18 years, thereby producing estimates solely determined by the demographic evolution, leading to a limited increase in the estimated number of children and adolescents with these diagnoses between 2013 and 2019 (Figure 1.28).

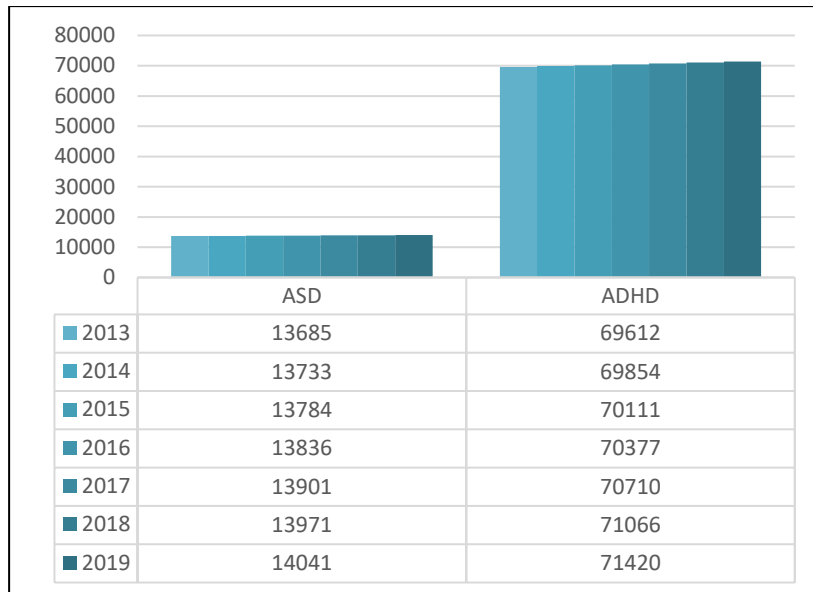


Figure 1.28 Estimated number of children and adolescents between 0 and 18 years with ASD and ADHD in Flanders between 2013 and 2019, based on constant overall prevalence percentages (International meta-analysis, MacKay et al, 2016; Polanczyk et al., 2008) and the demographic evolution of the Flemish population (Federal Planning Bureau, Statbel).

When using the mounting estimates based on primary care registration by NIVEL in the Netherlands of two diagnoses relating to ADHD, estimates for this disorder lead to much lower numbers than the estimate based on the international meta-analysis of Polanczyk et al. (2008). The resulting yearly increase is considerably stronger though, amounting to 13,6% between 2016 and 2019, as compared to the demographic evolution driven increase of 1,5% shown in Figure 1.28 above in the same three-year time period.

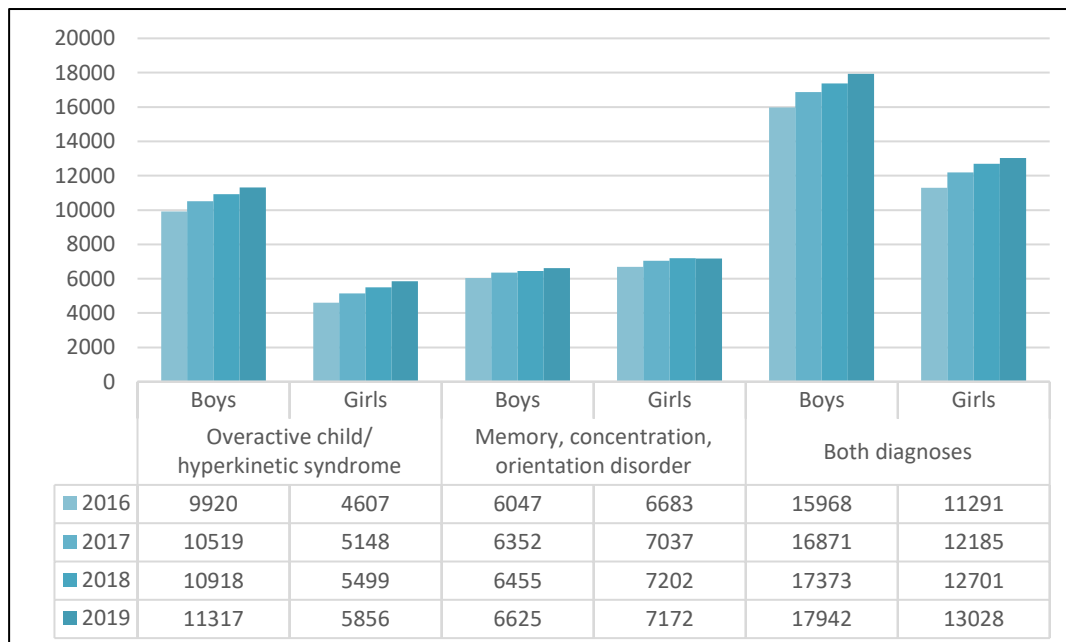


Figure 1.29 Estimated number of boys and girls between 0 and 18 years with ADHD in Flanders between 2016 and 2019, based on gender-specific prevalence percentages for ADHD-related primary care diagnoses (NIVEL) and the demographic evolution of the Flemish population (Federal Planning Bureau, Statbel).



Although both figures may give some indication as to the number of children with Autism Spectrum Disorder or ADHD in Flanders, available prevalence data are insufficient to produce reliable estimates and are therefore not suited as a means of predicting future care needs for ASD and ADHD.

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## Part III - Appendix 2

### Regression models for care periods and face-to-face contacts in the Centers for Mental Health Care

Predictors in regression models 1 to 2f are limited to region (province) and year dummies. The dataset consists of 19 CGG (excluding Brussels) and 8 years (2012-2019): N=152 cases.

In regression models 3 to 5h, in addition to the province dummies, a needs factor is included, which is either:

- In models 3 to 4f, the meta-analysis prevalence percentage for any mental illness, mood disorders, anxiety disorders, and substance-related disorders, applied to the Flemish population between 2012 and 2019 (see Appendix 1): N=152 cases
- In models 5 to 5h, the HIS-prevalence percentages for any mental illness, mood disorders, anxiety disorders, problematic substance use, and problematic alcohol use, applied to the Flemish population in 2008, 2013, and 2018 (see Appendix 1), leading to the following number of cases: 19 CGG\*3 years: N=57

Regression models 1-1f and 3-3f / 2-2f and 4-4f predict:

- the total number of care periods / FTF-contacts (=face-to-face contacts in the last 2 years)
- a-c: the total number of care periods / FTF-contacts per age target group (children & adolescents, adults, elderly people)
- d-f: the total number of care periods / FTF-contacts per main diagnosis (mood disorder, anxiety disorder, substance-related disorder)

Regression models 5-5h predict:

- the total number of care periods
- a-h: the total number of care periods per main diagnosis for the adult and/or elderly target group
- Note: FTF-contacts are not used as a dependent variable, due to unreliable data in 2008.

**Regression model 1: Predicting the total number of care periods in the Centers for Mental Health Care**

- Predictors: Year dummies (reference 2012); Province dummies (reference West-Flanders)

**Model Summary**

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,428	,183	,119	1131,850

**ANOVA**

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	40254572,466	11	3659506,588	2,857	,002
	Residual	179351832,349	140	1281084,517		
	Total	219606404,816	151			

**Coefficients**

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	<b>2339,352</b>	314,692		7,434	,000
	Year=2013	<b>75,316</b>	367,221	,021	,205	,838
	Year=2014	<b>56,474</b>	367,221	,016	,154	,878
	Year=2015	<b>96,000</b>	367,221	,026	,261	,794
	Year=2016	<b>133,842</b>	367,221	,037	,364	,716
	Year=2017	<b>80,053</b>	367,221	,022	,218	,828
	Year=2018	<b>-39,053</b>	367,221	-,011	-,106	,915
	Year=2019	<b>-134,947</b>	367,221	-,037	-,367	,714
	Province=Antwerp	<b>1183,906</b>	282,963	,402	4,184	,000
	Province=East Flanders	<b>27,588</b>	268,442	,010	,103	,918
	Province=Flemish Brabant	<b>551,021</b>	305,634	,167	1,803	,074
	Province=Limburg	<b>1051,563</b>	305,634	,319	3,441	,001

### Regression model 1a: Predicting the total number of care periods for children and adolescents in the Centers for Mental Health Care

- Predictors: Year dummies (reference 2012); Province dummies (reference West-Flanders)

#### Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,377	,142	,075	235,319

#### ANOVA

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	1285770,920	11	116888,265	2,111	,023
	Residual	7752494,757	140	55374,963		
	Total	9038265,678	151			

#### Coefficients

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	<b>583,954</b>	65,427		8,925	,000
	Year=2013	<b>21,632</b>	76,348	,029	,283	,777
	Year=2014	<b>-15,368</b>	76,348	-,021	-,201	,841
	Year=2015	<b>-27,368</b>	76,348	-,037	-,358	,721
	Year=2016	<b>-30,368</b>	76,348	-,041	-,398	,691
	Year=2017	<b>-49,474</b>	76,348	-,067	-,648	,518
	Year=2018	<b>-71,895</b>	76,348	-,098	-,942	,348
	Year=2019	<b>-86,789</b>	76,348	-,118	-1,137	,258
	Province=Antwerp	<b>175,563</b>	58,830	,294	2,984	,003
	Province=East Flanders	<b>18,200</b>	55,811	,033	,326	,745
	Province=Flemish Brabant	<b>148,083</b>	63,543	,221	2,330	,021
Province=Limburg	<b>209,458</b>	63,543	,313	3,296	,001	

### Regression model 1b: Predicting the total number of care periods for adults in the Centers for Mental Health Care

- Predictors: Year dummies (reference 2012); Province dummies (reference West-Flanders)

#### Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,423	,179	,114	861,625

#### ANOVA

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	22631211,380	11	2057382,853	2,771	,003
	Residual	103935733,560	140	742398,097		
	Total	126566944,941	151			

#### Coefficients

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	1554,446	239,561		6,489	,000
	Year=2013	35,368	279,548	,013	,127	,900
	Year=2014	44,000	279,548	,016	,157	,875
	Year=2015	77,421	279,548	,028	,277	,782
	Year=2016	101,263	279,548	,037	,362	,718
	Year=2017	56,579	279,548	,021	,202	,840
	Year=2018	-15,158	279,548	-,005	-,054	,957
	Year=2019	-74,789	279,548	-,027	-,268	,789
	Province=Antwerp	924,688	215,406	,413	4,293	,000
	Province=East Flanders	7,844	204,352	,004	,038	,969
	Province=Flemish Brabant	245,177	232,665	,098	1,054	,294
	Province=Limburg	690,344	232,665	,276	2,967	,004



**Regression model 1c: Predicting the total number of care periods for elderly people in the Centers for Mental Health Care**

- Predictors: Year dummies (reference 2012); Province dummies (reference West-Flanders)

**Model Summary**

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,542	,293	,238	115,224

**ANOVA**

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	771367,175	11	70124,289	5,282	,000
	Residual	1858718,378	140	13276,560		
	Total	2630085,553	151			

**Coefficients**

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	200,952	32,036		6,273	,000
	Year=2013	18,316	37,384	,046	,490	,625
	Year=2014	27,842	37,384	,070	,745	,458
	Year=2015	45,947	37,384	,116	1,229	,221
	Year=2016	62,947	37,384	,158	1,684	,094
	Year=2017	72,947	37,384	,183	1,951	,053
	Year=2018	48,000	37,384	,121	1,284	,201
	Year=2019	26,632	37,384	,067	,712	,477
	Province=Antwerp	83,656	28,806	,259	2,904	,004
	Province=East Flanders	1,544	27,328	,005	,056	,955
	Province=Flemish Brabant	157,760	31,114	,437	5,070	,000
	Province=Limburg	151,760	31,114	,421	4,878	,000

### Regression model 1d: Predicting the total number of care periods for mood disorders in the Centers for Mental Health Care

- Predictors: Year dummies (reference 2012); Province dummies (reference West-Flanders)
- Mood disorders (2012-2017) or Mood disorders + Bipolar mood disorders (2018-2019)

#### Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,250	,062	-,011	254,620

#### ANOVA

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	602856,154	11	54805,105	,845	,595
	Residual	9076395,425	140	64831,396		
	Total	9679251,579	151			

#### Coefficients

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	591,724	70,793		8,359	,000
	Year=2013	16,842	82,610	,022	,204	,839
	Year=2014	22,421	82,610	,029	,271	,786
	Year=2015	37,474	82,610	,049	,454	,651
	Year=2016	61,474	82,610	,081	,744	,458
	Year=2017	55,789	82,610	,073	,675	,501
	Year=2018	1,842	82,610	,002	,022	,982
	Year=2019	-83,632	82,610	-,110	-1,012	,313
	Province=Antwerp	68,125	63,655	,110	1,070	,286
	Province=East Flanders	-41,500	60,388	-,072	-,687	,493
	Province=Flemish Brabant	29,958	68,755	,043	,436	,664
	Province=Limburg	80,125	68,755	,116	1,165	,246

**Regression model 1e: Predicting the total number of care periods for anxiety disorders in the Centers for Mental Health Care**

- Predictors: Year dummies (reference 2012); Province dummies (reference West-Flanders)
- Anxiety disorders (2012-2017) or Anxiety, OCD, Stressor or Trauma-related disorders (2018-2019)

**Model Summary**

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,327	,107	,037	127,937

**ANOVA**

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	274812,237	11	24982,931	1,526	,128
	Residual	2291490,282	140	16367,788		
	Total	2566302,520	151			

**Coefficients**

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	225,401	35,571		6,337	,000
	Year=2013	3,789	41,508	,010	,091	,927
	Year=2014	5,895	41,508	,015	,142	,887
	Year=2015	18,684	41,508	,048	,450	,653
	Year=2016	23,000	41,508	,059	,554	,580
	Year=2017	24,368	41,508	,062	,587	,558
	Year=2018	21,684	41,508	,055	,522	,602
	Year=2019	99,368	41,508	,253	2,394	,018
	Province=Antwerp	65,281	31,984	,205	2,041	,043
	Province=East Flanders	-12,625	30,343	-,043	-,416	,678
	Province=Flemish Brabant	15,625	34,547	,044	,452	,652
	Province=Limburg	48,833	34,547	,137	1,414	,160

### Regression model 1f: Predicting the total number of care periods for substance-related disorders and addiction in the Centers for Mental Health Care

- Predictors: Year dummies (reference 2012); Province dummies (reference West-Flanders)

#### Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,403	,163	,097	362,978

#### ANOVA

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	3582113,776	11	325646,707	2,472	,007
	Residual	18445396,303	140	131752,831		
	Total	22027510,079	151			

#### Coefficients

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	180,071	100,920		1,784	,077
	Year=2013	13,842	117,766	,012	,118	,907
	Year=2014	23,632	117,766	,021	,201	,841
	Year=2015	16,632	117,766	,014	,141	,888
	Year=2016	8,632	117,766	,007	,073	,942
	Year=2017	-,316	117,766	,000	-,003	,998
	Year=2018	-40,211	117,766	-,035	-,341	,733
	Year=2019	-26,526	117,766	-,023	-,225	,822
	Province=Antwerp	315,594	90,744	,338	3,478	,001
	Province=East Flanders	42,444	86,088	,049	,493	,623
	Province=Flemish Brabant	-26,948	98,015	-,026	-,275	,784
	Province=Limburg	331,969	98,015	,318	3,387	,001

**Regression model 2: Predicting the total number of face-to-face contacts in the last 2 years of treatment in the Centers for Mental Health Care**

- Predictors: Year dummies (reference 2012); Province dummies (reference West-Flanders)

**Model Summary**

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,463	,214	,153	12306,313

**ANOVA**

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	5783552195,615	11	525777472,329	3,472	,000
	Residual	21202347055,589	140	151445336,111		
	Total	26985899251,204	151			

**Coefficients**

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	<b>33143,523</b>	3421,567		9,687	,000
	Year=2013	<b>567,105</b>	3992,695	,014	,142	,887
	Year=2014	<b>755,211</b>	3992,695	,019	,189	,850
	Year=2015	<b>1027,053</b>	3992,695	,025	,257	,797
	Year=2016	<b>1086,000</b>	3992,695	,027	,272	,786
	Year=2017	<b>337,368</b>	3992,695	,008	,084	,933
	Year=2018	<b>-750,316</b>	3992,695	-,019	-,188	,851
	Year=2019	<b>-2523,105</b>	3992,695	-,063	-,632	,528
	Province=Antwerp	<b>11718,813</b>	3076,578	,359	3,809	,000
	Province=East Flanders	<b>-5058,337</b>	2918,698	-,167	-1,733	,085
	Province=Flemish Brabant	<b>3416,479</b>	3323,084	,093	1,028	,306
	Province=Limburg	<b>-2455,979</b>	3323,084	-,067	-,739	,461

**Regression model 2a: Predicting the total number of face-to-face contacts in the last 2 years of treatment for children and adolescents in the Centers for Mental Health Care**

- Predictors: Year dummies (reference 2012); Province dummies (reference West-Flanders)

**Model Summary**

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,459	,211	,149	2662,315

**ANOVA**

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	264799492,553	11	24072681,141	3,396	,000
	Residual	992309152,157	140	7087922,515		
	Total	1257108644,711	151			

**Coefficients**

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	6791,212	740,213		9,175	,000
	Year=2013	433,263	863,769	,050	,502	,617
	Year=2014	416,105	863,769	,048	,482	,631
	Year=2015	240,263	863,769	,028	,278	,781
	Year=2016	122,737	863,769	,014	,142	,887
	Year=2017	-243,053	863,769	-,028	-,281	,779
	Year=2018	-482,000	863,769	-,055	-,558	,578
	Year=2019	-912,263	863,769	-,105	-1,056	,293
	Province=Antwerp	3262,844	665,579	,463	4,902	,000
	Province=East Flanders	213,156	631,424	,033	,338	,736
	Province=Flemish Brabant	1981,781	718,907	,251	2,757	,007
Province=Limburg	1336,823	718,907	,170	1,860	,065	

**Regression model 2b: Predicting the total number of face-to-face contacts in the last 2 years of treatment for adults in the Centers for Mental Health Care**

- Predictors: Year dummies (reference 2012); Province dummies (reference West-Flanders)

**Model Summary**

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,439	,192	,129	9333,024

**ANOVA**

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	2904255042,607	11	264023185,692	3,031	,001
	Residual	12194746588,735	140	87105332,777		
	Total	15099001631,342	151			

**Coefficients**

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	23068,951	2594,893		8,890	,000
	Year=2013	-28,053	3028,033	-,001	-,009	,993
	Year=2014	23,421	3028,033	,001	,008	,994
	Year=2015	319,526	3028,033	,011	,106	,916
	Year=2016	445,947	3028,033	,015	,147	,883
	Year=2017	-18,895	3028,033	-,001	-,006	,995
	Year=2018	-710,053	3028,033	-,024	-,234	,815
	Year=2019	-1776,000	3028,033	-,059	-,587	,558
	Province=Antwerp	7470,938	2333,256	,306	3,202	,002
	Province=East Flanders	-4264,562	2213,521	-,188	-1,927	,056
	Province=Flemish Brabant	893,396	2520,204	,033	,354	,724
Province=Limburg	-3557,062	2520,204	-,130	-1,411	,160	

### Regression model 2c: Predicting the total number of face-to-face contacts in the last 2 years of treatment for elderly people in the Centers for Mental Health Care

- Predictors: Year dummies (reference 2012); Province dummies (reference West-Flanders)

#### Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,407	,165	,100	1758,322

#### ANOVA

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	85722462,495	11	7792951,136	2,521	,006
	Residual	432837493,183	140	3091696,380		
	Total	518559955,678	151			

#### Coefficients

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	3283,360	488,872		6,716	,000
	Year=2013	161,895	570,475	,029	,284	,777
	Year=2014	315,684	570,475	,057	,553	,581
	Year=2015	467,263	570,475	,084	,819	,414
	Year=2016	517,316	570,475	,093	,907	,366
	Year=2017	599,316	570,475	,107	1,051	,295
	Year=2018	441,737	570,475	,079	,774	,440
	Year=2019	165,158	570,475	,030	,290	,773
	Province=Antwerp	985,031	439,581	,217	2,241	,027
	Province=East Flanders	-1006,931	417,023	-,240	-2,415	,017
	Province=Flemish Brabant	541,302	474,801	,107	1,140	,256
Province=Limburg	-235,740	474,801	-,047	-,497	,620	



**Regression model 2d: Predicting the total number of face-to-face contacts in the last 2 years of treatment for mood disorders in the Centers for Mental Health Care**

- Predictors: Year dummies (reference 2012); Province dummies (reference West-Flanders)
- Mood disorders (2012-2017) or Mood disorders + Bipolar mood disorders (2018-2019)

**Model Summary**

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,372	,139	,071	3700,047

**ANOVA**

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	308537077,590	11	28048825,235	2,049	,028
	Residual	1916648703,088	140	13690347,879		
	Total	2225185780,678	151			

**Coefficients**

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	9397,734	1028,737		9,135	,000
	Year=2013	84,263	1200,454	,007	,070	,944
	Year=2014	284,632	1200,454	,025	,237	,813
	Year=2015	555,947	1200,454	,048	,463	,644
	Year=2016	700,158	1200,454	,061	,583	,561
	Year=2017	551,526	1200,454	,048	,459	,647
	Year=2018	-176,895	1200,454	-,015	-,147	,883
	Year=2019	-960,000	1200,454	-,083	-,800	,425
	Province=Antwerp	748,969	925,012	,080	,810	,419
	Province=East Flanders	-2314,013	877,543	-,266	-2,637	,009
	Province=Flemish Brabant	-597,979	999,127	-,057	-,599	,550
Province=Limburg	-2679,271	999,127	-,255	-2,682	,008	

**Regression model 2e: Predicting the total number of face-to-face contacts in the last 2 years of treatment for anxiety disorders in the Centers for Mental Health Care**

- Predictors: Year dummies (reference 2012); Province dummies (reference West-Flanders)
- Anxiety disorders (2012-2017) or Anxiety, OCD, stressor- or trauma-related disorders (2018-2019)

**Model Summary**

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,462	,213	,152	1505,944

**ANOVA**

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	86154383,362	11	7832216,669	3,454	,000 <sup>b</sup>
	Residual	317501273,454	140	2267866,239		
	Total	403655656,816	151			

**Coefficients**

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	3102,847	418,703		7,411	,000
	Year=2013	41,263	488,593	,008	,084	,933
	Year=2014	79,421	488,593	,016	,163	,871
	Year=2015	150,842	488,593	,031	,309	,758
	Year=2016	166,684	488,593	,034	,341	,734
	Year=2017	170,684	488,593	,035	,349	,727
	Year=2018	309,263	488,593	,063	,633	,528
	Year=2019	637,316	488,593	,129	1,304	,194
	Province=Antwerp	1575,375	376,486	,394	4,184	,000
	Province=East Flanders	-257,181	357,166	-,069	-,720	,473
	Province=Flemish Brabant	239,385	406,651	,054	,589	,557
Province=Limburg	-464,948	406,651	-,104	-1,143	,255	

**Regression model 2f: Predicting the total number of face-to-face contacts in the last 2 years of treatment for substance-related disorders in the Centers for Mental Health Care**

- Predictors: Year dummies (reference 2012); Province dummies (reference West-Flanders)

**Model Summary**

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,353	,125	,056	3079,177

**ANOVA**

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	189357100,810	11	17214281,892	1,816	,057 <sup>b</sup>
	Residual	1327386334,953	140	9481330,964		
	Total	1516743435,763	151			

**Coefficients**

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	2473,582	856,114		2,889	,004
	Year=2013	62,368	999,017	,007	,062	,950
	Year=2014	103,263	999,017	,011	,103	,918
	Year=2015	67,842	999,017	,007	,068	,946
	Year=2016	56,053	999,017	,006	,056	,955
	Year=2017	14,263	999,017	,001	,014	,989
	Year=2018	-249,947	999,017	-,026	-,250	,803
	Year=2019	-247,000	999,017	-,026	-,247	,805
	Province=Antwerp	2336,563	769,794	,302	3,035	,003
	Province=East Flanders	-34,087	730,291	-,005	-,047	,963
	Province=Flemish Brabant	-897,979	831,473	-,104	-1,080	,282
Province=Limburg	1224,688	831,473	,141	1,473	,143	

**Regression model 3: Predicting the total number of care periods in the Centers for Mental Health Care**

- Predictors: Estimated Flemish population of children and adolescents/adults/elderly people with any mental disorder; Province dummies (reference West-Flanders)
- Meta-analysis prevalences for any mental disorder (Polanczyk, children and adolescents, not gender-specific; Steel, adults and elderly people, gender-specific) applied to Flemish population per age group

**Model Summary**

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,428 <sup>a</sup>	,183	,143	1116,168

**ANOVA<sup>a</sup>**

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	40206845,131	7	5743835,019	4,610	,000 <sup>b</sup>
	Residual	179399559,684	144	1245830,276		
	Total	219606404,816	151			

**Coefficients<sup>a</sup>**

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	-223529,106	662178,436		-,338	,736
	Province=Antwerp	1183,906	279,042	,402	4,243	,000
	Province=East Flanders	27,588	264,722	,010	,104	,917
	Province=Flemish Brabant	551,021	301,400	,167	1,828	,070
	Province=Limburg	1051,563	301,400	,319	3,489	,001
	FlempopMetaMIyoung	-,336	,975	-,491	-,345	,731
	FlempopmetaMIadult	,439	,981	,041	,448	,655
	FlempopmetaMIelderly	,051	,151	,472	,336	,737

**Regression model 3a: Predicting the total number of care periods for children and adolescents in the Centers for Mental Health Care**

- Predictors: Estimated Flemish population of children and adolescents with any mental disorder; Province dummies (reference West-Flanders)
- Meta-analysis prevalences for any mental disorder (Polanczyk, not gender-specific) applied to Flemish population per age group

**Model Summary**

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,375 <sup>a</sup>	,141	,111	230,626

**ANOVA<sup>a</sup>**

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	1272749,705	5	254549,941	4,786	,000 <sup>b</sup>
	Residual	7765515,973	146	53188,466		
	Total	9038265,678	151			

**Coefficients<sup>a</sup>**

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	3665,012	1796,476		2,040	,043
	Province=Antwerp	175,563	57,657	,294	3,045	,003
	Province=East Flanders	18,200	54,698	,033	,333	,740
	Province=Flemish Brabant	148,083	62,276	,221	2,378	,019
	Province=Limburg	209,458	62,276	,313	3,363	,001
	FlempopMetaMlyoung	-,018	,011	-,133	-1,734	,085

### Regression model 3b: Predicting the total number of care periods for adults in the Centers for Mental Health Care

- Predictors: Estimated Flemish population of adult men / adult women with any mental disorder; Province dummies (reference West-Flanders)
- Meta-analysis prevalences for any mental disorder (Steel, gender-specific) applied to Flemish population per age group

#### Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,422 <sup>a</sup>	,178	,144	847,125

#### ANOVA<sup>a</sup>

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	22511912,648	6	3751985,441	5,228	,000 <sup>b</sup>
	Residual	104055032,292	145	717620,912		
	Total	126566944,941	151			

#### Coefficients<sup>a</sup>

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	-237796,628	373663,974		-,636	,526
	Province=Antwerp	924,688	211,781	,413	4,366	,000
	Province=East Flanders	7,844	200,913	,004	,039	,969
	Province=Flemish Brabant	245,177	228,750	,098	1,072	,286
	Province=Limburg	690,344	228,750	,276	3,018	,003
	FlempopMetaMI_MenAdult	,355	,659	,058	,538	,591
	FlempopMetaMI_WomenAdult	,420	,659	,069	,638	,524

**Regression model 3c: Predicting the total number of care periods for elderly people in the Centers for Mental Health Care**

- Predictors: Estimated Flemish population of elderly men/elderly women with any mental disorder; Province dummies (reference West-Flanders)
- Meta-analysis prevalences for any mental disorder (Steel, gender-specific) applied to Flemish population per age group

**Model Summary**

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,523 <sup>a</sup>	,273	,248	114,421

**ANOVA<sup>a</sup>**

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	718615,511	5	143723,102	10,978	,000 <sup>b</sup>
	Residual	1911470,042	146	13092,261		
	Total	2630085,553	151			

**Coefficients<sup>a</sup>**

Model		Unstandardized Coefficients		Standardized Coefficients Beta	t	Sig.
		B	Std. Error			
1	(Constant)	-130,675	270,351		-,483	,630
	Province=Antwerp	83,656	28,605	,259	2,924	,004
	Province=East Flanders	1,544	27,137	,005	,057	,955
	Province=Flemish Brabant	157,760	30,897	,437	5,106	,000
	Province=Limburg	151,760	30,897	,421	4,912	,000
	FlempopMetaMI_WomenElderly	,002	,002	,097	1,370	,173

**Excluded Variables<sup>a</sup>**

Model	Beta In	t	Sig.	Partial Correlation	Collinearity Statistics Tolerance	
1	FlempopMetaMI_MenElderly	-7,724 <sup>b</sup>	-,977	,330	-,081	7,962E-5

### Regression model 3d: Predicting the total number of care periods for mood disorders in the Centers for Mental Health Care

- Predictors: Estimated Flemish population of children and adolescents/adult men/adult women/elderly men/elderly women with any mood disorder; Province dummies (reference West-Flanders)
- Meta-analysis prevalences for any mood disorder (Polanczyk, children and adolescents, not gender-specific; Steel, adults and elderly people, gender-specific) applied to Flemish population per age group
- Mood disorders (2012-2017) or Mood disorders + Bipolar mood disorders (2018-2019)

#### Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,240 <sup>a</sup>	,057	,005	252,592

#### ANOVA<sup>a</sup>

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	555469,452	8	69433,682	1,088	,375 <sup>b</sup>
	Residual	9123782,127	143	63802,672		
	Total	9679251,579	151			

#### Coefficients<sup>a</sup>

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	-126819,132	149632,490		-,848	,398
	Province=Antwerp	68,125	63,148	,110	1,079	,282
	Province=East Flanders	-41,500	59,907	-,072	-,693	,490
	Province=Flemish Brabant	29,958	68,208	,043	,439	,661
	Province=Limburg	80,125	68,208	,116	1,175	,242
	FlempopMetamoodyoung	-,784	1,323	-1,057	-,592	,554
	FlempopMetamoodadultmen	,851	1,181	,138	,720	,472
	FlempopMetamoodadultwomen	,657	,634	,145	1,036	,302
	FlempopMetamoodelderlywomen	,115	,207	1,030	,556	,579

#### Excluded Variables<sup>a</sup>

Model		Beta In	t	Sig.	Partial Correlation	Collinearity Statistics Tolerance
1	FlempopMetamoodelderlymen	-7,589 <sup>b</sup>	-,751	,454	-,063	6,473E-5



**Regression model 3e: Predicting the total number of care periods for anxiety disorders in the Centers for Mental Health Care**

- Predictors: Estimated Flemish population of children and adolescents/adult men/adult women/elderly men/elderly women with any mood disorder; Province dummies (reference West-Flanders)
- Meta-analysis prevalences for any anxiety disorder (Polanczyk, children and adolescents, not gender-specific; Steel, adults and elderly people, gender-specific) applied to Flemish population per age group
- Anxiety disorders (2012-2017) or Anxiety, OCD, Stressor or Trauma-related disorders (2018-2019)

**Model Summary**

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,306a	,094	,043	127,544

**ANOVA<sup>a</sup>**

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	240042,964	8	30005,371	1,844	,073b
	Residual	2326259,556	143	16267,549		
	Total	2566302,520	151			

**Coefficients<sup>a</sup>**

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	65734,200	75555,752		,870	,386
	Province=Antwerp	65,281	31,886	,205	2,047	,042
	Province=East Flanders	-12,625	30,250	-,043	-,417	,677
	Province=Flemish Brabant	15,625	34,441	,044	,454	,651
	Province=Limburg	48,833	34,441	,137	1,418	,158
	FlempopMetaanxietyyoung	-,037	,267	-,243	-,139	,890
	FlempopMetaanxietyadultmen	-,355	,555	-,120	-,639	,524
	FlempopMetaanxietyadultwomen	-,239	,268	-,122	-,889	,375
	FlempopMetaanxietyelderlywomer	,019	,088	,387	,213	,831

**Excluded Variables<sup>a</sup>**

Model		Beta In	t	Sig.	Partial Correlation	Collinearity Statistics Tolerance
1	FlempopMetaanxietyelderlymen	9,941b	1,005	,317	,084	6,473E-5

### Regression model 3f: Predicting the total number of care periods for substance-related disorders for adults and elderly people in the Centers for Mental Health Care

- Predictors: Estimated Flemish population of adult men/adult women/elderly men/elderly women with any substance-related disorder; Province dummies (reference West-Flanders)
- Meta-analysis prevalences for any substance-related disorder (Steel, gender-specific) applied to Flemish population per age group

#### Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,407a	,166	,125	337,659

#### ANOVA<sup>a</sup>

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	3261317,342	7	465902,477	4,086	,000b
	Residual	16417986,553	144	114013,796		
	Total	19679303,895	151			

#### Coefficients<sup>a</sup>

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	-32706,008	182591,732		-,179	,858
	Province=Antwerp	282,750	84,415	,320	3,350	,001
	Province=East Flanders	26,856	80,083	,033	,335	,738
	Province=Flemish Brabant	-29,260	91,178	-,030	-,321	,749
	Province=Limburg	327,156	91,178	,332	3,588	,000
	FlempopMetasubstanceadultmen	,001	,834	,000	,001	,999
	FlempopMetasubstanceadultwomen	,949	2,624	,040	,362	,718
	FlempopMetasubstanceelderlywomen	-,034	,086	-,058	-,392	,696

#### Excluded Variables<sup>a</sup>

Model	Beta In	t	Sig.	Partial Correlation	Collinearity Statistics Tolerance	
1	FlempopMetasubstanceelderlymen	-,164b	-,019	,985	-,002	7,890E-5

**Regression model 4: Predicting the total number of face-to-face contacts in the last 2 years of treatment in the Centers for Mental Health Care**

- Predictors: Estimated Flemish population of children and adolescents/adults/elderly people with any mental disorder; Province dummies (reference West-Flanders)
- Meta-analysis prevalences for any mental disorder (Polanczyk, children and adolescents, not gender-specific; Steel, adults and elderly people, gender-specific) applied to Flemish population per age group

**Model Summary**

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,462 <sup>a</sup>	,214	,175	12140,401

**ANOVA<sup>a</sup>**

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	5761833398,797	7	823119056,971	5,585	,000 <sup>b</sup>
	Residual	21224065852,407	144	147389346,197		
	Total	26985899251,204	151			

**Coefficients<sup>a</sup>**

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	-2669063,736	7202423,254		-,371	,711
	Province=Antwerp	11718,813	3035,100	,359	3,861	,000
	Province=East Flanders	-5058,338	2879,349	-,167	-1,757	,081
	Province=Flemish Brabant	3416,479	3278,283	,093	1,042	,299
	Province=Limburg	-2455,979	3278,283	-,067	-,749	,455
	FlempopMetaMIyoung	-3,574	10,606	-,470	-,337	,737
	FlempopmetaMIadult	5,169	10,666	,044	,485	,629
	FlempopmetaMIelderly	,513	1,638	,432	,313	,754

### Regression model 4a: Predicting the total number of face-to-face contacts in the last 2 years of treatment for children and adolescents in the Centers for Mental Health Care

- Predictors: Estimated Flemish population of children and adolescents with any mental disorder; Province dummies (reference West-Flanders)
- Meta-analysis prevalences for any mental disorder (Polanczyk, not gender-specific) applied to Flemish population per age group

#### Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,452 <sup>a</sup>	,204	,177	2617,657

#### ANOVA<sup>a</sup>

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	256698021,749	5	51339604,350	7,493	,000 <sup>b</sup>
	Residual	1000410622,962	146	6852127,555		
	Total	1257108644,711	151			

#### Coefficients<sup>a</sup>

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	42474,256	20390,385		2,083	,039
	Province=Antwerp	3262,844	654,414	,463	4,986	,000
	Province=East Flanders	213,156	620,832	,033	,343	,732
	Province=Flemish Brabant	1981,781	706,848	,251	2,804	,006
	Province=Limburg	1336,823	706,848	,170	1,891	,061
	FlempopMetaMlyoung	-,212	,121	-,129	-1,753	,082

**Regression model 4b: Predicting the total number of face-to-face contacts in the last 2 years of treatment for adults in the Centers for Mental Health Care**

- Predictors: Estimated Flemish population of adult men / adult women with any mental disorder; Province dummies (reference West-Flanders)
- Meta-analysis prevalences for any mental disorder (Steel, gender-specific) applied to Flemish population per age group

**Model Summary**

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,437 <sup>a</sup>	,191	,157	9180,815

**ANOVA<sup>a</sup>**

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	2877333441,318	6	479555573,553	5,690	,000 <sup>b</sup>
	Residual	12221668190,024	145	84287366,828		
	Total	15099001631,342	151			

**Coefficients<sup>a</sup>**

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	-2706047,088	4049626,120		-,668	,505
	Province=Antwerp	7470,938	2295,204	,306	3,255	,001
	Province=East Flanders	-4264,562	2177,421	-,188	-1,959	,052
	Province=Flemish Brabant	893,396	2479,103	,033	,360	,719
	Province=Limburg	-3557,062	2479,103	-,130	-1,435	,153
	FlempopMetaMI_MenAdult	4,913	7,140	,074	,688	,492
	FlempopMetaMI_WomenAdult	4,131	7,139	,062	,579	,564

### Regression model 4c: Predicting the total number of face-to-face contacts in the last 2 years of treatment for elderly people in the Centers for Mental Health Care

- Predictors: Estimated Flemish population of elderly men/elderly women with any mental disorder; Province dummies (reference West-Flanders)
- Meta-analysis prevalences for any mental disorder (Steel, gender-specific) applied to Flemish population per age group

#### Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,396a	,156	,128	1730,892

#### ANOVA<sup>a</sup>

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	81145819,029	5	16229163,806	5,417	,000b
	Residual	437414136,648	146	2995987,237		
	Total	518559955,678	151			

#### Coefficients<sup>a</sup>

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	1049,253	4089,691		,257	,798
	Province=Antwerp	985,031	432,723	,217	2,276	,024
	Province=East Flanders	-1006,931	410,517	-,240	-2,453	,015
	Province=Flemish Brabant	541,302	467,394	,107	1,158	,249
	Province=Limburg	-235,740	467,394	-,047	-,504	,615
	FlempopMetaMI_WomenElderly	,015	,023	,048	,630	,530

#### Excluded Variables<sup>a</sup>

Model		Beta In	t	Sig.	Partial Correlation	Collinearity Statistics Tolerance
1	FlempopMetaMI_MenElderly	-4,942b	-,579	,564	-,048	7,962E-5

### Regression model 4d: Predicting the total number of face-to-face contacts in the last 2 years of treatment for mood disorders in the Centers for Mental Health Care

- Predictors: Estimated Flemish population of children and adolescents/adult men/adult women/elderly men/elderly women with any mood disorder; Province dummies (reference West-Flanders)
- Meta-analysis prevalences for any mood disorder (Polanczyk, children and adolescents, not gender-specific; Steel, adults and elderly people, gender-specific) applied to Flemish population per age group
- Mood disorders (2012-2017) or Mood disorders + Bipolar mood disorders (2018-2019)

#### Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,369a	,136	,088	3665,869

#### ANOVA<sup>a</sup>

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	303466903,147	8	37933362,893	2,823	,006b
	Residual	1921718877,531	143	13438593,549		
	Total	2225185780,678	151			

#### Coefficients<sup>a</sup>

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	-1070847,893	2171617,728		-,493	,623
	Province=Antwerp	748,969	916,467	,080	,817	,415
	Province=East Flanders	-2314,013	869,437	-,266	-2,662	,009
	Province=Flemish Brabant	-597,979	989,898	-,057	-,604	,547
	Province=Limburg	-2679,271	989,898	-,255	-2,707	,008
	FlempopMetaMood_Young	-10,124	19,207	-,900	-,527	,599
	FlempopMetamoodadultmen	6,084	17,147	,065	,355	,723
	FlempopMetamoodadultwomen	6,852	9,195	,100	,745	,457
	FlempopMetamoodelderlywomen	1,433	3,007	,845	,477	,634

#### Excluded Variables<sup>a</sup>

Model		Beta In	t	Sig.	Partial Correlation	Collinearity Statistics Tolerance
1	FlempopMetamoodelderlymen	-5,567b	-,575	,566	-,048	6,473E-5

### Regression model 4e: Predicting the total number of face-to-face contacts in the last 2 years of treatment for anxiety disorders in the Centers for Mental Health Care

- Predictors: Estimated Flemish population of children and adolescents/adult men/adult women/elderly men/elderly women with any mood disorder; Province dummies (reference West-Flanders)
- Meta-analysis prevalences for any anxiety disorder (Polanczyk, children and adolescents, not gender-specific; Steel, adults and elderly people, gender-specific) applied to Flemish population per age group
- Anxiety disorders (2012-2017) or Anxiety, OCD, Stressor or Trauma-related disorders (2018-2019)

#### Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,461a	,212	,168	1491,321

#### ANOVA<sup>a</sup>

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	85618007,415	8	10702250,927	4,812	,000b
	Residual	318037649,400	143	2224039,506		
	Total	403655656,816	151			

#### Coefficients<sup>a</sup>

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	339660,560	883441,340		,384	,701
	Province=Antwerp	1575,375	372,830	,394	4,225	,000
	Province=East Flanders	-257,181	353,698	-,069	-,727	,468
	Province=Flemish Brabant	239,385	402,703	,054	,594	,553
	Province=Limburg	-464,948	402,703	-,104	-1,155	,250
	FlempopMetaanxiety_Young	,372	3,126	,194	,119	,905
	FlempopMetaanxietyadultmen	-2,372	6,489	-,064	-,366	,715
	FlempopMetaanxietyadultwomen	-1,163	3,139	-,047	-,370	,712
	FlempopMetaanxietyelderlywomen	-,072	1,027	-,119	-,070	,944

#### Excluded Variables<sup>a</sup>

Model		Beta In	t	Sig.	Partial Correlation	Collinearity Statistics Tolerance
1	FlempopMetaanxietyelderlymen	3,759b	,406	,685	,034	6,473E-5



**Regression model 4f: Predicting the total number of face-to-face contacts in the last 2 years of treatment for substance-related disorders in the Centers for Mental Health Care**

- Predictors: Estimated Flemish population of adult men/adult women/elderly men/elderly women with any substance-related disorder; Province dummies (reference West-Flanders)
- Meta-analysis prevalences for any substance-related disorder (Steel, gender-specific) applied to Flemish population per age group

**Model Summary**

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,353 <sup>a</sup>	,124	,082	2939,785

**ANOVA<sup>a</sup>**

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	176665905,840	7	25237986,549	2,920	,007 <sup>b</sup>
	Residual	1244496732,055	144	8642338,417		
	Total	1421162637,895	151			

**Coefficients<sup>a</sup>**

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	-291072,067	1589710,491		-,183	,855
	Province=Antwerp	2186,688	734,946	,292	2,975	,003
	Province=East Flanders	-126,619	697,231	-,018	-,182	,856
	Province=Flemish Brabant	-909,302	793,833	-,108	-1,145	,254
	Province=Limburg	1210,281	793,833	,144	1,525	,130
	FlempopMetasubstanceadultmen	,430	7,264	,011	,059	,953
	FlempopMetasubstanceadultwomen	6,797	22,849	,034	,297	,767
	FlempopMetasubstanceelderlywomen	-,199	,752	-,040	-,264	,792

**Excluded Variables<sup>a</sup>**

Model		Beta In	t	Sig.	Partial Correlation	Collinearity Statistics Tolerance
1	FlempopMetasubstanceelderlymen	-,647 <sup>b</sup>	-,073	,942	-,006	7,890E-5

Cases: 19 CGG (excluding Brussels) \* 3 years (2008-2013-2018) = N = 57

Dependent: all care periods (FTF-contacts 2008 not reliable)

### Regression model 5a: Predicting the total number of care periods for adults in the Centers for Mental Health Care

- Predictors: Estimated Flemish population of adult men/adult women with probable mental disorder; Province dummies (reference West-Flanders)
- Age group and gender-specific HIS prevalences for probable mental disorder applied to Flemish population

#### Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,379 <sup>a</sup>	,144	,041	830,273

#### ANOVA<sup>a</sup>

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	5777910,160	6	962985,027	1,397	,234 <sup>b</sup>
	Residual	34467660,822	50	689353,216		
	Total	40245570,982	56			

#### Coefficients<sup>a</sup>

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	949,082	2028,377		,468	,642
	Province=Antwerp	756,500	338,958	,367	2,232	,030
	Province=East Flanders	127,567	321,563	,067	,397	,693
	Province=Flemish Brabant	225,500	366,116	,098	,616	,541
	Province=Limburg	667,389	366,116	,290	1,823	,074
	FlempopHISMIMenAdult	,007	,035	,235	,189	,851
	FlempopHISMIWomenAdult	-,003	,031	-,119	-,096	,924

**Regression model 5b: Predicting the total number of care periods for elderly people in the Centers for Mental Health Care**

- Predictors: Estimated Flemish population of elderly men/elderly women with probable mental disorder; Province dummies (reference West-Flanders)
- Age group and gender-specific HIS prevalences for probable mental disorder applied to Flemish population

**Model Summary**

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,660 <sup>a</sup>	,435	,368	107,810

**ANOVA<sup>a</sup>**

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	447956,296	6	74659,383	6,423	,000 <sup>b</sup>
	Residual	581147,844	50	11622,957		
	Total	1029104,140	56			

**Coefficients<sup>a</sup>**

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	-548,825	159,668		-3,437	,001
	Province=Antwerp	86,833	44,013	,263	1,973	,054
	Province=East Flanders	19,633	41,755	,064	,470	,640
	Province=Flemish Brabant	142,056	47,540	,386	2,988	,004
	Province=Limburg	122,944	47,540	,334	2,586	,013
	FlempopHISMIMenElderly	,000	,001	,044	,324	,748
	FlempopHISMIWomenElderly	,005	,001	,490	3,584	,001

### Regression model 5c: Predicting the total number of care periods for mood disorders for adults in the Centers for Mental Health Care

- Predictors: Estimated Flemish population of adult men/adult women with any mood disorder; Province dummies (reference West-Flanders)
- Age group and gender-specific HIS prevalences for any mood disorder applied to Flemish population
- Mood disorders (2012-2017) or Mood disorders + Bipolar mood disorders (2018-2019)

#### Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,225 <sup>a</sup>	,051	-,063	199,211

#### ANOVA<sup>a</sup>

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	105654,677	6	17609,113	,444	,846 <sup>b</sup>
	Residual	1984251,217	50	39685,024		
	Total	2089905,895	56			

#### Coefficients<sup>a</sup>

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	425,690	107,253		3,969	,000
	Province=Antwerp	39,083	81,328	,083	,481	,633
	Province=East Flanders	-54,283	77,154	-,125	-,704	,485
	Province=Flemish Brabant	-6,639	87,844	-,013	-,076	,940
	Province=Limburg	7,028	87,844	,013	,080	,937
	FlempopHISmoodMenAdult	,001	,001	,170	,979	,332
	FlempopHISmoodWomenAdult	,000	,001	-,048	-,278	,783

**Regression model 5d: Predicting the total number of care periods for mood disorders for elderly people in the Centers for Mental Health Care**

- Predictors: Estimated Flemish population of elderly men/elderly women with any mood disorder; Province dummies (reference West-Flanders)
- Age group and gender-specific HIS prevalences for any mood disorder applied to Flemish population
- Mood disorders (2012-2017) or Mood disorders + Bipolar mood disorders (2018-2019)

**Model Summary**

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,613 <sup>a</sup>	,376	,301	38,524

**ANOVA<sup>a</sup>**

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	44704,741	6	7450,790	5,021	,000 <sup>b</sup>
	Residual	74203,294	50	1484,066		
	Total	118908,035	56			

**Coefficients<sup>a</sup>**

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	102,347	19,675		5,202	,000
	Province=Antwerp	10,083	15,727	,090	,641	,524
	Province=East Flanders	4,650	14,920	,045	,312	,757
	Province=Flemish Brabant	44,139	16,987	,352	2,598	,012
	Province=Limburg	20,028	16,987	,160	1,179	,244
	FlempopHISmoodMenElderly	,002	,000	1,035	4,270	,000
	FlempopHISmoodWomenElderly	-,002	,000	-1,130	-4,661	,000

### Regression model 5e: Predicting the total number of care periods for anxiety disorders for adults in the Centers for Mental Health Care

- Predictors: Estimated Flemish population of adult men/adult women with any anxiety disorder; Province dummies (reference West-Flanders)
- Age group and gender-specific HIS prevalences for anxiety disorder applied to Flemish population
- Anxiety disorders (2012-2017) or Anxiety, OCD, Stressor or Trauma-related disorders (2018-2019)

#### Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,247 <sup>a</sup>	,061	-,052	101,067

#### ANOVA<sup>a</sup>

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	33217,210	6	5536,202	,542	,774 <sup>b</sup>
	Residual	510730,930	50	10214,619		
	Total	543948,140	56			

#### Coefficients<sup>a</sup>

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	151,552	159,348		,951	,346
	Province=Antwerp	52,167	41,261	,218	1,264	,212
	Province=East Flanders	12,517	39,143	,056	,320	,750
	Province=Flemish Brabant	1,806	44,567	,007	,041	,968
	Province=Limburg	31,028	44,567	,116	,696	,490
	FlempopHISAnxietyMenAdult	,001	,003	,252	,268	,790
	FlempopHISAnxietyWomenAdult	,000	,002	-,111	-,118	,907

**Regression model 5f: Predicting the total number of care periods for anxiety disorders for elderly people in the Centers for Mental Health Care**

- Predictors: Estimated Flemish population of elderly men/elderly women with any anxiety disorder; Province dummies (reference West-Flanders)
- Age group and gender-specific HIS prevalences for anxiety disorder applied to Flemish population
- Anxiety disorders (2012-2017) or Anxiety, OCD, Stressor or Trauma-related disorders (2018-2019)

**Model Summary**

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,596 <sup>a</sup>	,355	,278	9,690

**ANOVA<sup>a</sup>**

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	2586,581	6	431,097	4,591	,001 <sup>b</sup>
	Residual	4694,927	50	93,899		
	Total	7281,509	56			

**Coefficients<sup>a</sup>**

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	30,909	8,983		3,441	,001
	Province=Antwerp	4,500	3,956	,162	1,138	,261
	Province=East Flanders	1,233	3,753	,048	,329	,744
	Province=Flemish Brabant	9,611	4,273	,310	2,249	,029
	Province=Limburg	4,833	4,273	,156	1,131	,263
	FlempopHISAnxietyMenElderly	-,004	,001	-2,003	-4,605	,000
	FlempopHISAnxietyWomenElderly	,001	,000	1,901	4,372	,000

### Regression model 5g: Predicting the total number of care periods for substance-related disorders for adults in the Centers for Mental Health Care

- Predictors: Estimated Flemish population of adult men/adult women with substance-related disorder; Province dummies (reference West-Flanders)
- Age group and gender-specific HIS prevalences for substance use (problematic alcohol+problematic cannabis+problematic other illicit drug)

#### Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,398 <sup>a</sup>	,159	,058	283,648

#### ANOVA<sup>a</sup>

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	758675,306	6	126445,884	1,572	,175 <sup>b</sup>
	Residual	4022802,202	50	80456,044		
	Total	4781477,509	56			

#### Coefficients<sup>a</sup>

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	-1375,974	6588,912		-,209	,835
	Province=Antwerp	211,833	115,799	,298	1,829	,073
	Province=East Flanders	52,767	109,856	,080	,480	,633
	Province=Flemish Brabant	-16,389	125,077	-,021	-,131	,896
	Province=Limburg	284,944	125,077	,359	2,278	,027
	FlempopHISsubstanceMen	-,003	,009	-,488	-,287	,775
	FlempopHISsubstanceWomen	,023	,094	,424	,250	,804



**Regression model 5h: Predicting the total number of care periods for substance-related disorders for elderly people in the Centers for Mental Health Care**

- Predictors: Estimated Flemish population of elderly men/elderly women with substance-related disorder; Province dummies (reference West-Flanders)
- Age group and gender-specific HIS prevalences for substance use (problematic alcohol use)

**Model Summary**

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,395 <sup>a</sup>	,156	,055	29,542

**ANOVA<sup>a</sup>**

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	8078,744	6	1346,457	1,543	,184 <sup>b</sup>
	Residual	43637,817	50	872,756		
	Total	51716,561	56			

**Coefficients<sup>a</sup>**

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	-128,020	486,588		-,263	,794
	Province=Antwerp	12,083	12,061	,164	1,002	,321
	Province=East Flanders	,333	11,442	,005	,029	,977
	Province=Flemish Brabant	-2,444	13,027	-,030	-,188	,852
	Province=Limburg	28,556	13,027	,346	2,192	,033
	FlempopHISAlcoholMenElderly	,002	,010	,105	,214	,831
	FlempopHISAlcoholWomenElderly	,004	,026	,069	,140	,889



## Part III - Appendix 3

### Regression models for waiting time in the Centers for Mental Health Care

Cases: 20 CGG \* 10 years (2010-2019) = N = 200

#### Regression model 1a: Predicting the mean waiting time to first face-to-face contact for children and adolescents in the Centers for Mental Health Care

- Predictors: Province dummies (reference=West Flanders), year dummies (reference=2010)

**Model Summary<sup>a</sup>**

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,281 <sup>b</sup>	,079	,014	33,210

**ANOVA<sup>a,b</sup>**

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	17547,635	13	1349,818	1,224	,265 <sup>c</sup>
	Residual	205135,560	186	1102,879		
	Total	222683,195	199			

**Coefficients<sup>a,b</sup>**

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	46,570	8,786		5,300	,000
	Province=Antwerp	19,400	7,426	,233	2,612	,010
	Province=Limburg	-2,625	8,021	-,028	-,327	,744
	Province=East Flanders	16,095	7,045	,209	2,285	,023
	Province=Flem Brabant (incl.Brus)	10,600	7,426	,127	1,427	,155
	Year=2011	5,000	10,502	,045	,476	,635
	Year=2012	2,250	10,502	,020	,214	,831
	Year=2013	-2,900	10,502	-,026	-,276	,783
	Year=2014	-,400	10,502	-,004	-,038	,970
	Year=2015	3,550	10,502	,032	,338	,736
	Year=2016	5,450	10,502	,049	,519	,604
	Year=2017	11,050	10,502	,099	1,052	,294
	Year=2018	9,150	10,502	,082	,871	,385
	Year=2019	1,400	10,502	,013	,133	,894

**Regression model 1b: Predicting the mean waiting time to first face-to-face contact for adults in the Centers for Mental Health Care**

- Predictors: Province dummies (reference=West Flanders), year dummies (reference=2008)

**Model Summary<sup>a</sup>**

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,304 <sup>b</sup>	,093	,062	24,889

**ANOVA<sup>a,b</sup>**

Model	Sum of Squares	df	Mean Square	F	Sig.
1 Regression	24432,369	13	1879,413	3,034	,000 <sup>c</sup>
Residual	239109,221	386	619,454		
Total	263541,590	399			

**Coefficients<sup>a,b</sup>**

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	41,542	4,656		8,922	,000
	Province=Antwerp	7,762	3,935	,121	1,973	,049
	Province=Limburg	-8,646	4,251	-,120	-2,034	,043
	Province=East Flanders	5,777	3,733	,097	1,548	,123
	Province=Flem Brabant (incl.Bruss)	-7,088	3,935	-,110	-1,801	,072
	Year=2011	-,825	5,565	-,010	-,148	,882
	Year=2012	-2,425	5,565	-,028	-,436	,663
	Year=2013	-1,325	5,565	-,015	-,238	,812
	Year=2014	,100	5,565	,001	,018	,986
	Year=2015	6,825	5,565	,080	1,226	,221
	Year=2016	6,450	5,565	,075	1,159	,247
	Year=2017	10,050	5,565	,117	1,806	,072
	Year=2018	8,725	5,565	,102	1,568	,118
	Year=2019	5,625	5,565	,066	1,011	,313

**Regression model 1b: Predicting the mean waiting time to first face-to-face contact for elderly people in the Centers for Mental Health Care**

- Predictors: Province dummies (reference=West Flanders), year dummies (reference=2008)

**Model Summary<sup>a</sup>**

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,211 <sup>b</sup>	,045	-,022	24,126

**ANOVA<sup>a,b</sup>**

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	5049,603	13	388,431	,667	,793 <sup>c</sup>
	Residual	108263,117	186	582,060		
	Total	113312,720	199			

**Coefficients<sup>a,b</sup>**

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	40,945	6,383		6,415	,000
	Province=Antwerp	-5,850	5,395	-,098	-1,084	,280
	Province=Limburg	-10,192	5,827	-,153	-1,749	,082
	Province=East Flanders	-5,085	5,118	-,093	-,994	,322
	Province=Flem Brabant (incl.Bruss)	-9,375	5,395	-,158	-1,738	,084
	Year=2011	-7,950	7,629	-,100	-1,042	,299
	Year=2012	-9,250	7,629	-,117	-1,212	,227
	Year=2013	-1,650	7,629	-,021	-,216	,829
	Year=2014	-6,250	7,629	-,079	-,819	,414
	Year=2015	-7,500	7,629	-,095	-,983	,327
	Year=2016	-5,050	7,629	-,064	-,662	,509
	Year=2017	2,450	7,629	,031	,321	,748
	Year=2018	-2,850	7,629	-,036	-,374	,709
	Year=2019	-2,150	7,629	-,027	-,282	,778



## Part III - Appendix 4

### Regression models for waiting list, waiting times, and clients in the Centers for Ambulatory Rehabilitation

Regression models 1 to 1b predict the number of people on the waiting list. Predictors in regression model 1 are limited to region (province) and year dummies. The dataset consists of 45 CAR locations and 6 years (2013-2018), with missing data: N=235 cases

- In regression model 1a year dummies are replaced by a prevalence estimate for ASD (MacKay, 2016) applied to the Flemish population between 2013 and 2018 (see Appendix 1, N=235 cases)
- In regression model 2a year dummies are replaced by a gender-specific prevalence estimate for AD(H)D (primary care registration data, NIVEL) applied to the Flemish population between 2016 and 2018 (see Appendix 1, N=117 cases)

Regression models 2a to 2e predict the mean waiting time for ASD and AD(H)D number of people on the waiting list. Predictors in regression model 2a and 2c are limited to region (province) and year dummies. The dataset consists of 45 CAR locations and 6 years (2013-2018), with missing data: N=241 cases for ASD waiting times; N=225 for ADHD waiting times.

- In regression model 2b year dummies are replaced by a prevalence estimate for ASD (MacKay, 2016) applied to the Flemish population between 2013 and 2018 (see Appendix 1, N=241 cases)
- In regression model 2d year dummies are replaced by a prevalence estimate for ADHD (Polanczyk, 2008) applied to the Flemish population between 2013 and 2018 (see Appendix 1, N=225 cases)
- In regression model 2e year dummies are replaced by a gender-specific prevalence estimate for ADHD (primary care registration data, NIVEL) applied to the Flemish population between 2016 and 2018 (see Appendix 1, N=108 cases)

Regression model 3 predicts the total number of clients receiving treatment on December 31, regression model 3a-b the total number of clients receiving treatment for autism on December 31 and model 3c-e the total number of clients receiving treatment for AD(H)D on December 31. Predictors in regression models 3, 3a, and 3c are limited to region (province) and year dummies. The dataset consists of 35 CAR locations with complete time series 6 year (2013-2018) time series for the ongoing treatment variable. N=210 cases.

- In regression model 3b year dummies are replaced by a prevalence estimate for ASD (MacKay, 2016) applied to the Flemish population between 2013 and 2018 (see Appendix 1)
- In regression model 3d year dummies are replaced by a prevalence estimate for ADHD (Polanczyk, 2008) applied to the Flemish population between 2013 and 2018 (see Appendix 1)
- In regression model 3e year dummies are replaced by a gender-specific prevalence estimate for ADHD (primary care registration data, NIVEL) applied to the Flemish population between 2016 and 2018 (see Appendix 1, N=105 cases)

### Regression model 1: Predicting the number of people on the waiting list in the Centers for Ambulatory Rehabilitation

- Predictors: Province dummies (reference=West Flanders); year dummies (reference=2013)

#### Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,394	,155	,121	50,594

#### ANOVA

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	105783,513	9	11753,724	4,592	<,001 <sup>b</sup>
	Residual	575935,151	225	2559,712		
	Total	681718,664	234			

#### Coefficients

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	85,061	10,035		8,476	<,001
	Prov=Antwerp	-42,368	11,375	-,270	-3,725	<,001
	Prov=East Flanders	-24,370	8,544	-,226	-2,852	,005
	Prov=Flem. Brabant	-38,123	12,493	-,214	-3,052	,003
	Prov=Limburg	-69,914	13,842	-,345	-5,051	<,001
	Year=2014	4,126	11,396	,029	,362	,718
	Year=2015	17,660	11,466	,122	1,540	,125
	Year=2016	19,116	11,707	,128	1,633	,104
	Year=2017	23,463	11,322	,165	2,072	,039
	Year=2018	27,758	11,387	,194	2,438	,016



### Regression model 1a: Predicting the number of people on the waiting list in the Centers for Ambulatory Rehabilitation

- Predictors: Province dummies (reference=West Flanders); Meta-analysis prevalence for ASD (Autism Spectrum Disorder) (MacKay) applied to Flemish population of children and adolescents

#### Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,390	,152	,133	50,245

#### ANOVA

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	103591,787	5	20718,357	8,207	<,001 <sup>b</sup>
	Residual	578126,877	229	2524,572		
	Total	681718,664	234			

#### Coefficients

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	-1253,015	462,629		-2,708	,007
	Prov=Limburg	-69,689	13,741	-,344	-5,072	<,001
	Prov=Antwerp	-42,376	11,289	-,270	-3,754	<,001
	Prov=East Flanders	-24,075	8,469	-,223	-2,843	,005
	Prov=Flem. Brabant	-37,898	12,399	-,213	-3,056	,003
	Meta_ASD	,098	,033	,178	2,926	,004

### Regression model 1b: Predicting the number of people on the waiting list in the Centers for Ambulatory Rehabilitation

- Predictors: Province dummies (reference=West Flanders); Primary care registration prevalence for ADHD (gender-specific, NIVEL) applied to Flemish population of children and adolescents

#### Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,423	,179	,142	56,334

#### ANOVA

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	76867,497	5	15373,499	4,844	<,001 <sup>b</sup>
	Residual	352256,161	111	3173,479		
	Total	429123,658	116			

#### Coefficients

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	38,618	132,888		,291	,772
	Prov=Limburg	-91,003	21,800	-,400	-4,174	<,001
	Prov=Antwerp	-63,556	17,900	-,361	-3,551	<,001
	Prov=East Flanders	-37,727	13,474	-,311	-2,800	,006
	Prov=Flem. Brabant	-50,447	19,675	-,253	-2,564	,012
	Neth_ADHD	,003	,005	,054	,622	,536

### Regression model 2a: Predicting the mean waiting time for children and adolescents with autism in the Centers for Ambulatory Rehabilitation

- Predictors: Province dummies (reference=West Flanders); year dummies (reference=2013)

#### Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,385	,149	,115	4,2306

#### ANOVA

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	721,451	9	80,161	4,479	<,001 <sup>b</sup>
	Residual	4134,428	231	17,898		
	Total	4855,879	240			

#### Coefficients

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	9,687	,834		11,616	<,001
	Prov=Antwerp	-,850	,952	-,064	-,893	,373
	Prov=East Flanders	-,647	,708	-,072	-,914	,362
	Prov=Flem. Brabant	-2,299	1,045	-,153	-2,201	,029
	Prov=Limburg	-4,758	1,157	-,279	-4,111	<,001
	Year=2014	,284	,941	,024	,302	,763
	Year=2015	,145	,941	,012	,154	,877
	Year=2016	1,528	,953	,125	1,603	,110
	Year=2017	1,601	,940	,134	1,703	,090
	Year=2018	3,538	,952	,290	3,716	<,001

### Regression model 2b: Predicting the mean waiting time for children and adolescents with autism in the Centers for Ambulatory Rehabilitation

- Predictors: Province dummies (reference=West Flanders); Meta-analysis prevalence for ASD (Autism Spectrum Disorder) (MacKay) applied to Flemish population of children and adolescents

#### Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,372	,139	,120	4,2189

#### ANOVA

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	673,099	5	134,620	7,563	<,001 <sup>b</sup>
	Residual	4182,780	235	17,799		
	Total	4855,879	240			

#### Coefficients

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	-151,750	38,796		-3,911	<,001
	Prov=Limburg	-4,760	1,154	-,279	-4,126	<,001
	Prov=Antwerp	-,868	,948	-,066	-,915	,361
	Prov=East Flanders	-,661	,705	-,074	-,937	,350
	Prov=Flem. Brabant	-2,300	1,041	-,153	-2,210	,028
	Meta_ASD	,012	,003	,254	4,192	<,001

### Regression model 2c: Predicting the mean waiting time for children and adolescents with AD(H)D in the Centers for Ambulatory Rehabilitation

- Predictors: Province dummies (reference=West Flanders); year dummies (reference=2013)

#### Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,360	,129	,093	4,8514

#### ANOVA

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	752,126	9	83,570	3,551	<,001 <sup>b</sup>
	Residual	5060,336	215	23,536		
	Total	5812,462	224			

#### Coefficients

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	8,976	,985		9,115	<,001
	Prov=Antwerp	2,547	1,286	,143	1,980	,049
	Prov=East Flanders	,010	,818	,001	,012	,991
	Prov=Flem. Brabant	,928	1,240	,054	,749	,455
	Prov=Limburg	-4,284	1,359	-,223	-3,152	,002
	Year=2014	1,173	1,093	,089	1,074	,284
	Year=2015	1,471	1,114	,108	1,320	,188
	Year=2016	2,014	1,130	,145	1,782	,076
	Year=2017	2,948	1,123	,215	2,626	,009
	Year=2018	3,779	1,138	,269	3,320	,001

### Regression model 2d: Predicting the mean waiting time for children and adolescents with AD(H)D in the Centers for Ambulatory Rehabilitation

- Predictors: Province dummies (reference=West Flanders); Meta-analysis prevalence for ADHD (Polanczyk) applied to Flemish population of children and adolescents

#### Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,358	,128	,108	4,8104

#### ANOVA

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	744,808	5	148,962	6,437	<,001 <sup>b</sup>
	Residual	5067,654	219	23,140		
	Total	5812,462	224			

#### Coefficients

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	-160,597	46,094		-3,484	<,001
	Prov=Limburg	-4,282	1,347	-,223	-3,178	,002
	Prov=Antwerp	2,564	1,273	,144	2,014	,045
	Prov=East Flanders	,010	,809	,001	,012	,990
	Prov=Flem. Brabant	,924	1,228	,054	,753	,453
	Meta_ADHD	,002	,001	,236	3,721	<,001

### Regression model 2e: Predicting the mean waiting time for children and adolescents with AD(H)D in the Centers for Ambulatory Rehabilitation

- Predictors: Province dummies (reference=West Flanders); Primary care registration prevalence for ADHD (gender-specific, NIVEL) applied to Flemish population of children and adolescents

#### Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,422	,178	,138	4,9491

#### ANOVA

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	541,470	5	108,294	4,421	,001 <sup>b</sup>
	Residual	2498,365	102	24,494		
	Total	3039,835	107			

#### Coefficients

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	-6,928	11,999		-,577	,565
	Prov=Limburg	-5,854	2,001	-,289	-2,926	,004
	Prov=Antwerp	1,999	2,112	,093	,946	,346
	Prov=East Flanders	-,366	1,174	-,034	-,312	,756
	Prov=Flem. Brabant	4,405	1,845	,241	2,387	,019
	Neth_ADHD	,001	,000	,143	1,583	,117

### Regression model 3: Predicting the total number of clients in treatment on December 31 in the Centers for Ambulatory Rehabilitation

- Predictors: Province dummies (reference=West Flanders); year dummies (reference=2013)

#### Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,522	,272	,239	76,356

#### ANOVA

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	435979,601	9	48442,178	8,309	<,001 <sup>b</sup>
	Residual	1166056,380	200	5830,282		
	Total	1602035,981	209			

#### Coefficients

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	189,041	17,343		10,900	<,001
	Prov=Limburg	-64,278	22,042	-,206	-2,916	,004
	Prov=Antwerp	-114,989	18,876	-,461	-6,092	<,001
	Prov=East Flanders	-20,840	14,802	-,119	-1,408	,161
	Prov=Flem. Brabant	-123,847	20,122	-,451	-6,155	<,001
	Year=2014	2,714	18,253	,012	,149	,882
	Year=2015	4,457	18,253	,019	,244	,807
	Year=2016	,429	18,253	,002	,023	,981
	Year=2017	-2,343	18,253	-,010	-,128	,898
	Year=2018	-,171	18,253	-,001	-,009	,993



### Regression model 3a: Predicting the total number of clients in treatment for autism on December 31 in the Centers for Ambulatory Rehabilitation

- Predictors: Province dummies (reference=West Flanders), year dummies (reference=2013)

#### Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,352	,124	,084	21,540

#### ANOVA

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	13097,015	9	1455,224	3,137	,001 <sup>b</sup>
	Residual	92792,051	200	463,960		
	Total	105889,067	209			

#### Coefficients

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	42,117	4,892		8,609	<,001
	Prov=Limburg	-13,139	6,218	-,164	-2,113	,036
	Prov=Antwerp	-14,783	5,325	-,230	-2,776	,006
	Prov=East Flanders	-15,574	4,176	-,347	-3,730	<,001
	Prov=Flem. Brabant	-23,750	5,676	-,337	-4,184	<,001
	Year=2014	2,571	5,149	,043	,499	,618
	Year=2015	5,743	5,149	,095	1,115	,266
	Year=2016	6,657	5,149	,110	1,293	,198
	Year=2017	9,457	5,149	,157	1,837	,068
	Year=2018	12,371	5,149	,205	2,403	,017

### Regression model 3b: Predicting the total number of clients in treatment for autism on December 31 in the Centers for Ambulatory Rehabilitation

- Predictors: Province dummies (reference=West Flanders); Meta-analysis prevalence for ASD (Autism Spectrum Disorder) (MacKay) applied to Flemish population of children and adolescents

#### Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,351	,123	,102	21,334

#### ANOVA

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	13044,906	5	2608,981	5,733	<,001 <sup>b</sup>
	Residual	92844,161	204	455,118		
	Total	105889,067	209			

#### Coefficients

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	-529,797	209,309		-2,531	,012
	Prov=Limburg	-13,139	6,158	-,164	-2,133	,034
	Prov=Antwerp	-14,783	5,274	-,230	-2,803	,006
	Prov=East Flanders	-15,574	4,136	-,347	-3,766	<,001
	Prov=Flem. Brabant	-23,750	5,622	-,337	-4,225	<,001
	Meta_ASD	,042	,015	,181	2,762	,006

### Regression model 3c: Predicting the total number of clients in treatment for AD(H)D on December 31 in the Centers for Ambulatory Rehabilitation

- Predictors: Province dummies (reference=West Flanders); year dummies (reference=2013)

#### Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,610	,373	,344	14,951

#### ANOVA

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	26544,467	9	2949,385	13,194	<,001 <sup>b</sup>
	Residual	44706,561	200	223,533		
	Total	71251,029	209			

#### Coefficients

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	35,348	3,396		10,409	<,001
	Prov=Limburg	-19,722	4,316	-,300	-4,570	<,001
	Prov=Antwerp	-27,133	3,696	-,515	-7,341	<,001
	Prov=East Flanders	-2,118	2,898	-,057	-,731	,466
	Prov=Flem. Brabant	-25,083	3,940	-,433	-6,366	<,001
	Year=2014	,257	3,574	,005	,072	,943
	Year=2015	,343	3,574	,007	,096	,924
	Year=2016	-2,171	3,574	-,044	-,608	,544
	Year=2017	-3,200	3,574	-,065	-,895	,372
	Year=2018	-4,314	3,574	-,087	-1,207	,229

### Regression model 3d: Predicting the total number of clients in treatment for AD(H)D on December 31 in the Centers for Ambulatory Rehabilitation

- Predictors: Province dummies (reference=West Flanders); Meta-analysis prevalence for ADHD (Polanczyk) applied to Flemish population of children and adolescents

#### Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,609	,371	,356	14,818

#### ANOVA

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	26457,434	5	5291,487	24,099	<,001 <sup>b</sup>
	Residual	44793,594	204	219,576		
	Total	71251,029	209			

#### Coefficients

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	276,568	145,328		1,903	,058
	Prov=Limburg	-19,722	4,278	-,300	-4,611	<,001
	Prov=Antwerp	-27,133	3,663	-,515	-7,407	<,001
	Prov=East Flanders	-2,118	2,873	-,057	-,737	,462
	Prov=Flem. Brabant	-25,083	3,905	-,433	-6,424	<,001
	Meta_ADHD	-,003	,002	-,093	-1,670	,096

### Regression model 3e: Predicting the total number of clients in treatment for AD(H)D on December 31 in the Centers for Ambulatory Rehabilitation

- Predictors: Province dummies (reference=West Flanders); Primary care registration prevalence for ADHD (gender-specific, NIVEL) applied to Flemish population of children and adolescents

#### Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,584	,341	,307	14,534

#### ANOVA

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	10803,758	5	2160,752	10,229	<,001 <sup>b</sup>
	Residual	20911,899	99	211,231		
	Total	31715,657	104			

#### Coefficients

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	52,852	35,262		1,499	,137
	Prov=Limburg	-17,000	5,933	-,274	-2,865	,005
	Prov=Antwerp	-25,156	5,081	-,506	-4,951	<,001
	Prov=East Flanders	-2,379	3,985	-,068	-,597	,552
	Prov=Flem. Brabant	-23,556	5,416	-,431	-4,349	<,001
	Neth_ADHD	-,001	,001	-,050	-,607	,545



## Part III - Appendix 5

### Regression models for new care episodes in the Rehabilitation Centers for Addiction

In all reported regression models, programs in the Rehabilitation Centers for Addiction are restricted to NIHDI-Flemish Government financed programs only.

Predictors in regression models 1 to 3c are limited to region (province) and time dummies. In model 2d an additional supply factor (the number of new care episodes for addiction in the Centers for Mental Health Care) is included.

In regression models 4 to 9 province dummies and a needs factor are included, which is either:

- The meta-analysis prevalence percentage for substance-related disorders (model 4a and 4b), applied to the Flemish population between 2011 and 2019 (see Appendix 1), leading to the following number of cases for ambulatory and in-patient programs, respectively:
  - number of ambulatory programs\* 9 years: N = 108
  - number of in-patient programs\*9 years: N = 117
- The HIS-prevalence percentages for (problematic) use of specific substances, applied to the Flemish population in 2013 and 2018 (see Appendix 1), leading to the following number of cases for ambulatory and in-patient programs, respectively:
  - number of ambulatory programs\*2 years: N=24
  - number of in-patient programs\*2years: N=26

Regression models 1 to 4 predict the total number of new care episodes in the (ambulatory or in-patient programs of the) Rehabilitation Centers for Addiction. Regression models 5 to 9 predict the number of new care episodes per problem drug or primary drug.

### Regression model 1: Predicting the total number of new care episodes in the Rehabilitation Centers for Addiction

- Cases: number of programs\* 9 years (2011-2019): N = 225
- Predictors: Province dummies (reference=West Flanders), year dummies (reference=2011)

#### Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,239 <sup>a</sup>	,057	,004	218,079

#### ANOVA

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	609553,649	12	50796,137	1,068	,389 <sup>b</sup>
	Residual	10082355,311	212	47558,280		
	Total	10691908,960	224			

#### Coefficients

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	229,764	52,420		4,383	,000
	Province=Antwerp	13,844	45,975	,025	,301	,764
	Province=East Flanders	-102,228	41,441	-,219	-2,467	,014
	Province=Flemish Brabant	-66,117	48,764	-,111	-1,356	,177
	Province=Limburg	18,319	53,087	,027	,345	,730
	Year=2012	,320	61,682	,000	,005	,996
	Year=2013	17,440	61,682	,025	,283	,778
	Year=2014	8,280	61,682	,012	,134	,893
	Year=2015	16,880	61,682	,024	,274	,785
	Year=2016	13,480	61,682	,019	,219	,827
	Year=2017	21,960	61,682	,032	,356	,722
	Year=2018	17,920	61,682	,026	,291	,772
	Year=2019	7,640	61,682	,011	,124	,902



### Regression model 2a: Predicting the total number of ambulatory new care episodes in the Rehabilitation Centers for Addiction

- Cases: number of ambulatory programs\* 9 years (2011-2019): N = 108
- Predictors: Province dummies (reference=West Flanders), year dummies (reference=2011)

#### Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,649 <sup>b</sup>	,421	,348	194,047

#### ANOVA

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	2602022,370	12	216835,198	5,759	,000 <sup>c</sup>
	Residual	3577170,398	95	37654,425		
	Total	6179192,769	107			

#### Coefficients

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	328,296	64,682		5,076	,000
	Province=Antwerp	191,278	59,047	,298	3,239	,002
	Province=East Flanders	-178,194	49,402	-,351	-3,607	,000
	Province=Flemish Brabant	-65,389	59,047	-,102	-1,107	,271
	Province=Limburg	282,444	74,689	,326	3,782	,000
	Year=2012	2,333	79,220	,003	,029	,977
	Year=2013	33,833	79,220	,044	,427	,670
	Year=2014	16,833	79,220	,022	,212	,832
	Year=2015	38,417	79,220	,050	,485	,629
	Year=2016	32,917	79,220	,043	,416	,679
	Year=2017	51,167	79,220	,067	,646	,520
	Year=2018	41,333	79,220	,054	,522	,603
	Year=2019	26,500	79,220	,035	,335	,739

### Regression model 2b: Predicting the total number of ambulatory new care episodes in the Rehabilitation Centers for Addiction

- Cases: number of ambulatory programs\* 7 years (2013-2019): N = 84
- Predictors: Province dummies (reference=West Flanders), year dummies (reference=2013), total number of new care episodes for addiction in the Centers for Mental Health Care per province (=other supply variable)

#### Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,659 <sup>a</sup>	,435	,349	194,635

#### ANOVA

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	2099189,193	11	190835,381	5,038	,000 <sup>b</sup>
	Residual	2727567,795	72	37882,886		
	Total	4826756,988	83			

#### Coefficients

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	351,406	73,055		4,810	,000
	Province=Antwerp	157,487	144,537	,245	1,090	,280
	Province=East Flanders	-191,152	79,949	-,376	-2,391	,019
	Province=Flemish Brabant	-42,655	67,309	-,066	-,634	,528
	Province=Limburg	299,289	118,260	,345	2,531	,014
	Year=2014	-16,888	79,461	-,025	-,213	,832
	Year=2015	5,313	79,542	,008	,067	,947
	Year=2016	,612	79,819	,001	,008	,994
	Year=2017	21,381	81,948	,031	,261	,795
	Year=2018	8,317	79,562	,012	,105	,917
	Year=2019	-2,621	82,815	-,004	-,032	,975
	NewepisodesinCGGperprov	,043	,215	,043	,202	,841

### Regression model 3a: Predicting the total number of in-patient new care episodes in the Rehabilitation Centers for Addiction

- Cases: number of in-patient programs\* 9 years (2011-2019): N = 117
- Predictors: Province dummies (reference=West Flanders), year dummies (reference=2011)

#### Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,246 <sup>b</sup>	,060	-,048	72,878

#### ANOVA

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	35557,514	12	2963,126	,558	,871 <sup>c</sup>
	Residual	552358,452	104	5311,139		
	Total	587915,966	116			

#### Coefficients

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	73,030	25,656		2,847	,005
	Province=Antwerp	-9,426	22,176	-,056	-,425	,672
	Province=East Flanders	30,750	21,038	,200	1,462	,147
	Province=Flemish Brabant	-9,833	24,293	-,050	-,405	,686
	Province=Limburg	,278	24,293	,001	,011	,991
	Year=2012	-1,538	28,585	-,007	-,054	,957
	Year=2013	2,308	28,585	,010	,081	,936
	Year=2014	,385	28,585	,002	,013	,989
	Year=2015	-3,000	28,585	-,013	-,105	,917
	Year=2016	-4,462	28,585	-,020	-,156	,876
	Year=2017	-5,000	28,585	-,022	-,175	,861
	Year=2018	-3,692	28,585	-,016	-,129	,897
	Year=2019	-9,769	28,585	-,043	-,342	,733

### Regression model 3b: Predicting the total number of in-patient crisis new care episodes in the Rehabilitation Centers for Addiction

- Cases: number of in-patient crisis programs\* 9 years (2011-2019): N = 54
- Predictors: Province dummies (reference=West Flanders), year dummies (reference=2011)

#### Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,860 <sup>b</sup>	,740	,664	46,308

#### ANOVA

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	250355,741	12	20862,978	9,729	,000 <sup>c</sup>
	Residual	87921,296	41	2144,422		
	Total	338277,037	53			

#### Coefficients

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	130,241	23,579		5,524	,000
	Province=Antwerp	-47,667	18,905	-,284	-2,521	,016
	Province=East Flanders	146,556	21,830	,690	6,714	,000
	Province=Flemish Brabant	-26,444	21,830	-,125	-1,211	,233
	Province=Limburg	-25,222	21,830	-,119	-1,155	,255
	Year=2012	-3,167	26,736	-,013	-,118	,906
	Year=2013	2,500	26,736	,010	,094	,926
	Year=2014	1,000	26,736	,004	,037	,970
	Year=2015	-10,500	26,736	-,042	-,393	,697
	Year=2016	-14,333	26,736	-,057	-,536	,595
	Year=2017	-12,667	26,736	-,050	-,474	,638
	Year=2018	-14,667	26,736	-,058	-,549	,586
	Year=2019	-25,333	26,736	-,101	-,948	,349

**Regression model 3c: Predicting the total number of long-term in-patient new care episodes in the Rehabilitation Centers for Addiction**

- Cases: number of long-term in-patient programs\* 9 years (2011-2019): N = 63
- Predictors: Province dummies (reference=West Flanders), year dummies (reference=2011)

**Model Summary**

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,402 <sup>b</sup>	,162	-,040	26,548

**ANOVA**

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	6794,974	12	566,248	,803	,645 <sup>c</sup>
	Residual	35240,455	50	704,809		
	Total	42035,429	62			

**Coefficients**

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	16,651	12,954		1,285	,205
	Province=Antwerp	15,667	12,515	,212	1,252	,216
	Province=East Flanders	26,407	10,218	,506	2,584	,013
	Province=Flemish Brabant	6,778	12,515	,092	,542	,591
	Province=Limburg	25,778	12,515	,349	2,060	,045
	Year=2012	-,143	14,191	-,002	-,010	,992
	Year=2013	2,143	14,191	,026	,151	,881
	Year=2014	-,143	14,191	-,002	-,010	,992
	Year=2015	3,429	14,191	,042	,242	,810
	Year=2016	4,000	14,191	,049	,282	,779
	Year=2017	1,571	14,191	,019	,111	,912
	Year=2018	5,714	14,191	,070	,403	,689
	Year=2019	3,571	14,191	,043	,252	,802

### Regression model 4a: Predicting the total number of ambulatory new care episodes in the Rehabilitation Centers for Addiction

- Predictors: Province dummies (reference=West Flanders), estimated Flemish population with substance-related disorder (meta-analysis Steel et al. 2014, constant gender-specific prevalence percentages)

#### Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,647 <sup>b</sup>	,418	,390	187,711

#### ANOVA<sup>b</sup>

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	2585165,522	5	517033,104	14,674	,000 <sup>c</sup>
	Residual	3594027,246	102	35235,561		
	Total	6179192,769	107			

#### Coefficients

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	-2770,251	5257,515		-,527	,599
	Province=Antwerp	191,278	57,119	,298	3,349	,001
	Province=East Flanders	-178,194	47,789	-,351	-3,729	,000
	Province=Flemish Brabant	-65,389	57,119	-,102	-1,145	,255
	Province=Limburg	282,444	72,250	,326	3,909	,000
	FlempopMetasubstance	,016	,026	,045	,595	,553

### Regression model 4b: Predicting the total number of in-patient new care episodes in the Rehabilitation Centers for Addiction

- Predictors: Province dummies (reference=West Flanders), estimated Flemish population with substance-related disorder (meta-analysis Steel et al. 2014, constant gender-specific prevalence percentages)

#### Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,245 <sup>b</sup>	,060	,017	70,568

#### ANOVA

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	35147,968	5	7029,594	1,412	,226 <sup>c</sup>
	Residual	552767,998	111	4979,892		
	Total	587915,966	116			

#### Coefficients

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	888,633	1899,001		,468	,641
	Province=Antwerp	-9,426	21,473	-,056	-,439	,662
	Province=East Flanders	30,750	20,371	,200	1,509	,134
	Province=Flemish Brabant	-9,833	23,523	-,050	-,418	,677
	Province=Limburg	,278	23,523	,001	,012	,991
	FlempopMetasubstance	-,004	,010	-,040	-,431	,667

### Regression model 4c: Predicting the total number of ambulatory new care episodes in the Rehabilitation Centers for Addiction

- Predictors: Province dummies (reference=West Flanders), estimated Flemish population with substance use (alcohol+cannabis+other illicit drug, HIS, age category and gender-specific prevalence percentages)

#### Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,656 <sup>b</sup>	,431	,272	209,828

#### ANOVA

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	599315,792	5	119863,158	2,722	,053 <sup>c</sup>
	Residual	792498,208	18	44027,678		
	Total	1391814,000	23			

#### Coefficients

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	329,304	342,453		,962	,349
	Province=Antwerp	197,167	135,443	,305	1,456	,163
	Province=East Flanders	-172,208	113,320	-,337	-1,520	,146
	Province=Flemish Brabant	-53,333	135,443	-,083	-,394	,698
	Province=Limburg	313,167	171,324	,359	1,828	,084
	FlempopHISsubstance	5,665E-5	,001	,016	,088	,931



### Regression model 4d: Predicting the total number of in-patient new care episodes in the Rehabilitation Centers for Addiction

- Predictors: Province dummies (reference=West Flanders), estimated Flemish population with substance use (alcohol+cannabis+other illicit drug, HIS, age category and gender-specific prevalence percentages)

#### Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,214 <sup>b</sup>	,046	-,193	77,952

#### ANOVA

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	5813,426	5	1162,685	,191	,962 <sup>c</sup>
	Residual	121529,958	20	6076,498		
	Total	127343,385	25			

#### Coefficients

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	96,724	124,599		,776	,447
	Province=Antwerp	-6,833	50,318	-,041	-,136	,893
	Province=East Flanders	25,875	47,736	,171	,542	,594
	Province=Flemish Brabant	-11,250	55,120	-,058	-,204	,840
	Province=Limburg	2,153E-14	55,120	,000	,000	1,000
	FlempopHISsubstance	-4,532E-5	,000	-,043	-,196	,846

### Regression model 4e: Predicting the total number of ambulatory new care episodes in the Rehabilitation Centers for Addiction

- Predictors: Province dummies (reference=West Flanders), estimated Flemish population with polydrug use (HIS, age category and gender-specific prevalence percentages)

#### Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,656 <sup>b</sup>	,431	,272	209,828

#### ANOVA

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	599315,792	5	119863,158	2,722	,053 <sup>c</sup>
	Residual	792498,208	18	44027,678		
	Total	1391814,000	23			

#### Coefficients

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	352,835	106,218		3,322	,004
	Province=Antwerp	197,167	135,443	,305	1,456	,163
	Province=East Flanders	-172,208	113,320	-,337	-1,520	,146
	Province=Flemish Brabant	-53,333	135,443	-,083	-,394	,698
	Province=Limburg	313,167	171,324	,359	1,828	,084
	FlempopHISpolydrug	8,455E-5	,001	,016	,088	,931

**Regression model 4f: Predicting the total number of in-patient new care episodes in the Rehabilitation Centers for Addiction**

- Predictors: Province dummies (reference=West Flanders), estimated Flemish population with polydrug use (HIS, age category and gender-specific prevalence percentages)

**Model Summary**

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,214 <sup>b</sup>	,046	-,193	77,952

**ANOVA**

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	5813,426	5	1162,685	,191	,962 <sup>c</sup>
	Residual	121529,958	20	6076,498		
	Total	127343,385	25			

**Coefficients**

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	77,899	44,963		1,733	,099
	Province=Antwerp	-6,833	50,318	-,041	-,136	,893
	Province=East Flanders	25,875	47,736	,171	,542	,594
	Province=Flemish Brabant	-11,250	55,120	-,058	-,204	,840
	Province=Limburg	2,153E-14	55,120	,000	,000	1,000
	FlempopHISpolydrug	-6,764E-5	,000	-,043	-,196	,846

**Regression model 5a: Predicting the total number of ambulatory new care episodes for problematic opioid use in the Rehabilitation Centers for Addiction**

- Predictors: Province dummies (reference=West Flanders), estimated Flemish population with opioids use (HIS, age category and gender-specific prevalence percentages)

**Model Summary**

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,605 <sup>b</sup>	,366	,189	44,624

**ANOVA**

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	20651,875	5	4130,375	2,074	,116 <sup>c</sup>
	Residual	35844,083	18	1991,338		
	Total	56495,958	23			

**Coefficients**

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	94,564	26,235		3,604	,002
	Province=Antwerp	59,167	28,805	,454	2,054	,055
	Province=East Flanders	-20,458	24,100	-,199	-,849	,407
	Province=Flemish Brabant	-23,583	28,805	-,181	-,819	,424
	Province=Limburg	-5,833	36,436	-,033	-,160	,875
	FlempopHISopiooids	-,001	,001	-,137	-,727	,476

**Regression model 5b: Predicting the total number of in-patient new care episodes for problematic opioid use in the Rehabilitation Centers for Addiction**

- Predictors: Province dummies (reference=West Flanders), estimated Flemish population with opioids use (HIS, age category and gender-specific prevalence percentages)

**Model Summary**

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,351 <sup>b</sup>	,123	-,096	27,899

**ANOVA**

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	2185,484	5	437,097	,562	,728 <sup>c</sup>
	Residual	15566,670	20	778,333		
	Total	17752,154	25			

**Coefficients**

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	30,834	17,977		1,715	,102
	Province=Antwerp	-10,333	18,008	-,167	-,574	,572
	Province=East Flanders	8,625	17,084	,152	,505	,619
	Province=Flemish Brabant	-10,250	19,727	-,142	-,520	,609
	Province=Limburg	-10,250	19,727	-,142	-,520	,609
	FlempopHISopiooids	,000	,001	-,135	-,647	,525

### Regression model 5c: Predicting the total number of ambulatory new care episodes for primary opioid use in the Rehabilitation Centers for Addiction

- Predictors: Province dummies (reference=West Flanders), estimated Flemish population with opioids use (HIS, age category and gender-specific prevalence percentages)

#### Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,800 <sup>b</sup>	,640	,540	2,696

#### ANOVA

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	232,792	5	46,558	6,405	,001 <sup>c</sup>
	Residual	130,833	18	7,269		
	Total	363,625	23			

#### Coefficients

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	3,629	1,585		2,289	,034
	Province=Antwerp	2,167	1,740	,207	1,245	,229
	Province=East Flanders	-,208	1,456	-,025	-,143	,888
	Province=Flemish Brabant	-,833	1,740	-,080	-,479	,638
	Province=Limburg	10,667	2,201	,757	4,846	,000
	FlempopHISopiooids	-6,392E-5	,000	-,161	-1,136	,271

**Regression model 5d: Predicting the total number of in-patient new care episodes for primary opioid use in the Rehabilitation Centers for Addiction**

- Predictors: Province dummies (reference=West Flanders), estimated Flemish population with opioids use (HIS, age category and gender-specific prevalence percentages)

**Model Summary**

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,366 <sup>b</sup>	,134	-,082	1,714

**ANOVA**

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	9,106	5	1,821	,620	,686 <sup>c</sup>
	Residual	58,779	20	2,939		
	Total	67,885	25			

**Coefficients**

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	,239	1,105		,216	,831
	Province=Antwerp	1,500	1,107	,391	1,356	,190
	Province=East Flanders	,875	1,050	,250	,833	,414
	Province=Flemish Brabant	,250	1,212	,056	,206	,839
	Province=Limburg	-2,486E-16	1,212	,000	,000	1,000
	FlempopHISopiooids	-1,180E-5	,000	-,071	-,343	,735

**Regression model 6a: Predicting the total number of ambulatory new care episodes for problematic cocaine use in the Rehabilitation Centers for Addiction**

- Predictors: Province dummies (reference=West Flanders), estimated Flemish population with cocaine use (HIS, age category and gender-specific prevalence percentages)

**Model Summary**

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,692 <sup>b</sup>	,478	,333	61,861

**ANOVA**

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	63143,000	5	12628,600	3,300	,027 <sup>c</sup>
	Residual	68882,833	18	3826,824		
	Total	132025,833	23			

**Coefficients**

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	19,270	33,344		,578	,570
	Province=Antwerp	52,500	39,931	,264	1,315	,205
	Province=East Flanders	-39,250	33,409	-,249	-1,175	,255
	Province=Flemish Brabant	18,500	39,931	,093	,463	,649
	Province=Limburg	46,000	50,510	,171	,911	,374
	FlempopHIScocaine	,001	,000	,510	2,996	,008



**Regression model 6b: Predicting the total number of in-patient new care episodes for problematic cocaine use in the Rehabilitation Centers for Addiction**

- Predictors: Province dummies (reference=West Flanders), estimated Flemish population with cocaine use (HIS, age category and gender-specific prevalence percentages)

**Model Summary**

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,489 <sup>b</sup>	,239	,049	27,616

**ANOVA**

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	4800,644	5	960,129	1,259	,320 <sup>c</sup>
	Residual	15253,240	20	762,662		
	Total	20053,885	25			

**Coefficients**

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	4,550	16,669		,273	,788
	Province=Antwerp	4,000	17,826	,061	,224	,825
	Province=East Flanders	9,375	16,911	,156	,554	,585
	Province=Flemish Brabant	-2,000	19,528	-,026	-,102	,919
	Province=Limburg	10,750	19,528	,140	,551	,588
	FlempopHIScocaine	,000	,000	,458	2,351	,029

**Regression model 6c: Predicting the total number of ambulatory new care episodes for primary cocaine use in the Rehabilitation Centers for Addiction**

- Predictors: Province dummies (reference=West Flanders), estimated Flemish population with cocaine use (HIS, age category and gender-specific prevalence percentages)

**Model Summary**

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,666 <sup>b</sup>	,444	,290	20,090

**ANOVA**

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	5805,125	5	1161,025	2,877	,044 <sup>c</sup>
	Residual	7264,833	18	403,602		
	Total	13069,958	23			

**Coefficients**

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	-2,865	10,829		-,265	,794
	Province=Antwerp	-6,333	12,968	-,101	-,488	,631
	Province=East Flanders	-12,208	10,850	-,247	-1,125	,275
	Province=Flemish Brabant	11,167	12,968	,178	,861	,401
	Province=Limburg	-15,333	16,403	-,182	-,935	,362
	FlempopHIScocaine	,000	,000	,552	3,140	,006

**Regression model 6d: Predicting the total number of in-patient new care episodes for primary cocaine use in the Rehabilitation Centers for Addiction**

- Predictors: Province dummies (reference=West Flanders), estimated Flemish population with cocaine use (HIS, age category and gender-specific prevalence percentages)

**Model Summary**

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,640 <sup>b</sup>	,409	,261	5,561

**ANOVA**

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	428,144	5	85,629	2,769	,047 <sup>c</sup>
	Residual	618,471	20	30,924		
	Total	1046,615	25			

**Coefficients**

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	1,710	3,357		,510	,616
	Province=Antwerp	-6,750	3,590	-,448	-1,880	,075
	Province=East Flanders	-3,875	3,405	-,282	-1,138	,269
	Province=Flemish Brabant	,750	3,932	,043	,191	,851
	Province=Limburg	-5,750	3,932	-,327	-1,462	,159
	FlempopHIScocaine	,000	,000	,461	2,680	,014

**Regression model 7a: Predicting the total number of ambulatory new care episodes for problematic stimulants (other than cocaine) use in the Rehabilitation Centers for Addiction**

- Predictors: Province dummies (reference=West Flanders), estimated Flemish population with other stimulant use (HIS, age category and gender-specific prevalence percentages)

**Model Summary**

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,688 <sup>b</sup>	,474	,328	48,284

**ANOVA**

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	37812,458	5	7562,492	3,244	,029 <sup>c</sup>
	Residual	41964,500	18	2331,361		
	Total	79776,958	23			

**Coefficients**

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	28,536	26,396		1,081	,294
	Province=Antwerp	31,500	31,167	,204	1,011	,326
	Province=East Flanders	-31,625	26,076	-,259	-1,213	,241
	Province=Flemish Brabant	2,500	31,167	,016	,080	,937
	Province=Limburg	85,000	39,424	,407	2,156	,045
	FlempopHISstimulants	,001	,000	,379	2,219	,040

**Regression model 7b: Predicting the total number of in-patient new care episodes for problematic stimulants (other than cocaine) use in the Rehabilitation Centers for Addiction**

- Predictors: Province dummies (reference=West Flanders), estimated Flemish population with other stimulant use (HIS, age category and gender-specific prevalence percentages)

**Model Summary**

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,444 <sup>b</sup>	,197	-,003	20,071

**ANOVA**

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	1981,654	5	396,331	,984	,452 <sup>c</sup>
	Residual	8056,962	20	402,848		
	Total	10038,615	25			

**Coefficients**

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	2,990	12,242		,244	,810
	Province=Antwerp	1,500	12,956	,032	,116	,909
	Province=East Flanders	14,750	12,291	,346	1,200	,244
	Province=Flemish Brabant	4,000	14,192	,073	,282	,781
	Province=Limburg	8,000	14,192	,147	,564	,579
	FlempopHISstimulants	,000	,000	,329	1,642	,116

**Regression model 7c: Predicting the total number of ambulatory new care episodes for primary stimulants (other than cocaine) use in the Rehabilitation Centers for Addiction**

- Predictors: Province dummies (reference=West Flanders), estimated Flemish population with other stimulant use (HIS, age category and gender-specific prevalence percentages)

**Model Summary**

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,474 <sup>b</sup>	,225	,010	1,634

**ANOVA**

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	13,958	5	2,792	1,046	,421 <sup>c</sup>
	Residual	48,042	18	2,669		
	Total	62,000	23			

**Coefficients**

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	,240	,893		,268	,792
	Province=Antwerp	1,667	1,055	,386	1,580	,131
	Province=East Flanders	-,208	,882	-,061	-,236	,816
	Province=Flemish Brabant	-,333	1,055	-,077	-,316	,756
	Province=Limburg	,167	1,334	,029	,125	,902
	FlempopHISstimulants	1,445E-5	,000	,207	1,000	,331

**Regression model 7d: Predicting the total number of in-patient new care for primary stimulants (other than cocaine) use in the Rehabilitation Centers for Addiction**

- Predictors: Province dummies (reference=West Flanders), estimated Flemish population with other stimulant use (HIS, age category and gender-specific prevalence percentages)

**Model Summary**

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,346 <sup>b</sup>	,120	-,100	,285

**ANOVA**

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	,221	5	,044	,544	,741 <sup>c</sup>
	Residual	1,625	20	,081		
	Total	1,846	25			

**Coefficients**

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	2,359E-16	,174		,000	1,000
	Province=Antwerp	-2,633E-16	,184	,000	,000	1,000
	Province=East Flanders	,125	,175	,217	,716	,482
	Province=Flemish Brabant	,250	,202	,339	1,240	,229
	Province=Limburg	-2,152E-16	,202	,000	,000	1,000
	FlempopHISstimulants	,000	,000	,000	,000	1,000

### Regression model 8a: Predicting the total number of ambulatory new care episodes for problematic cannabis use in the Rehabilitation Centers for Addiction

- Predictors: Province dummies (reference=West Flanders), estimated Flemish population with problematic cannabis use (HIS, age category and gender-specific prevalence percentages)

#### Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,567 <sup>b</sup>	,322	,133	146,979

#### ANOVA

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	184359,000	5	36871,800	1,707	,184 <sup>c</sup>
	Residual	388848,958	18	21602,720		
	Total	573207,958	23			

#### Coefficients

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	93,331	104,636		,892	,384
	Province=Antwerp	88,917	94,874	,214	,937	,361
	Province=East Flanders	-103,833	79,378	-,317	-1,308	,207
	Province=Flemish Brabant	-18,083	94,874	-,044	-,191	,851
	Province=Limburg	146,167	120,008	,261	1,218	,239
	FlempopHIScannabis	,001	,001	,209	1,079	,295



**Regression model 8b: Predicting the total number of in-patient new care episodes for problematic cannabis use in the Rehabilitation Centers for Addiction**

- Predictors: Province dummies (reference=West Flanders), estimated Flemish population with problematic cannabis use (HIS, age category and gender-specific prevalence percentages)

**Model Summary**

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,529 <sup>b</sup>	,280	,100	28,082

**ANOVA**

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	6127,221	5	1225,444	1,554	,218 <sup>c</sup>
	Residual	15771,740	20	788,587		
	Total	21898,962	25			

**Coefficients**

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	-11,163	21,089		-,529	,602
	Province=Antwerp	-8,250	18,127	-,120	-,455	,654
	Province=East Flanders	10,875	17,197	,173	,632	,534
	Province=Flemish Brabant	-7,000	19,857	-,087	-,353	,728
	Province=Limburg	-,500	19,857	-,006	-,025	,980
	FlempopHIScannabis	,000	,000	,457	2,409	,026

**Regression model 8c: Predicting the total number of ambulatory new care episodes for primary cannabis use in the Rehabilitation Centers for Addiction**

- Predictors: Province dummies (reference=West Flanders), estimated Flemish population with problematic cannabis use (HIS, age category and gender-specific prevalence percentages)

**Model Summary**

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,536 <sup>b</sup>	,287	,089	118,812

**ANOVA**

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	102214,500	5	20442,900	1,448	,255 <sup>c</sup>
	Residual	254092,000	18	14116,222		
	Total	356306,500	23			

**Coefficients**

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	206,359	84,584		2,440	,025
	Province=Antwerp	38,000	76,693	,116	,495	,626
	Province=East Flanders	-82,000	64,166	-,317	-1,278	,218
	Province=Flemish Brabant	-32,000	76,693	-,098	-,417	,681
	Province=Limburg	121,000	97,009	,274	1,247	,228
	FlempopHIScannabis	-,001	,001	-,209	-1,051	,307

**Regression model 8d: Predicting the total number of in-patient new care episodes for primary cannabis use in the Rehabilitation Centers for Addiction**

- Predictors: Province dummies (reference=West Flanders), estimated Flemish population with problematic cannabis use (HIS, age category and gender-specific prevalence percentages)

**Model Summary**

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,462 <sup>b</sup>	,214	,017	11,424

**ANOVA**

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	709,663	5	141,933	1,088	,397 <sup>c</sup>
	Residual	2610,221	20	130,511		
	Total	3319,885	25			

**Coefficients**

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	26,280	8,579		3,063	,006
	Province=Antwerp	-8,500	7,374	-,317	-1,153	,263
	Province=East Flanders	-3,375	6,996	-,138	-,482	,635
	Province=Flemish Brabant	-8,500	8,078	-,271	-1,052	,305
	Province=Limburg	-12,000	8,078	-,383	-1,485	,153
	FlempopHIScannabis	,000	,000	-,303	-1,528	,142

**Regression model 9a: Predicting the total number of ambulatory new care episodes for problematic alcohol use in the Rehabilitation Centers for Addiction**

- Predictors: Province dummies (reference=West Flanders), estimated Flemish population with problematic alcohol use (HIS, age category and gender-specific prevalence percentages)

**Model Summary**

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,805 <sup>b</sup>	,648	,550	35,050

**ANOVA**

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	40627,417	5	8125,483	6,614	,001 <sup>c</sup>
	Residual	22112,417	18	1228,468		
	Total	62739,833	23			

**Coefficients**

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	889,628	176,748		5,033	,000
	Province=Antwerp	11,333	22,624	,083	,501	,622
	Province=East Flanders	-18,667	18,929	-,172	-,986	,337
	Province=Flemish Brabant	25,083	22,624	,183	1,109	,282
	Province=Limburg	58,833	28,618	,318	2,056	,055
	FlempopHISalcohol	-,002	,001	-,673	-4,811	,000

**Regression model 9b: Predicting the total number of in-patient new care episodes for problematic alcohol use in the Rehabilitation Centers for Addiction**

- Predictors: Province dummies (reference=West Flanders), estimated Flemish population with problematic alcohol use (HIS, age category and gender-specific prevalence percentages)

**Model Summary**

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,719 <sup>b</sup>	,517	,397	15,747

**ANOVA**

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	5314,426	5	1062,885	4,287	,008 <sup>c</sup>
	Residual	4959,112	20	247,956		
	Total	10273,538	25			

**Coefficients**

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	343,077	76,448		4,488	,000
	Province=Antwerp	-,167	10,164	-,004	-,016	,987
	Province=East Flanders	4,625	9,643	,107	,480	,637
	Province=Flemish Brabant	3,250	11,135	,059	,292	,773
	Province=Limburg	15,000	11,135	,272	1,347	,193
	FlempopHISalcohol	-,001	,000	-,673	-4,334	,000

**Regression model 9c: Predicting the total number of ambulatory new care episodes for primary alcohol use in the Rehabilitation Centers for Addiction**

- Predictors: Province dummies (reference=West Flanders), estimated Flemish population with problematic alcohol use (HIS, age category and gender-specific prevalence percentages)

**Model Summary**

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,819 <sup>b</sup>	,671	,580	10,054

**ANOVA**

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	3716,917	5	743,383	7,354	,001 <sup>c</sup>
	Residual	1819,583	18	101,088		
	Total	5536,500	23			

**Coefficients**

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	104,005	50,702		2,051	,055
	Province=Antwerp	6,833	6,490	,168	1,053	,306
	Province=East Flanders	-4,417	5,430	-,137	-,813	,427
	Province=Flemish Brabant	9,583	6,490	,235	1,477	,157
	Province=Limburg	39,833	8,209	,725	4,852	,000
	FlempopHISalcohol	,000	,000	-,247	-1,827	,084

**Regression model 9d: Predicting the total number of in-patient new care episodes for primary alcohol use in the Rehabilitation Centers for Addiction**

- Predictors: Province dummies (reference=West Flanders), estimated Flemish population with problematic alcohol use (HIS, age category and gender-specific prevalence percentages)

**Model Summary**

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,648 <sup>b</sup>	,420	,275	3,104

**ANOVA**

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	139,490	5	27,898	2,896	,040 <sup>c</sup>
	Residual	192,663	20	9,633		
	Total	332,154	25			

**Coefficients**

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	8,326	15,068		,553	,587
	Province=Antwerp	4,250	2,003	,501	2,121	,047
	Province=East Flanders	4,125	1,901	,533	2,170	,042
	Province=Flemish Brabant	2,500	2,195	,252	1,139	,268
	Province=Limburg	8,000	2,195	,808	3,645	,002
	FlempopHISalcohol	-2,230E-5	,000	-,086	-,505	,619

