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The choice between institutional care and homecare in the Dutch system of long-term care

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Summary

Background: In order to foster the client-centeredness of long-term care (LTC), individuals entitled to institutional care under the Long-term Care Act (LCA) are having the opportunity to receive their LTC at home. They could do this by either choosing a personal budget (PGB), complete in-home package (VPT) or homecare services (MPT) as their LTC delivery alternative. However, as the LCA has been implemented recently, not much information is available about the predictors of this LTC delivery choice. This limits the policymaker's understanding of patient behavior and hampers the interpretation of any future developments in the LTC delivery choice. The objective of the current study is therefore to provide a more precise understanding of the individual and regional factors that are important in explaining the LTC delivery choice.

Methods: This study uses a unique dataset, provided the Central Administration Office (CAK), which includes all LTC-users older than 18 years. Traditional logistic regressions and multilevel logistic regressions are used to model the choice between homecare (i.e. PGB-, VPT- and MPT-users merged into one category) and institutional care. The latter model accounts for the clustered structure of the dataset. In the second part of the analysis, multinomial logistic regressions are conducted to test whether the variables influence the probability of choosing one of the four LTC delivery alternatives in particular.

Results: It turns out that younger individuals and individuals with partner are more likely to choose homecare. In the disabled care, these effects are mainly driven by the impact on the probability of using PGB. This might be because both variables act as a proxy for the presence of a supporting environment in this sector. Besides, income appears to be negatively related to the probability of using institutional care. Hence, individuals with a relatively high income seems to be deterred by the high copayment they have to pay for institutional care. Alternatively, the positive association between income, living standards and education could play a role. Although the level of disability, reflected in the care intensity package (ZZP), seems to be positively related to the use of institutional care, the sensitivity analysis did not imply that the exclusion of ZZP in the main analysis has resulted in an omitted variable bias. Lastly, it is found that part of the variance in the LTC delivery choice can be explained by variables at the level of the municipality and the health office region.

Conclusion: This study concludes that both individual and regional factors are important in explaining the LTC delivery choice. This suggests that individuals in a certain region tend to make more similar LTC delivery choices than would be predicted by chance. Moreover, it is found that an analysis on the decision between institutional care and homecare does not reflect all relevant information for

policymakers. In fact, the directions of the effects are not necessarily the same across the three homecare alternatives.

Samenvatting

Achtergrond: Om maatwerk binnen de Wet langdurige zorg (WLZ) te bevorderen, hebben individuen met een WLZ indicatie de mogelijkheid om de langdurige zorg thuis te ontvangen. Zij kunnen dit bewerkstelligen door een persoonsgebonden budget (PGB), een volledig pakket thuis (VPT) of een modulair pakket thuis (MPT) te kiezen als leveringsvorm. Aangezien de WLZ slechts recent is geïmplementeerd, is er nog maar weinig bekend over de factoren die de keuze voor een leveringsvorm voorspellen. Het gevolg is dat beleidsmedewerkers niet volledig zicht hebben op de beweegredenen achter een de keuze voor een leveringsvorm. Hierdoor blijft het ook moeilijk om ontwikkelingen in het gebruik van de leveringsvormen te begrijpen. Het doel van deze studie is daarom om een meer volledig beeld te creëren van de individuele en regionale factoren die de keuze voor een bepaalde leveringsvorm van mensen met een WLZ indicatie kunnen verklaren.

Methode: Tijdens deze studie is er gebruik gemaakt van een databestand van het CAK, waarin mensen ouder dan 18 jaar met een WLZ indicatie geregistreerd staan. Logistische regressies en een multilevel model zijn gebruikt om te voorspellen waar de langdurige zorg ontvangen wordt: thuis of in een intramurale instelling. Het multilevel model corrigeert voor het geclusterde karakter van de dataset. In het tweede deel van de analyse wordt er ook onderscheid gemaakt tussen de leveringsvormen PGB, VPT en MPT. Multinomiale logistische regressies zijn toegepast om het effect van de variabelen op de keuze tussen de vier leveringsvormen te bepalen.

Resultaten: Mensen met een lagere leeftijd en mensen met een partner hebben een grotere kans om langdurige zorg thuis te ontvangen. In de gehandicaptenzorg blijken deze groepen in het bijzonder een voorkeur te hebben voor PGB. Dit kan verklaard worden door het feit dat beide variabelen een goede voorspeller zijn van de aanwezigheid van een ondersteunende omgeving. Een ander belangrijk resultaat van deze studie is dat de relatie tussen inkomen en het gebruik van intramurale zorg negatief is. Het lijkt er dus op dat mensen met een hoog inkomen afgeschrikt worden door de hoge eigenbijdrage die zij moeten betalen voor intramurale zorg. Ook zouden de positieve relaties tussen inkomen, leefstandaarden en educatie een rol kunnen spelen. Hoewel de ernst van de beperkingen, gereflecteerd in het zorgzwaartepakket (ZZP), ook een belangrijke voorspeller is van de keuze voor een bepaalde leveringsvorm, wijst de gevoeligheidsanalyse uit dat het uitsluiten van ZZP in de hoofdanalyse de resultaten niet heeft beïnvloed. Als laatst blijken ook regionale factoren een rol te spelen in de keuze voor een bepaalde leveringsvorm.

Conclusie: De studie concludeert dat naast individuele factoren ook regionale factoren belangrijk zijn om het gebruik van een bepaalde leveringsvorm te voorspellen. Dit laatste suggereert dat de observaties binnen een regio niet volledig onafhankelijk zijn. Daarnaast kan er geconcludeerd worden dat veel relevante informatie verworpen wordt als gebruikers van PGB, VPT en MPT samen worden gevoegd in een categorie.

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1. Introduction

In the Netherlands, a major reform of the long-term care (LTC) system is taking place since 2015. An important aim of this reform is to increase the fiscal sustainability of the LTC scheme. Additionally, the reform enables LTC to become more client-centered. As a consequence of this reform, individuals with low or mild disabilities are no longer eligible for institutional care. Instead, these patients are now entitled to the Social Support Act (WMO) and/or the Health Insurance Act (ZVW) which cover tailor-made extramural healthcare services. The individuals in need of daily and permanent care remain eligible for institutional care under the Long-term Care Act (WLZ). However, these individuals are not obliged to move to an institutional setting as this might not fit the needs and preferences of the patient. Hence, in order to guarantee LTC to be client-centered, these individuals could also decide to receive LTC at home by either choosing a Personal Budget (PGB), Complete In-Home Package (VPT) or Homecare Services (MPT) as their LTC delivery alternative.

The policymakers of the Ministry of Health see that around a quarter of the individuals who are eligible to institutional care have decided not to move to an institution yet but to receive their LTC at home. The question then arises as to what the characteristics of these individuals are. According to de Meijer et al. (2015) the probability of receiving LTC at home is negatively related to the level of disability, age, being female and living alone among the elderly. However, this study and many others (e.g. van Campen & van Gameren, 2005; de Meijer et al., 2009; van Gameren & Woittiez) also include 65+ individuals who are not entitled to institutional care as specified by the new WLZ. Besides, these results do not tell whether these characteristics have an impact on a certain homecare alternative in particular. Moreover, next to the individual characteristics, also regional variables could influence the LTC delivery choice, as the utilization of the alternatives seems to differ across regions.

The objective of this study is to provide a fuller and more precise understanding of the factors that influence the LTC delivery decision of individuals entitled to institutional care by answering the following research question: *Which individual and regional factors have a significant effect on the patient's choice between institutional care, personal budget, complete in-home package and homecare services in the Dutch system of long-term care?* By doing so, a distinction is made between the elderly care and the disabled care. The generated knowledge is important to get a better understanding of patient behavior. This helps policymakers interpreting any developments in the LTC delivery choice and could be used to build future policy upon. For example, the established relationships could be employed to steer individuals into a certain LTC delivery alternative, might that become a policy goal in the future.

Andersen's Behavioral Model acts as a guide to select potentially relevant individual and regional variables (Andersen & Newman, 1973). The potential effects of these variables on choosing either homecare or institutional care are discussed with policymakers of the Dutch Ministry of Health. The resulting hypotheses are tested by employing both a traditional logistic model and a multilevel logistic model. From the first, the effects of certain variables at the level of the municipality and the region are derived. However, this model does not account for the clustered structure of the dataset. The directions of the effects of the individual characteristics are therefore derived from the multilevel logistic regression. This model eliminates the presence of atomistic fallacy and disentangles the variability at the individual, municipality and health office region level. In the second part of the analysis, the homecare category is broken down into the three underlying alternatives: PGB, VPT and MPT. Using multinomial logistic regressions, it is then analyzed whether the variables have a specific effect on one or more LTC delivery alternative(s) in particular.

The main results are as follows. Firstly, it turns out that individual characteristics are important predictors of the LTC delivery choice. Specifically, older individuals and individuals without partner tend to be more likely to choose institutional care in both the elderly care and the disabled care. In contrast, income turns out to be negatively related to the probability of using institutional care. Secondly, although this study has not identified the underlying mechanisms, it has been found that the municipalities and health office regions are important predictors of the LTC delivery choice.

This paper is organized in six chapters. The next chapter describes the theoretical framework including background information about the LTC provision in the Netherlands and motivations for the expected relevance of the investigated variables. The dataset is described in the third chapter and the methodology in the fourth chapter. The results are then presented in the fifth chapter and the sixth chapter ends with the conclusion.

2. Theoretical framework

This chapter starts with a short description of the system of long-term care provision in the Netherlands. Additionally, it presents an explanation of the four LTC delivery alternatives and the reasons for their introduction. Thereafter, section 2.4 introduces the behavioral model which categorizes the predictors of healthcare utilization. Along with this, the impact of these predictors on the decision between institutional care and homecare is motivated on grounds of expert opinions and literature.

2.1 The provision of long-term care

In order to protect individuals against the high life-time costs of LTC, the Dutch government exploits a new public LTC insurance scheme: the Long-term Care Act. Just like the predecessor, the AWBZ, this scheme is funded by social premiums paid by everyone who pays income taxes. Additional funding comes from taxes and income-related copayments (Ministry of Health, Welfare and Sport, 2011).

Before individuals can start using LTC, they have to follow a so-called care trajectory (van Gameren & Woittiez, 2005). This trajectory starts with a need and is followed by demand, need assessment, in some cases a waiting list and ends with the actual use of LTC. Specifically, when the health of individuals start to decline, there may come a point at which these individuals develop a need for daily and permanent care. This need could then be turned into a demand by applying for LTC at the Care Assessment Agency (CIZ). This center assesses the diseases, impairments and disabilities and determines whether these are likely to result in serious harm to the individual or might prevent individuals to call for help in critical situations. If it does, individuals become entitled to LTC.

This eligibility assessment is always issued on the basis of a (dominant) fundamental that indicate the (most severe) impairments of the patient. From these fundamentals, the CIZ derives a so-called care intensity package (ZZP) which indicates the type and intensity of the needed care. The higher the number of the ZZP, the more intensive care is needed. The fundamentals could also be applied to divide patients within three types of care: elderly, disabled and mental care (table 1).

Fundamentals	**Type of LTC**
Psycho geriatric conditions	Elderly care
Chronic somatic conditions	Elderly care
Physically disabled	Disabled care
Mental retardation	Disabled care
Sensory disabilities	Disabled care
Chronic psychiatric conditions	Mental care

Table 1: relationship between the fundamentals and the three types of LTC.

After the patient got entitled to LTC, the CIZ transmits the assessment decision electronically to a health office, of which there are 32 across the Netherlands. These offices are responsible for the actual implementation of LTC. At this point, the patients have to decide which LTC delivery alternative they are going to use. The next paragraph elaborates on these alternatives.

2.2 Current care delivery alternatives

Patients entitled to institutional care under the WLZ are allowed to receive this care at home, unless the health office determines that homecare is not safe and/or effective given the health status and supporting environment of the individual. In the case of a PGB it is also checked if the patients are able to regulate certain administrative tasks themselves. As a consequence of this assessment, certain patients are not allowed to receive LTC at home, whereas others can choose freely between certain LTC delivery alternatives.

Within homecare, the LTC delivery alternatives complete in-home package (VPT), homecare services (MPT) and personal budgets (PGB) are distinguished. Next to institutional care, VPT and MPT are types of care in kind, which indicates that patients receive care from health care provider(s) that are contracted by the health office. VPT and MPT differ in the sense that VPT could only be delivered by one healthcare provider, whereas MPT by multiple. Moreover, MPT could be combined with PGB and VPT not. Lastly, MPT-users could decide to use only certain modules of the LTC-package.

In contrast to care in kind alternatives, PGB offers patients the possibility to organize the needed care themselves. In order to do so, PGB users have to write a budget plan in which they indicate the type(s) of care they would like to purchase from which informal and/or formal caregivers and how much this is expected to cost. This document needs to be approved by the health office. The Social Insurance Bank pays LTC providers on the basis of invoices submitted by the patients.

The four LTC delivery alternatives have in common that they all include fundamental LTC services such as assistance in activities of daily living, transport and personal care; they differ with respect to the inclusion of certain other services. Table 2 summarizes these differences. Additionally, this table presents which healthcare services are covered by the WMO or the ZVW. A cross indicates that the costs are not covered by healthcare acts.

As can be derived from this table, institutional care is the most comprehensive alternative within the WLZ. In fact, next to the fundamental LTC services, the WLZ also covers costs of living, meals, dental care and nursing home physicians for institutionalized patients. When the patient chooses VPT instead, respite care (i.e. temporary institutional care) is covered by the WLZ, but the costs of living, dental care, general practitioners and general treatment are not. This latter service includes healthcare services like physical therapy. MPT is the least extensive care package. In fact, the WLZ only covers respite care and the fundamental LTC services. When patients choose to use PGB, also costs of domestic support could be covered.

	Institutional care	VPT	MPT	PGB
Housing	WLZ	x	x	x
Meals	WLZ	WLZ	x	x
Domestic support	WLZ	WLZ	WMO	WLZ
General treatments	WLZ	ZVW	ZVW	ZVW
General practitioner	WLZ	ZVW	ZVW	ZVW
Dental care	WLZ	x	x	x
Respite care	x	WLZ	WLZ	WLZ

Table 2: LTC services that are covered by either the Long-term Care Act (WLZ), Social Support Act (WMO) or Health Insurance Act (ZVW) depending on the chosen LTC delivery alternative.

In accordance with the extensity of the LTC delivery alternatives, the highest average copayment has to be paid for institutional care and the second highest for VPT. Compared to the copayment for VPT, the average monthly copayments for MPT and PGB are €136 lower as meals are not included in the latter. Next to the LTC delivery alternative, the height of the copayments also depends on the income, assets, marital status and the retirement status of the individual.

2.3 Historical development of delivery alternatives

The freedom to choose between the four different LC delivery alternatives has not always been present. In fact, the AWBZ (the predecessor of the WLZ) initially focused on intensive intramural care in order to guarantee the quality and accessibility of these facilities. Specifically, the AWBZ has been introduced in 1968 to cover expenses on long-term hospital care (i.e. with a duration of more than one year) and nursing homes. Since that time, also extramural forms of care got included, which expanded the scope of the AWBZ. This expansion came with rising AWBZ expenditures (figure 1).

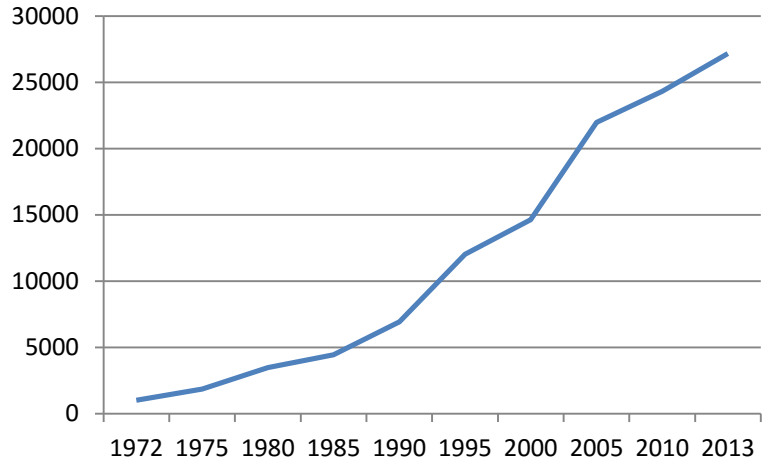

Figure 1: AWBZ expenditures in millions of euro's along the years (source: CBS Statline).

2.3.1 Introduction personal budgets

One of the reasons for the introduction of personal budgets in 1997 was that caps on healthcare spending were driving up waiting lists, which deteriorated the performance of the system. Additionally, the introduction of a new alternative would provide patients larger choice and more control over their healthcare (White, 2011). This empowers patients, enables continuity of care by family members and makes care more tailor-made (van Ginneken, Groenewegen, & McKee, 2012). Besides, the greater degree of choice might stimulate the efficiency and innovation of care in kind as healthcare providers could feel an increased pressure to attract patients (Gadsby, 2013). However, this stimulating effect of personal budgets has often been questioned (White, 2011). It has even been argued that the PGB reduces the innovation of care in kind as most new providers use this alternative to finance their services. Consequently, this care does not come available as care in kind. Nonetheless, clients seem to value PGB, since research has shown that budget holders are more satisfied with their care than clients receiving care in kind (AVI-cliëntenmonitor, 2015).

2.3.2 Introduction complete in-home package

The introduction of VPT in 2007 has enlarged the patient's freedom of choice as it provides the opportunity to use care in kind at home (van Dijk - Jonkman, Hengeveld, & Welling, 2010). Initially, healthcare providers were obliged to reserve institutional capacity when providing VPT. However, this criterion was eliminated in 2009 to foster the supply of this LTC delivery alternative.

2.3.3 Introduction homecare services

Also in the period of the AWBZ individuals had the option to redeem certain parts of the care they are entitled to. Back then, LTC could already be delivered by multiple providers and there existed also an option to combine care in kind with PGB. However, along with the LTC reforms in 2015 it has been decided to give this alternative an actual name: MPT.

MPT is often applied during periods in which patients have to wait for institutionalization because this alternative allows their existing care utilization (under for example the Social Support Act) to be expanded easily and temporarily by the amount their current WLZ eligibility requires (Pansier-Mast, Veldhuis, & Welling, 2012). However, MPT is also used by those who are not on a waiting list. This might be explained by the unique characteristics of MPT. In fact, certain individuals might prefer different types of care to be delivered by different healthcare providers. Moreover, some individuals would like to combine care in kind and personal budgets as they want particular types of care to be provided by their informal caregiver. These informal caregivers could then be paid with the PGB. Lastly, individuals might prefer MPT simply because they do not want all healthcare services to be covered by the WLZ. Instead, they might want certain types of care to be delivered by informal caregivers without paying them.

As discussed in the previous paragraphs, the LTC delivery alternatives differ significantly. As a result, one could expect that the utilization of the LTC delivery alternatives is varying across individuals and even across regions. The next paragraph discusses factors that may help explaining these choices.

2.4 Explanatory factors

So far, most conducted research on the decision between homecare and institutional care has focused on the USA (e.g., Muramatsu, et al., 2007; Kaye, LaPlante & Harrington, 2009; Weissert & Frederick, 2013). Besides, when studies focus on the Dutch system of LTC, the developments in the utilization of the personal budgets are of main interest (e.g., Sadiraj, et al., 2011; van der Torre, Ooms & de Klerk, 2013) or the study population also includes individuals not entitled to LTC as specified by the WLZ (e.g. van Campen & van Gameren, 2005; de Meijer et al., 2009; de Meijer et al., 2015). As a consequence, hypotheses about the relationship between explanatory variables and the LTC delivery choice of Dutch individuals who are eligible for institutional care cannot be easily derived from literature. For that reason, brainstorm sessions have been held with policymakers of the Dutch Ministry of Health to generate hypotheses about the effects on the utilization of either homecare or institutional care. The policymakers are experienced with the long-term care system and have regular contact with people actually working in the LTC field.

Andersen's Behavioral Model acted as a guide in the selection of relevant variables (Andersen & Newman, 1973). As can be seen in figure 2, this model illustrates the relationships between personal characteristics and healthcare utilization. Adaptations of the model recognize that outcomes in turn might impact the personal characteristics of the patient (Gelberg, Andersen, & Leake, 2000). For example, an inadequate use of healthcare might deteriorate the evaluated health of the individual. Consequently, his utilization might have to be increased.

In the current study, relevant variables are exclusively derived from the part of the model that structures the personal characteristics. Regional variables are based on the place individuals live and are therefore also presented in this part of the model (see community resources). As figure 2 illustrates, these determinants are categorized into predisposing, enabling and need characteristics. Predisposing factors are characteristics of individuals which may explain the use of healthcare services even though they do not directly relate to the utilization. In other words, they exist prior to the moment that the need of LTC arises and can be considered to be exogenous. These factors can be further divided into demographic, social structural and attitudinal-beliefs variables. Next, enabling factors are interpreted as necessary but not sufficient conditions for healthcare utilization. Hence, they indicate the extent to which individuals are able to use the healthcare services to which they

tend to be predisposed at the moment they actually need this care. Lastly, need factors display the health status of individuals and are therefore most directly related to healthcare use

The next subparagraphs elaborate on the relationship between predisposing, enabling and need factors on the one hand and the LTC delivery choice on the other hand. Due to limited amount of data, these subparagraphs only focus on the variables for which data is available. In figure 2, these variables are shown in bold.

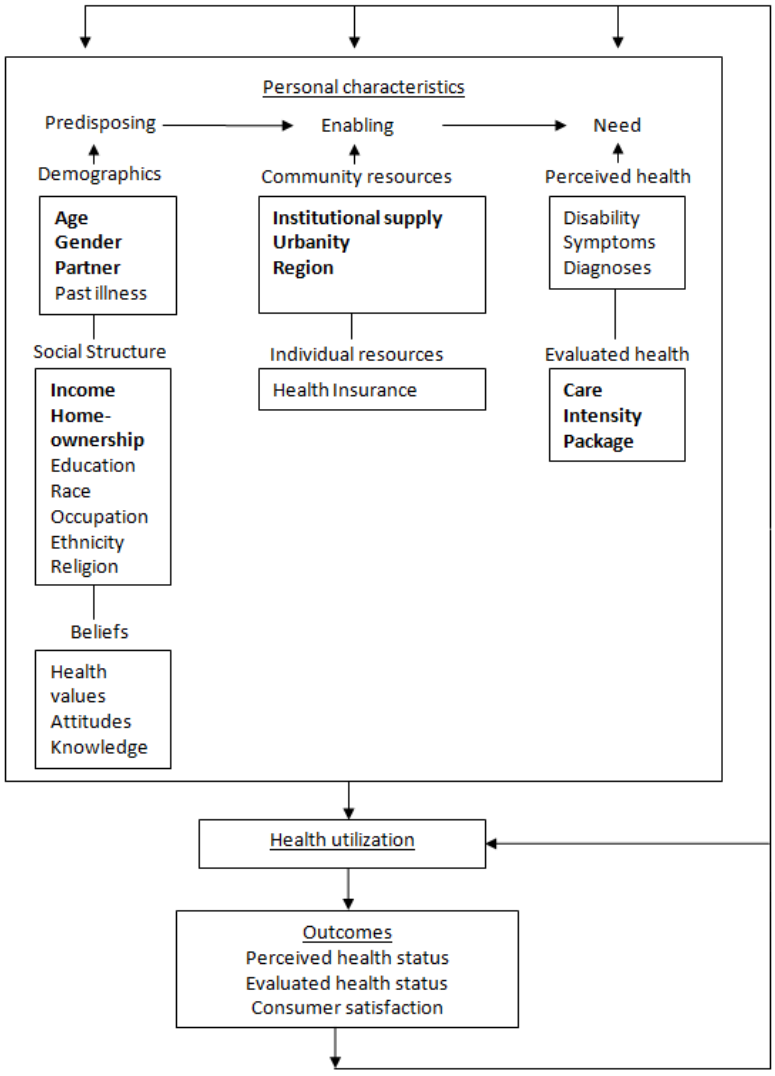

Figure 2: adaptation of Andersen's Behavioral Model appearing in Gelberg, Andersen en Leake (2000).

2.4.1 Predisposing factors

Age, as an example of a demographic variable, does not trigger the decision for institutional care per se. In other words, it is not because someone turns 75 that he decides to move to an institutional setting. For that reason, this variable is classified as being a predisposing factor. Age is expected to be positively related to the probability of institutional care because of three underlying mechanisms. First, when individuals are getting older they might become less reluctant to move to an institutional

setting. In the elderly care, this might simply be because individuals tend to associate the onset of institutional care as something that is part of getting older. For the disabled individuals, this diminishing reluctance might be caused by the fact that as individuals are getting older it becomes less likely that they still have their parents. In that case, it is no longer an option to be cared for by your parents, which might increases the attractiveness of institutional care. Second, it is widely known that health deteriorates when individuals get older. As a consequence, institutional care might suit the needs of the older individuals better, simply because their needs are higher. Hence, the effect of age on the probability of institutional could also be confounded by the health status of the individual. Lastly, as this study is using cross-sectional data, a positive effect of age could also reflect a so-called cohort effect. In fact, the proportion of individuals that chooses institutional care is declining along the years. This might be because extramural alternatives become better available to patients and/or because patients' views on extramural alternatives change. The high current average age across the institutional care users is then driven by a high proportion of institutional care users within the older generations.

Next, policy makers expect partnership to be positively correlated with homecare. In fact, individuals with a partner might have a strong desire to stay in their current house with their partner. Moreover, this partner could perform some care-giving activities. This makes it less likely that someone has to move to an institutional setting. Also, health offices are more inclined to approve LTC to be delivered at home when the individual still has a partner.

Once eligible for LTC, the gender of an individual is not expected to have a significant impact on the LTC delivery choice. Nevertheless, this study assumes that the interaction term between partner and gender might actually have a significant effect. In fact, men are more likely to be dependent on a supporting environment and when their partner passes away, they might be more likely to choose institutional care compared to females, ceteris paribus.

Although income is most often considered as an enabling factor, the current study classifies it as a predisposing factor. In fact, Dutch citizens are publicly insured against the high costs of LTC, so income is less of an enabling factor in the LTC delivery choice. Specifically, income is classified as a social structure variable, which reflects the status of individuals in their society, for two reasons. First, income is positively correlated with the living standards of individuals, which for instance reflects the size of their houses. As a consequence, these individuals might be less willing to move to an inpatient setting as these apartments tend to be considerably smaller and perhaps less luxurious. Second, income is also positively related to education, which is in turn negatively related to the

impairments of individuals (Timmermans & Woittiez, 2004). Hence, the lower educated tend to have more severe disabilities, which increases the probability of using institutional care as homecare may not be provided safely and effectively. In summary this means that lower educated individuals tend to be predisposed to the use of institutional care. However, education might also have an enabling effect. In fact, higher educated individuals are more likely to understand the health care system and the possibilities they have and are therefore less inclined to opt for institutional care compared to the lower educated people. This enables them to use a homecare alternative. Finally, the relevance of income could also be driven by the fact that rich individuals have to pay a relatively large copayment for institutional care, which might have a deterrent effect.

2.4.2 Enabling factors

Within the enabling factors, distinction can be made between community resources and individual resources. Examples of community enabling resources are supply of institutional care, urbanity and the health office region of the country. An example of an individual resource is homeownership. The presence of these variables enables individuals to start using a specific LTC delivery alternative.

Firstly, since a higher supply might trigger patients to opt for institutional care, supply is expected to be positively related with institutional care utilization. However, regions with a high utilization of institutional care might also attract more providers of this type of care. Hence, a reverse causality arises here.

Secondly, the level of urbanity might also be another important predictor for the use of institutional care as it could be used as a proxy for the proximity and therefore the ease to get to certain facilities. In fact, as the number of visits to a remote pharmacist or supermarket could be reduced by moving to an institution, individuals in rural areas are expected to be more willing to move to an institution. However, institutions will also be more remote in rural areas. This might suggest that individuals in rural areas would actually be less willing to receive institutional care, because they have to move further. These counteracting effects are expected to be of about the same size so that the effect of urbanity becomes insignificant.

Additionally, the health office region and/or municipality of residence might be important because of cultural and/or religious differences across regions. Because of that, the onset of institutional care is more self-evident in certain regions. Alternatively, different health offices might have different judgments about whether homecare can be delivered safely and effectively. As a result of this, individuals in some regions might be more likely to be required to move to an institutional setting.

Lastly, not owning a house might enable renters to move to an institution quite easily. In fact, these individuals do not have to sell their houses. Another reason for the importance of this variable is that homeowners tend to have a strong desire to stay in their own property (Rouwendal & Thomese, 2010). These individuals are therefore less inclined to move to an institution.

2.4.3 Need factors

Ultimately, need factors are most directly related to healthcare use. In fact, the severity of the disease is a strong predictor of the effectiveness of homecare. When the needs of individuals are relatively high, institutional care may remain the only effective option. In line with this hypothesis, van Dijk-Jonkman et al. (2011) found that individuals with the less intensive care intensity packages are the most likely to choose a homecare alternatives.

3. Data

In this study, datasets are generated out of different sources. First, micro data is derived from the Central Administration Office (CAK), which collects this data for calculation of the required copayments. As a result, all LTC-users older than 18 years are included in the dataset. This increases the reliability of the results. The first of July 2015 was taken as the reference date in order to minimize the amount of individuals who are erroneously registered as WLZ-users after the long-term care reforms of January 2015. Any later date would not be possible as the CAK has not finalized this data yet.

As this study is only focusing on the elderly care and the disabled care, all individuals with mental problems are deleted from the dataset. This group is not of interest because 99.59% of these individuals get institutionalized. Information about the MPT users on the one hand and PGB, VPT and institutional care users on the other hand is registered in two separate datasets: respectively the MPT dataset and the care intensity package (ZZP)-dataset. The name of the latter dataset is derived from the fact that it includes ZZP as a variable, whereas the MPT dataset does not. Additionally, a new combined dataset is created which only includes the overlapping variables of the two separate datasets.

Data at the regional level is obtained from the electronic database of Statistics Netherlands. These variables were added to both the ZZP-dataset as the combined set. Statistics Netherlands uses the first of January 2015 as the reference date, which does not correspond to the reference date of the micro-level data. However, as these regional variables are not expected to change significantly in six months we consider the reference date mismatch to be negligible.

The first three paragraphs describe the CIH dataset, the MPT dataset and the regional data. In these paragraphs, also the needed adaptations are explained. Thereafter, regional differences and descriptive statistics about the combined dataset are presented. The last paragraph gives an overview of the variables of interest.

3.1 ZZP-dataset

The ZZP-dataset includes the following independent variables: age, gender, care intensity package, presence of a partner, total income in 2013, income out of savings and investments (i.e. assets without the inclusion of property) in 2013, municipality and health office region. The assigned ZZP illustrates the intensity and type of the care needed. This information is used to create two different datasets: one including elderly care users and the other only disabled care users (table 1). This allows us the analysis to be conducted in two different sectors.

In their calculations of the copayments, the CAK employs the registered total income of two years ago in order to avoid complex situations arising from changing current incomes. In the elderly care, most individuals are entitled to a pension which does not vary greatly over time. Hence, the total income of the elderly in 2015 is not expected to differ significantly from the income in 2013. The same yields for the disabled individuals as most disabled people lack salaries and government transfers are quite stable over time.

Although this two-year gap is not expected to have a significant impact on our analysis, the positive correlation between assets and total income might has. In fact, total income also includes four percent of the income from savings and investments. Moreover, individuals having a high income out of labor are likely to also have a large income out of savings and investments as well. Due to this correlation, multicollinearity might arise which will inflate the confidence intervals. In order to test the presence of multicollinearity the variance inflation factor (VIF) is calculated. This factor indicates the extent to which the variance of the coefficients has been inflated upwards. Generally, VIF estimates of 4 and 10 are applied as rule of thumbs to detect serious problems of multicollinearity (Studenmund, 2006). As the VIF estimates turn out to be below four, both income and assets are about to be considered in this study.

The municipality in which the individual lives is derived from the address at which the individual is registered on the first of July 2015. For institutional care users, this reflects the municipality in which the institution is located and not necessarily the municipality in which the individual has made the initial LTC delivery choice. In the elderly care, this is not expected to have a significant impact on the analysis as elderly individuals tend to choose an institution in their current municipality. In contrast,

disabled people are more often forced to move across these borders as institutional care is often limited for them. In order to reduce the number of mismatch as much as possible, the analysis of the disabled care only employs variables at the level of the health office region. In fact, health office regions include on average 12 municipalities, so not many disabled individuals will have moved across these borders for institutional care.

3.2 MPT dataset

A major limitation of the MPT dataset is that it does not include information about care intensity packages. Hence, individuals cannot be easily classified within the elderly care and the disabled care. In order to solve this problem, one could classify MPT-users older than 65 as elderly care users as age acts as a good proxy for the onset of elderly care. However, table 3 shows that approximately 10% of the 65+ individuals of the PGB-, VPT- and institutional care users does not use elderly care. Hence, this technique might classify many MPT-users in the wrong sector.

A better solution is to employ a more sophisticated imputation technique that classifies MPT-users to either the elderly, disabled or mental care. By applying this technique, missing values are replaced by reasonable guesses which are based on the age distribution of PGB-, VPT- or institutional care-users across the types of care. Thus, the chance that a 65+ MPT- user is in need of elderly care would be equal to the proportion of 65+ PGB-, VPT- or institutional care-users that use elderly care. Advantages of this technique include conceptual simplicity and an optimal use of the age distribution within the ZZP dataset, which gives more accurate estimates (Wang, 2003)

However, for 15.2 percent of the MPT-users it is not known to which age category they belong. As the majority of these observations also have missing values for many other variables, these observations are deleted. Subsequently, each observation gets a random number over the interval [0,1) assigned. In the age category 65+, all observations with a random number up to and including 0.896 get assigned to elderly care, all observations with a random numbers between 0.896 and 0.988 got assigned to disabled care and the remainder to mental care. The same was method was performed for the other age category. Thereafter, the individuals with mental problems are deleted.

	Elderly	Disabled	Mental
0-65	0.055	0.882	0.063
65+	0.896	0.092	0.013

Table 3: age distribution of all individuals using PGB, VPT or institutional care package across the elderly, disabled and mental care sectors.

3.3 Regional level data

In the elderly care, homeownership, distance to hospital and urbanity are considered on the municipality level and supply of institutional care on the health office level. In the disabled care, urbanity and supply of institutional care are included on the level of the health office region. These variables are discussed below.

First, as information about the homeownership is not available in the micro-level dataset, this variable had to be included on the municipality level. The average percentages of homeowners in municipalities are published by Statistics Netherlands. This data is merged to the combined dataset by using the municipality as the key variable.

Second, data about the average population density (i.e. urbanity) is also publicly available. This variable indicates the average number of citizens per square kilometer and is used as a proxy for the ease to get to facilities. Statistics Netherlands also publishes data about the average distance to certain facilities, but these turn out to be highly correlated with the population density (table 4). However, the distance to hospital and population density are just moderately correlated (r=-0.56), so these are the two variables considered in this study.

	PD	D_GP	D_H	D_P	D_S
Population density (PD)	1				
Distance to GP (D_GP)	-0.65	1			
Distance to hospital (D_H)	-0.56	0.61	1		
Distance to pharmacist (D_P)	-0.64	0.78	0.60	1	
Distance to supermarket (D_S)	-0.67	0.83	0.61	0.76	1

Table 4: correlation matrix population density and distances to GP, hospital, pharmacists and supermarket.

Third, this study only employs the number of different institutional care providers (i.e. not the number of locations) in health office regions as a predictor for institutional care because of the lack of data. This variable is considered to be a proxy for the choice individuals have. Since healthcare providers are attracted to regions in which many individuals use institutional care, reverse causality arises and relationships should not be interpreted as causations. This variable is not considered at the level of the municipality as the data is expected to be invalid at that level. This is due to the fact that all locations of an institutional care provider are by definition registered at the same municipality, but this might in practice not be the case. Instead, the probability that the locations of a certain institutional care provider are located in the same health office region is larger, which makes the employed variable more valid.

Lastly, municipalities and health office regions are also considered as variables. These variables are derived from the micro dataset in which the zip code is included as a variable. This information is also used to identify the regional distribution of the LTC delivery alternatives, which is presented in the next paragraph.

3.4 Regional distribution of the LTC delivery alternatives

As figure 5 shows, the proportion of LTC users that receive institutional care in a certain municipality varies from 0.33 to 0.96 across municipalities. The median proportion is 0.80, so in most municipalities the majority of all LTC users use institutional care. In contrast, the proportion of VPT users varies little across municipalities. In 36.13% of the municipalities, there are not even any VPT users. Since the median proportion is 0.0036 and the maximum proportion 0.13, it seems like VPT users are clustered in certain municipalities. The distribution of the MPT- and PGB-users across municipalities is relatively similar. In fact, the proportions of MPT- and PGB-users in a municipality have a median value of around 0.09 and a maximum value of relatively 0.49 and 0.38. In conclusion, the use of the four LTC delivery alternatives varies greatly across municipalities.

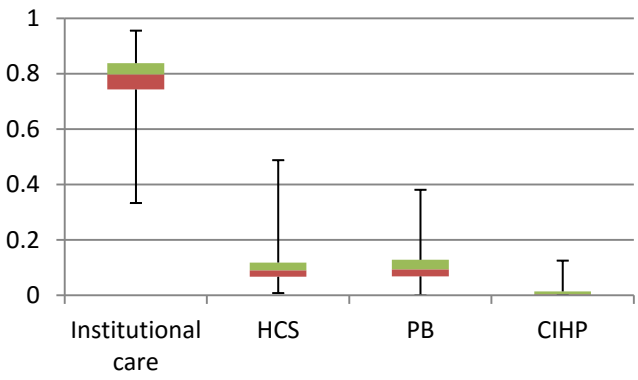

Figure 5: distribution of care delivery alternatives in municipalities.

When aggregating the municipalities to the 32 health office regions, a large part of the variation is eliminated as illustrated in figure 6. In fact, the proportion of LTC users that use institutional care in the health office region now only varies from 0.75 to 0.87 across health office regions. Moreover, there is only one health office region in which nobody uses VPT, compared to 142 of the 393 municipalities. Apparently, municipalities with high and low proportions of a certain LTC delivery alternative are located close to each other and are therefore belonging to the same health office region.

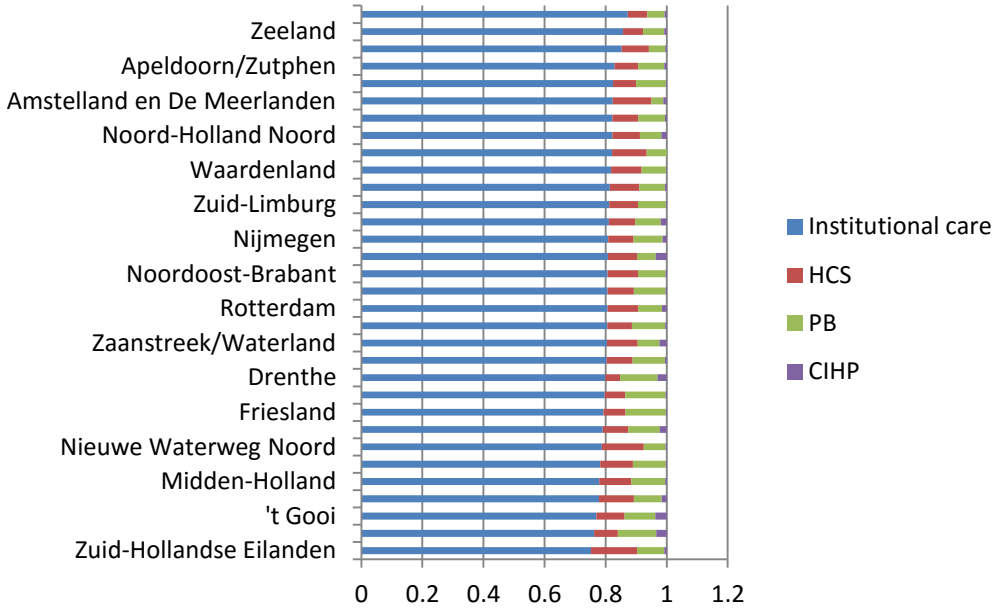

Figure 6: distribution of care delivery alternatives across the 32 health office regions.

3.5 Descriptive statistics of individual characteristics

The combined dataset includes 250,272 individuals of which 98,390 individuals are entitled to disabled care and 151,882 to elderly care. The overlapping independent variables at the individual level are age, gender, the presence of a partner, municipality, sector, income in 2013 and assets at 2013. Table 5 illustrates the distribution of the use of the LTC delivery alternatives in respectively the elderly care and the disabled care. It shows that the majority of both elderly and disabled individuals use institutional care. Besides, it shows that only a very small percentage of the LTC-users choose VPT in both the elderly and disabled care. As these are still respectively 1868 and 945 individuals, this will not make the results at the individual level invalid. However, as there are 393 municipalities, this does mean that there are only approximately 5 VPT-users per municipality in the elderly care. Hence, the effects of the variables at the municipality level on the probability of using VPT should be interpreted with care. In the disabled care, regional variables are only considered at the level of the health office region. As there are 32 of such regions, there are approximately thirty VPT-users per health office region. Again, this limits the power of the test. In other words, this limits the probability of rejecting a false null hypothesis (Wilson van Voorhis & Morgan, 2007).

	Elderly Percentage	Disabled percentage
Homecare services	9.18	8.62
Personal budget	3.07	19.33
Complete in-home package	1.23	0.96
Institutional care	86.51	71.09

Table 5: distribution of the LTC delivery alternatives in the elderly and disabled care.

In table 6, the data is divided into four groups; MPT, PGB, VPT and institutional care users. For these groups, the table shows the mean values for the individual variables in the elderly care (E), disable care (D) and total long-term care (T=E+D). This information can be used to determine whether some variables might be irrelevant to include in the model. In fact, If the average value of a particular variable does not vary significantly across the alternatives, the statistical models are not likely to report a significant effect of this variable on the probability of choosing a particular alternative either. To see whether these average values differ significantly across the four LTC delivery alternatives, the chi-squared test is performed for binomial variables and the ANOVA test for continuous variables. Table 6 shows that all variables seem relevant for explaining the LTC delivery choice because all mean values differ significantly across the LTC delivery alternatives.

These descriptive statistics suggest that MPT users are on average the youngest and VPT users on average the oldest in the elderly care. Furthermore, institutional care users turn out to have the lowest average income and savings/investments and PGB users the highest. Lastly, PGB users are most likely to have a partner and VPT users the least likely. In the disabled care, PGB users are the youngest and institutional care users the oldest. Besides, it shows that MPT users have the highest income and VPT users the lowest. Finally, in line with the elderly, disabled PGB users have most often a partner and disabled VPT users least often. The statistical models of the current study have to show whether these variables remain significant predictors of the LTC delivery choice after controlling for the other variables.

Variable	**MPT**			**PGB**			**VPT**			**Institutional care**		
Sector	***E***	***D***	***T***	***E***	***D***	***T***	***E***	***D***	***T***	***E***	***D***	***T***
Age	81.5*	45.5*	70.8*	82.3*	35.2*	44.5*	86.4*	39.34*	70.4*	85.6*	47.2*	71.6*
Male	0.21*	0.48*	0.34*	0.33*	0.58*	0.53*	0.27*	0.54*	0.36*	0.28*	0.56*	0.38*
Partner	0.23*	0.14*	0.20*	0.29*	0.19*	0.13*	0.17*	0.04*	0.12*	0.19*	0.16*	0.13*
Income	24787*	17711*	21980*	26778*	8430*	12238*	21719*	8008*	17267*	15081*	9515*	13015*
Savings and investments	49220*	16132*	35920*	137387*	1481*	40204*	80352*	8098*	56907*	30844*	14299*	25025*

Table 6: average values and proportions of the individual explanatory variables in the elderly care (E), disabled care (D) and total LTC (T=E+D). Except for savings and investments in the disabled care, all these differences are significant at the 1% significance level.
**p<0.01*

3.6 Overview explanatory variables

Table 7 summarizes the predictors of the LTC delivery choice. As said before, only the variables are presented for which data is available on the individual, municipality or health office region level. As disabled individuals are less likely to be living in the municipality at which they made their initial LTC delivery choice, only variables at the regional level are employed. However, due to this higher level of aggregation, the correlation between the regional variables becomes very strong. As a consequence, the impact of the average distance to the hospital and the average homeownership could not be investigated in an accurate way.

The second and third columns of table 7 indicate the expected relationship between the factors and the probability of getting institutionalized in respectively the elderly and disabled care. In the following chapters, these hypothesized relationships are going to be tested in order to find an answer to the research question: *Which individual and environmental factors have a significant effect on the patients' choices between institutional care, personal budget, complete in-home package and homecare services in the Dutch system of long-term care?*

Predictor	*Institutional care*		*Level of available data*	
	Elderly	*Disabled*	*Elderly*	*Disabled*
Predisposing				
Demographics				
Age	*+*	*+*	*Individual*	*Individual*
Male	*ns*	*Ns*	*Individual*	*Individual*
Partner	*-*	*-*	*Individual*	*Individual*
Male without partner	*+*	*Ns*	*Individual*	*Individual*
Enabling				
Individual resources				
Income	*-*	*-*	*Individual*	*Individual*
Assets	*-*	*-*	*Individual*	*Individual*
Homeowner	*-*	*X*	*Municipality*	*x*
Community resources				
Municipality	*s*	*X*	*Municipality*	*x*
Health office region	*s*	*S*	*Health Office*	*Health Office*
Distance to hospital	*+*	*X*	*Municipality*	*x*
Institutional care choice	*+*	*+*	*Health Office*	*Health Office*
Urbanity	*ns*	*Ns*	*Municipality*	*Health Office*
Need				
Evaluated health				
Care intensity package	*+*	*+*	*Individual*	*Individual*

Table 7: overview of the predictors for which data is available. Second column presents the expected relationships between predictor and the risk of institutionalization in the elderly care and the disabled care. +: positive relationship, -: negative relationship, ns: not significant s: significant relationship (when variable is unordered).The last column shows on which level the variable is measured.

4. Methodology

In this study several analyses are applied in order to test the effect of the potential predictors on the LTC delivery choice. First, the effect of individual and regional variables on choosing either institutional care or homecare (i.e. PGB, VPT and MPT together) is investigated by performing both the traditional logistic regressions and multilevel logistic regressions. From the former, the effects of certain variables at the level of the municipality and health office region can be derived. The latter then accounts for the clustered structure of the dataset and disentangles variability at different levels. From this latter analysis, the directions of the effects of individual variables are derived and the importance of the municipality and the health office region is determined. Variables at the level of the municipality and health office region were not added to the multilevel model as Stata was not able to produce the results of that complex model. Thereafter, multinomial logistic regressions investigate whether the variables also have an effect on a specific LTC delivery alternative (i.e. on either PGB, VPT, MPT or institutional care). Lastly, a sensitivity analysis is conducted in order to investigate the importance of the care intensity package and the robustness of the effects of the individual characteristics, the municipality and the health office region after controlling for ZZP.

4.1 (Multilevel) logistic regression

A logit model is applied to estimate the effect of individual and regional variables on the dichotomous dependent variable that represents either choosing institutional care or homecare. This model treats the probability of choosing institutional care as a function of individual and regional factors. In this type of model, the regional variables are considered as though they represent an inherent characteristic of the individual. However, by assuming that regional factors are relevant predictors of the LTC delivery choice, it could be stated that individuals in a particular regions are likely to make more similar LTC delivery choices than would be predicted by chance. This is also reflected by the uneven regional distribution of the utilization of the LTC delivery alternatives. For these reasons, this study supposes that the applied dataset has a clustered structure, which the traditional logit model does not account for. As a result, this model is likely to violate the assumption of independence. Hence, the standard errors will be underestimated, the Type I error rate will be too high and the statistics significance overestimated. This is referred to as atomistic fallacy, which should be avoided (Douglas, 2004).

Alternatively, the clustered dataset could be analyzed by aggregating the micro-level variables to the regional level. However, this discards all within-group variation, causing conclusions about individuals to be derived from regional estimates instead of individual estimates. This so called ecological fallacy reduces the efficiency of the estimators. Besides, the power of this analyzes is low because the

number of clusters is generally small. This increases the Type II error rate (Hedeker, Gibbons, & Flay, 1994).

Another model that accounts for the clustered structure of the data is a model that includes dummy variables for clusters (Snijders & Bosker, 2015). Because these effects are assumed to be fixed, this type of model is generally used when inference should only focus on the included groups. This often implies that the number of clusters is small, which is not the case in this study. In fact, in the Netherlands there are 393 different municipalities and 32 health office regions. As a result, this fixed effect model would estimate the effect of each single municipality and health office region. This makes it hard to determine the overall effect of municipalities and health office regions on the LTC delivery choice. Moreover, this model does not account for the fact that municipalities are clustered within health office regions.

In order to solve these problems, this study utilizes the random effect model. In this type of model, random components of cluster effects are included in the statistical model. Consequently, outcomes at the individual level are predicted by individual and cluster-level variables while simultaneously adjusting for the dependency between individuals in municipalities and municipalities in health office regions. This eliminates the presence of atomistic fallacy and ecological fallacy and disentangles the variability at various levels.

Data clustered at multiple levels is generally referred to as multilevel data and the random effect model as a multilevel model (Hedeker, Gibbons, & Flay, 1994). There exist three alternatives to the multilevel model. Figure 3 illustrates respectively the random intercept model, random slope model and the random intercept and slope model. As the figure shows, level-2 variables are assumed to have a direct impact on the dependent variable in the random intercept model. In the second model instead, level-2 variables influence the relationship between the micro-level variables and the dependent variable. The last model is a combination of these two.

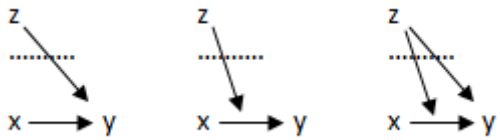

Figure 3: three alternatives to the random-effect model; respectively the random intercept model, random slope model and the random intercept and slope model.

This study assumes that regional variables only have a direct impact on the dependent variable. In other words, the relationships between age, gender, partnership, income and assets and LTC delivery alternative are assumed not to differ across regions. The next section therefore only elaborates on the random intercept model.

4.1.1 Random intercept model

In the simplest random intercept model, there are no explanatory variables. This model is equivalent to the random effects ANOVA model which examines the deviations of group means from the grand mean. Equation 3.4 shows the level-1 equation in its simplest form and equation 3.5 the level-2 equation. When the level-2 equation is plugged into the level-1 equation, a single equation arises as illustrated in equation 3.6.

$$Y_{ij} = \beta_{0j} + R_{ij} \quad (3.4)$$

$$\beta_{0j} = \gamma_{00} + U_{0j} \quad (3.5)$$

$$Y_{ij} = \gamma_{00} + U_{0j} + R_{ij} \quad (3.6)$$

where Y_{ij} is the dependent variable, β_{0j} is the intercept which represents the mean of each group, and R_{ij} is the residual or error. On the regional level, γ_{00} is intercept. This can be interpreted as the grand mean or the mean of the means of all regions. U_{0j} is the level-2 error which illustrates the deviation of each region's mean from the grand mean.

When adding individual-level predictors to the level-1 equation (3.4), the simplest random intercept model is extended. This will reduce the within-group error variance, as some of the 'unexplained' variance might now be explained by the added predictors. Moreover, confounds might be eliminated. Considering the scope of this study, it has been decided not to include regional-level predictors to the level-2 equation. Equation 3.7 illustrates the simplest random intercept model extended by one individual-level predictor (x_{ij}).

$$Y_{ij} = \gamma_{00} + \beta_1 x_{ij} + U_{0j} + R_{ij} \quad (3.7)$$

In the random intercept model, β_1 is equal across all municipalities. In other words, the slopes are assumed to be fixed and not varying. In contrast, intercepts vary across regions as level-2 errors (U_{0j}) are random variables. This error-term indicates the extent to which the mean of the region differs from the grand mean. The model assumes U_{0j} to be independent, normally distributed with mean zero and to have variance τ^2. By adding the micro-level variance (σ^2) to this level-2 variance, the total variance of the dependent variables Y_{ij} is calculated. Figure 4 visualizes the random intercept model.

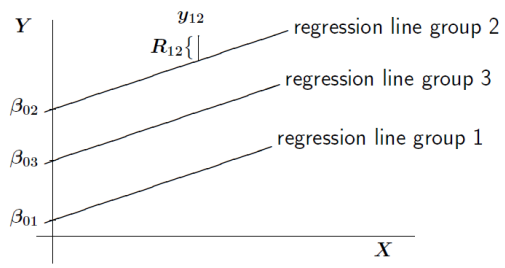

Figure 4: visualization of random intercept model (Snijders & Bosker, 2015).

4.2 Multinomial logistic regression

In the second part of the analysis, multinomial logistic (MNL) regressions are used to predict the probability of choosing either PGB, VPT, MPT or institutional care given a set of independent variables. MNL regressions apply when the dependent variable is nominal and consists of more than two possible discrete outcomes, which is clearly the case in this study. From these results, it could be determined whether the effects on choosing homecare are masking an effect on specific homecare alternative(s). No multilevel multinomial logistic regressions are estimated because Stata produces rather complex models from which no clear inference could be derived within the scope of this study.

Equation 3.1 illustrates the probability π_{ij} for individual *i* to choose LTC delivery alternative *j*:

$$Pr[Yi = j] = \pi_{ij} \tag{3.1}$$

Generally, the MNL regression takes the category which includes the highest amount of observations as the reference category (J). Subsequently, this category is compared to all other categories by computing the odds $\frac{\pi ij}{\pi iJ}$ for all *j*={ I,…,J-1). In words, the odds ratio states the probability that a particular alternative is chosen, divided by the probability that the reference alternative is chosen. As a result, there are 3 coefficients for each explanatory variable.

The MNL regression assumes the independent variables to be linearly related to the log odds, as defined in the following equation:

$$\log\frac{\pi ij}{\pi iJ} = \alpha_j + x_i\beta_j \tag{3.2}$$

where α_j is a constant, β_j is a vector for parameters for LTC delivery alternative *j* and x_i is a vector of independent variables for the *i*-th individual.

The exponential of equation 3.2 gives the probabilities $\pi_{ij.}$ Here the exponential of the coefficients of an explanatory variable states the percentage change of the probability of choosing alternative j relative to the probability of choosing the reference alternative when the independent variable changes by one unit (Heij et al., 2004).

$$\pi_{ij} = \frac{\exp(\alpha j + xi\beta j)}{\sum_{k=1}^{m}\exp(\alpha j + xi\beta j)}, for\ j = \{1,2,3,4\} \tag{3.3}$$

Alternatively, average marginal effects could be interpreted. This is less complicated in the multinomial case and will therefore be used in this study. Specifically, it shows the change in the

probability of choosing alternative *j* when an independent variable is increased by one unit and all other independent variables are set at their mean values.

4.3 Sensitivity analysis

As discussed in chapter 3, no information about the care intensity package is available in the combined dataset. Consequently, no correction can be made for the intensity of the needed care. However, as also motivated in the theoretical framework, this might be problematic as the effects of age and males who are living alone are expected to be confounded by the ZZP. Additionally, the effect of income could be influenced by ZZP because of its correlation with education. Lastly, regional differences might be explained by an uneven distribution of the presence of high ZZP's across regions. As ZZP is also expected to be related to the LTC delivery choice, omitted variable bias might arise.

In order to check the robustness of the results, a sensitivity analysis is performed within the ZZP dataset. MPT-users are not included in this dataset, so the effect of ZZP on the probability of using MPT cannot be identified. What is left is the effect of ZZP on choosing institutional care on the one hand or PGB and VPT on the other hand.

The impact that the inclusion of ZZP has on the effects of the individual characteristics and the variation explained by the municipality and the health office region is investigated by performing two multilevel models. The first model includes ZZP as an independent variable and the other model excludes ZZP. The coefficients and the significance levels produced by the extended model are then compared with the estimates of the other model. This analysis is conducted within both the elderly care and the different types of disabled care.

Individuals in need of elderly care get one out of seven different ZZP assigned. In contrast, individuals in need of disabled care are also categorized on basis of the exact disability they have. Specifically, as was illustrated in table 1, the disabled care consists of individuals with physical, mental or sensory disabilities. Within the mental disabilities a further distinction should be made between two levels of severity: individuals with a IQ between 50 and 70 (light mental disabilities) and individuals with a IQ lower than 50 (mental disabilities). Furthermore, within the group of individuals with sensory disabilities two conditions are distinguished: visual disabilities and auditory disabilities. Each of these five categories includes a different number of individuals and has a different number of ZZP's attached within the WLZ (table 8). For that reason, the effect of ZZP in the disabled care is analyzed by running logistic regressions in every disability category.

	Number of individuals	Number of ZZP's within the WLZ
Physical disabilities	234,883	5
Mental disabilities	71,390	6
Light mental disabilities	2,251	4
Auditory disabilities	846	3
Visual disabilities	1,206	4

Table 8: distributions of disabled individuals over the five groups of conditions.

5. Results

In this chapter the results regarding the effect of individual and regional variables on the LTC delivery choice are presented. In the first paragraph, the results of the traditional logistic regression model and the multilevel logistic regression model are shown. These models investigate the effects of the variables on choosing either institutional care or homecare. In the first model, variables at the municipality and regional level are included. The second model corrects for the clustered structure of the dataset. Although it does not include variables at the regional level, it does show the importance of the municipality and the region in explaining the LTC delivery choice. In the second paragraph, the multinomial logistic regressions are reported. These models investigate the effects on choosing either PGB, VPT, MPT or institutional care. In the last paragraph, the results of the sensitivity analysis within the ZZP-dataset are presented.

5.1 (Multilevel) logistic regression

Table 9 shows the average marginal effects of individual and regional variables on the probability of using institutional care. From this traditional logistic regression model, only the regional variables should be interpreted. In fact, these are not included in the multilevel model because of the errors reported by Stata. Nevertheless, as individual variables are actually included, their effects should be interpreted from the multilevel model. This improves the validity of the standard errors because multilevel models account for the clustered structure of the data. From the multilevel model, also the impact of living in a certain municipality and a certain region can be derived. The results of this model are presented in table 10 and 11 for respectively the elderly care and the disabled care.

The results presented in table 9 suggest that an increased distance to a hospital makes elderly LTC-users less likely to use institutional care. Hence, the fact that it can take rather long to go to a hospital when acute health problems appear does not stimulate individuals to move to an institution. Indeed, it seems to even discourage the use of institutional care. Next, it shows that an increased number of different institutional care providers in a health office region decreases the probability of

using institutional care in the disabled care. Thus, institutional care utilization is limited in regions where individuals have a relatively large choice between institutional care providers. This might be because these institutional care providers are all very small so that the total supply of institutional beds is in fact limited in that region.

Above stated results should be interpreted with care because the ordinal logistic regression treats the regional variables as though they represent an inherent characteristic of the individual, which is clearly not the case. This assumption is not made in the multilevel model, which will be discussed next.

	Elderly care (A)		Disabled care (B)	
	dy/dx	Sig.	dy/dx	Sig.
Age	.0036	0.000	.0071	0.000
Male	.0416	0.000	-.0181	0.002
Partner	-.0085	0.007	-.4398	0.000
Male without partner	-.0166	0.001	-	-
Income	-.0014	0.000	-.0019	0.000
Assets	.0001	0.000	.0001	0.103
Population density	-.0005	0.168	-.0001	0.888
Homeowner	-.0501	0.228	-	-
Distance to hospital	-.0015	0.016	-	-
Institutional care choice	.0010	0.247	-.0076	0.001

Table 9: logistic regression model in the elderly care (A) and the disabled care (B). This table shows the average marginal effects and the significance level. The LTC delivery alternative institutional care is applied as the dependent variable. Note- income is measured as additional €500,- income, assets are measured as an additional €1000,- assets, population density is measured as an additional 100 individuals per km^2 and institutional care choice is measured as the number of different institutional care providers per 1000 LTC-users in the health care office region. Male without partner, homeowner and distance to hospital are not considered in the disabled care.

The main results derived from the multilevel models are as follows (table 10 and 11). First, it shows that age is positively related to the probability of using institutional care in both the elderly and the disabled care. This seems to suggest that individuals become less resistant to institutional care when they are getting older. However, this effect might also be confounded by the care intensity package as this variable is expected to be positively related to age as well as to the probability of using institutional care. Lastly, this result might reflect a so-called cohort effect. In fact, the high current average age within the institutional care is could reflect the high proportion of institutional care users among the older generations. In the disabled care, the positive association between age and institutional care use might also be caused by the fact that younger disabled individuals are generally cared for by their parents which reduces the need for institutionalization.

Secondly, having a partner reduces the probability of using institutional care in the elderly care and the disabled care. Hence, having a supporting environment makes it more likely that somebody

receives LTC at home. In the elderly care, the negative effect of having a partner is even more negative for males than for females, as implied by the negative sign of the interaction term. This means that males without partners are the most likely to receive their care at home. They might be cared for by their children or other relatives, of which no information is available. Alternatively, these individuals might simply have less severe disabilities.

Thirdly, income is negatively related to the utilization of institutional care. Thus, elderly and disabled individuals with a higher income are less inclined to move to an intramural setting. Rich elderly might be deterred by the absolute copayment and/or the reduction in their current living conditions associated with the onset on institutional care. Alternatively, the wealthy elderly are generally better educated and therefore less likely to have severe disabilities and more likely to understand the alternatives they have. In the disabled care, the educations and living conditions of the disabled individuals are expected to play only a limited role because most disabled individuals will be low educated and will not have created high standards of living by themselves. Instead, the educations and livings conditions of their parents are expected to be relevant, but this is assumed to be not reflected in the individual's level of income. Hence, the negative effect of income on the probability of using institutional care tends to reflect the high copayment rich individuals have to pay for institutional care in particular.

Lastly, it shows that both the average variation of the health office region from the grand mean and the average variation of the municipalities from the regional mean are significantly different from zero in the elderly care (table 10). Hence, the LTC delivery decision of the elderly is not only impacted by the health office region in which they live, but also by the specific municipality in that health office region. In the disabled care, the average variance of the regions' means from the grand mean is also significantly different from zero (table 11). Hence, it seems that disabled individuals in one health office region make structurally different choices than disabled individuals in another health office region. The municipality level is not considered here because, as motivated before, one cannot assume that disabled individuals are still living in the same municipality as in which they made their LTC delivery choice. However, although there has been corrected for several individual characteristics, no correction is made for the distribution of care intensity packages across the regions. In other words, it could be that the regional differences in the use of institutional care is simply appearing because one region has relatively more individuals with severe diseases than another region. This is going to be checked in the sensitivity analysis.

	Elderly care		
Fixed effects	**Coef.**	**[95% CI]**	
Age	0.0036	0.0389	0.0427
Male	0.0457	0.4381	0.6093
Partner	-0.0092	-0.1707	-0.0389
Male without partner	-0.0162	-0.2849	-0.0852
Income	-0.0014	-0.1645	-0.0151
Assets	0.0001	0.0008	0.0010
Constant	-0.7840	-0.9495	-0.6186
Random effects	**σ^2**	**[95% CI]**	
Health office region	0.0887	0.0274	0.2870
Municipality	0.0172	0.0024	0.1235

Table 10: multilevel logistic regression model within the elderly care. In the upper part the average marginal effects and the significance levels of the fixed effects are presented. In the lower part, the random effects are presented. The LTC delivery alternative institutional care is applied as the dependent variable. Income is measured as additional €500 income, assets are measured as an additional €1000 assets.

	Disabled care		
Fixed effects	**Coef.**	**[95% CI]**	
Age	0.0071	.0411	.0435
Male	-0.3561	-2.2115	-2.0493
Partner	-0.0178	-.1416	-.0714
Income	-0.0019	-.0125	-.0104
Assets	0.0001	.0001	.0006
Constant	-.3655	-.4156	-.3154
Random effects	**σ^2**	**[95% CI]**	
Health office region	.2770861	.0940	.8171

Table 11: multilevel logistic regression model within the disabled care. In the upper part the average marginal effects and their significances of the fixed effects are presented. In the lower part, the random effect is presented. The LTC delivery alternative institutional care is used as the dependent variable. Income is measured as additional €500 income; assets are measured as an additional €1000 assets.

5.2 Multinomial regression analyses

Table 12 and 13 show the average marginal effects of the multinomial regression analyses within respectively the elderly and disabled care. The models analyze the effect of the individual and regional variables on choosing PGB, VPT, MPT or institutional care. The main findings are as follows.

First, the negative effect of age on the probability of using homecare is driven by the negative effect of age on MPT and PGB in the elderly care. Hence, although the positive effect of age on VPT is only small, it could be stated that younger individuals are reluctant to both the use of VPT and the use of institutional care. This might be because VPT is most similar to institutional care as VPT is delivered by only one institutional care provider.

In the disabled care, the negative effect of age on PGB is the main driver behind the negative effect of age on using homecare. Thus, age is not an important predictor of the utilization of VPT and MPT. This might be because these two homecare alternatives do not allow parents to get paid for the care-giving activities they perform. Instead, PGB does have this option. Moreover, the parents of these younger individuals could control the administrative side of the PGB, which makes PGB more appealing to younger individuals.

Secondly, having a partner has the largest positive effect on the utilization of PGB in the elderly care and the disabled care. Again, this might be because the PGB could be applied to pay partners and because these partners might manage the organization of the LTC. In the elderly care, having a partner turns out to influence the use of MPT and institutional care negatively. Hence, these alternatives are more frequently used by individuals without partner. The effect on MPT might arise from the fact that this alternative is frequently used by individuals waiting for an institutional bed to come available (Pansier-Mast, Veldhuis, & Welling, 2012). Hence, these individuals have actually decided to use institutional care but are not yet able to use this alternative.

Thirdly, the level of income is not able to differentiate individuals across the three homecare alternatives (i.e. PGB, VPT and MPT) in the elderly care. In other words, the level of income mainly differs between the homecare users and the institutional care users. In the disabled care, the level of income does not have a significant impact on the probability of choosing VPT or PGB. Indeed, it seems that the disabled individuals with the highest incomes are deterred by the relatively high co-payment for institutional care. They seem to prefer the alternative for which the lowest average copayment is required: MPT.

	MPT		**PGB**		**VPT**		**Institutional care**	
	dy/dx	Sig.	dy/dx	Sig.	dy/dx	Sig.	dy/dx	Sig.
Age	-.0025	0.000	-.0010	0.000	.0002	0.009	.0034	0.000
Male	-.0327	0.000	-.0072	0.000	-.0049	0.000	.0448	0.000
Partner	-.0081	0.000	.0161	0.000	-.0021	0.159	-.010	0.002
Male without partner	.0126	0.001	.0015	0.553	.0061	0.000	-.0202	0.000
Income	.0009	0.000	.0004	0.000	.0001	0.000	-.0014	0.000
Assets	-.0009	0.000	-0.000	0.252	-0.000	0.366	.0001	0.000
Population density	.0002	0.598	.0001	0.274	.0002	0.117	-.0005	0.157
Homeowner	-.0010	0.975	.0036	0.843	.0473	0.009	-.0500	0.228
Distance to hospital	.0010	0.040	.0008	0.010	-.0003	0.221	-.0014	0.020
Institutional care choice	-.0022	0.001	-.0001	0.809	.0010	0.036	.0011	0.188

Table 12: elderly care. This table shows the average marginal effects on the LTC delivery choice and the significance levels generated by multinomial logistic regression. Note- income is measured as additional €500,- income, assets are measured as an additional €1000,- assets, population density is measured as an additional 100 individuals per km^2 and institutional care choice is measured as the number of different institutional care providers per 1000 LTC-users in the health care office region.

	MPT		PGB		VPT		Institutional care	
	dy/dx	Sig.	dy/dx	Sig.	dy/dx	Sig.	dy/dx	Sig.
Age	0.0000	0.957	-0.0072	0.000	-0.0001	0.006	0.0073	0.000
Male	0.0215	0.000	-0.0045	0.357	0.0004	0.582	-0.0174	0.002
Partner	0.0080	0.017	0.4461	0.000	-0.0006	0.798	-0.4535	0.000
Income	0.0015	0.000	0.0001	0.527	0.0000	0.283	-0.0016	0.000
Assets	-0.0002	0.000	0.0001	0.023	0.0000	0.630	0.0001	0.044
Population density	0.0004	0.018	0.0005	0.628	0.0001	0.493	-0.000	0.997
Institutional care choice	0.0006	0.299	0.0058	0.011	0.0010	0.037	-0.0074	0.001

Table 13: disabled care. This model shows the average marginal effects on the LTC delivery choice and the significance levels generated by multinomial logistic regression*. Note- income is measured as additional €500,- income, assets are measured as an additional €1000,- assets, population density is measured as an additional 100 individuals per km^2 and institutional care choice is measured as the number of different institutional care providers per 1000 LTC-users in the health care office region.*

5.3 Sensitivity analysis

This sensitivity analyses investigates the impact of the intensity of the needed LTC on the LTC delivery choice and whether the results change after controlling for the care intensity package. The latter might for example be the case when ZZP relates significantly to both the LTC delivery choice and an individual characteristic. Besides, it might also be that regional differences in the utilization of the alternatives are explained by the distribution of ZZP's across regions. Table A1-A6 of the appendix show the results of the multilevel logistic regressions. The first column presents the results of the original model and the second column the results of the model that is extended with the independent variable ZZP. The main results are as follows.

Within the elderly care, having a higher ZZP increases the probability of using institutional care compared to having ZZP 4. Hence, individuals with more severe disabilities are more likely to move to an institutional setting. Additionally, table A1 shows that none of the effects of the original model loses significance or changes signs after controlling for ZZP. This implies that the exclusion of ZZP in the original model has not resulted in omitted variable bias in the elderly care.

Omitted variable bias seems not to arise in any types of the disabled care either. In fact, the coefficients and the significance levels hardly change after the inclusion of ZZP. For the individuals with mental and light mental disabilities, ZZP turns out to be an important predictor of the LTC delivery choice. Within these types of care, the needed care intensity is positively correlated with the probability of using institutional care. This makes intuitionally sense as homecare is less likely to suit individuals with severe disabilities. In contrast, against expectations, the ZZP of individuals with physical disabilities is negatively related to institutional care. This might be because a relatively large amount of MPT-users are entitled to the lower ZZP. As the MPT-users are not included in this analysis, the ratio of homecare users to institutional care users might be distorted across the ZZP's.

This would reduce the ratio for the lower ZZP relatively more. As no information is available about the care intensity packages of MPT-user, this statement cannot be verified.

Table A1-A7 also show that the average variation explained by the municipality and the health office region is still significantly different from zero after correcting for the care intensity package within every type of care. Hence, the regional differences do not seem to arisen due to a relatively large proportion of individuals with severe disabilities in certain regions.

6. Conclusion

This study investigates what the effects of individual and regional variables on the LTC delivery choice are. The hypotheses about the effects on choosing either institutional care or homecare are developed during brainstorm sessions with the policymakers of the Dutch Ministry of Health. In that process, Andersen's Behavioral Model acts as a guide to select relevant variables.

In order to test the hypotheses, this study starts with an analysis on the decision between institutional care and homecare. In that part of the analysis, multilevel logistic regressions account for the clustered structure of the dataset. In the second part of the study, the category homecare is broken down into the three underlying homecare alternatives, so that the LTC delivery choice could be investigated in more detail. By doing so, answers are found on the research question of this study: *Which individual and regional factors have a significant effect on the patient's choice between institutional care, personal budget, complete in-home package and homecare services in the Dutch system of long-term care?*

As illustrated in table 14, this study has established some of the hypothesized relationships (grey cells) between individual characteristics and the LTC delivery choice and rejected others (blank cells). The main results are as follows. First, in line with de Meijer et al. (2015) and the expectations of the policymakers, this study finds that age relates positively to the probability of using institutional care. Initially, this effect was expected to be confounded by the care intensity package. However, although the ZZP turns out to have a significant effect on the LTC delivery choice, the sensitivity analysis shows that the impact of age does not change substantially after controlling for the ZZP. Additional explanations for the effect of age could then be found in an appearing cohort effect or a reduced resistance against institutional care when one is getting older.

In the disabled care, the negative effect of age and the positive effect of having a partner on the probability of using homecare are mainly driven by the impact of these variables on one LTC delivery alternative: PGB. This similarity might arise because both variables are proxies for a supporting

environment. In fact, young individuals are more likely to still have their parents. As well as partners, these parents can take care of the disabled individuals. The PGB then allows them to financially compensate the time spend on care-giving activities. Moreover, having a supporting environment enables PGB as these relatives can take care of the administrative side of the PGB.

In line with the expectations, income turns out to be negatively associated with the use of institutional care in both the elderly and disabled care. In the elderly care, this is driven by a positive effect of income on all the homecare alternatives. Hence, income level seems to differentiate PGB, VPT and MPT-users from institutional care users. This it could be due to high copayment rich individuals have to pay for institutional care or due to the positive relation between living standards, education and income. In the disabled care, the positive effect of income on choosing homecare is mainly driven by the preference of rich people for MPT. Here the effect of income is expected to show the effect of the income-related copayment in particular.

Next to the individual variables, also the region and the municipality in which the individual lives influence the LTC delivery decision in the elderly care. Even after correcting for the differences in the severity of the disabilities. However, the level of urbanity, distance to hospital and the number of different institutional care providers in a region were not able to explain the regional differences within the design of the current study. One could then argue that these differences are mainly supply driven. In other words, it could be stated that these arise because the supply of the alternatives is unevenly distributed across the regions. Future research should confirm this. For that, accurate information about the locations of institutions needs to come available. If the regional differences are not (solely) driven by supply, (additional) explanations could be found in cultural and/or religious differences or different policies across health offices.

As the Long-term Care Act has just been implemented, information about the choices individuals make after they got entitled to LTC under this act is only scarce. The insights generated during the current study increases the understanding of the LTC delivery choice and helps policymakers interpreting any future developments in the utilization of the alternatives. Additionally, the new knowledge about the relevance of both individual and regional variables could be used to build future policy upon. For example, this information could be used to steer individuals into a certain LTC delivery alternative, might that become a policy goal in the future. The height of copayments might then be applied as a policy instrument, which could make a LTC delivery alternative more or less attractive for a certain group of individuals.

Limitations of this study are as follows. First, cross-sectional data has been employed. As a consequence, associations between determinants and the LTC delivery choice are only quantified at

a given point in time. Panel data would make it possible to investigate the change in the determinants and the change in the association between the determinants and the LTC delivery choice over time. This will benefit the predictions of future developments in the LTC delivery choice. Additionally, panel data would make it possible to disentangle the pure effect of age from the cohort effect. Second, this study has only shortly touched upon the concept of multilevel modeling. However, as can be derived from the results, regional variables really seem to influence the LTC delivery choice. This makes it rather likely that the dataset has a clustered structure. Future research should therefore improve the way the LTC delivery decision is modeled by also adding regional factors to the multilevel model and/or also considering slopes to vary across regions. For this extended model, more accurate relationships can be derived. Lastly, this study has not tested all potentially relevant variables of Andersen' Behavioral Model. For example, no micro data about the education and livings standards was available. As a consequence, it is not clear due to which underlying mechanism income is negatively related to the probability of institutional care.

The results of this paper provide quantitative evidence for the hypothesized predictors of the LTC delivery choice. Due to the very extensive dataset of CAK, the reliability of the results is high. This study concludes that both individual as regional variables are important predictors of the LTC delivery choice. Moreover it shows that useful information is discarded when the homecare alternatives are merged into one category. These results act as a starting point for a new field of research that will explore the reasons for the utilization of a certain LTC delivery alternative.

	Findings	
Predictor	Elderly	Disabled
Predisposing		
Demographics		
Age	+	+
Male	+	-
Partner	-	-
Male without partner	-	x
Income	-	-
Assets	+	ns
Enabling		
Individual resources		
Homeowner	ns	x
Community resources		
Municipality	s	x
Health office region	s	s
Distance to hospital	-	x
Institutional care choice	+	-
Urbanity	ns	ns
Need		
Evaluated health		
Care Intensity package	+	+

Table 14: average marginal effects derived from the traditional logistic regressions and the multilevel logistic regressions in the elderly and disabled care. The grey cells indicate accepted hypotheses and the black cells indicate rejected hypotheses. +: positive relationship, -: negative relationship, ns: not significant s: significant relationship (when variable is unordered).

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Appendix

	Elderly care					
	Original model			Original model + ZZP		
Fixed effects	Coef.	Sig.		Coef.	Sig	
Age	.0240	0.000		.0326	0.000	
Male	.2953	0.000		.2710	0.000	
Partner	-.3731	0.000		-.3878	0.000	
Male without partner	-.1767	0.000		-.1845	0.007	
Income	-.0102	0.000		-.0103	0.000	
Assets	-.0000	0.571		-.0001	0.442	
Constant	1.3544	0.000		.3516	0.087	
ZZP						
5				.1320	0.109	
6				.5509	0.000	
7				1.2292	0.000	
8				.5459	0.000	
9				3.6270	0.000	
10				.8459	0.000	
Random effects	**σ^2**	**[95% CI]**		**σ^2**	**[95% CI]**	
Municipality	.0812	.0211	.3001	0.0799	0.0199	0.0289
Health office region	.0181	.0034	.1289	0.0169	0.021	0.1223

Table A1: sensitivity analysis for elderly. The table shows the coefficients and the significance levels of the fixed effects and the 95% confidence intervals of the random effects for both the original model and the extended model. These results are produced by a multilevel model. ZZP 4 is used as the reference category. Note- income is measured as additional €500,- income; assets are measured as an additional €1000,- assets.

	Physical disabilities					
	Original model			Original model + ZZP		
Fixed effects	Coef.	Sig.		Coef.	Sig.	
Age	.0361	0.000		.03829	0.000	
Male	.2705	0.000		.2501	0.000	
Partner	-1.5802	0.000		-1.5433	0.000	
Income	-.0081	0.000		-.0081	0.000	
Assets	-.0007	0.016		-.0008	0.011	
ZZP						
4				-.3255	0.005	
5				-.8034	0.000	
6				-.4538	0.000	
7				-.0252	0.851	
8						
9						
Constant	-.1235	0.000		0.0969	0.530	
Random effects	**σ^2**	**[95% CI]**		**σ^2**	**[95% CI]**	
Health office region	.1755	.0955	.3224	.1751	.0952	.3997

Table A2: sensitivity analysis for individuals with physical disabilities. The table shows the coefficients and the significance levels of the fixed effects and the 95% confidence interval of the random effect for both the original model and the extended model. These results are produced by a multilevel model. ZZP 2 is used as the reference category, because ZZP 3 is not covered by the WLZ. Note- income is measured as additional €500,- income; assets are measured as an additional €1000,- assets.

	Mental disabilities					
	Original model			Original model + ZZP		
Fixed effects	Coef.	Sig.		Coef.	Sig.	
Age	.0680	0.000		.0691	0.005	
Male	-.1425	0.005		-.1412	0.001	
Partner	-.8591	0.103		-.7144	0.140	
Income	.0043	0.000		.0048	0.000	
Assets	-.0000	0.316		.0000	0.263	
ZZP						
4				-.2957	0.001	
5				-.1272	0.194	
6				.3605	0.000	
7				1.957	0.228	
8				.6038	0.001	
Constant	-1.241	0.000		-1.5137	0.000	
Random effects	**σ^2**	**[95% CI]**		**σ^2**	**[95% CI]**	
Health office region	.3020	.1513	.6029	.2966	.1509	.5830

Table A3: sensitivity analysis for individuals with mental disabilities. The table shows the coefficients and the significance levels of the fixed effects and the 95% confidence interval of the random effect for both the original model and the extended model. These results are produced by a multilevel model. ZZP 3 is used as the reference category. Note- income is measured as additional €500,- income; assets are measured as an additional €1000,- assets.

	Light mental disabilities					
	Original model			Original model + ZZP		
Fixed effects	Coef.	Sig.		Coef.	Sig.	
Age	-.1659	0.002		-.1756	0.001	
Male	-.4161	0.018		-.4211	0.021	
Partner	-1.0350	0.282		-1.1103	0.254	
Income	-.0026	0.796		-.0002	0.982	
Assets	0.0000	0.462		0.0000	0.452	
ZZP						
2				.2219	0.684	
3				-.1177	0.826	
4				2.1337	0.002	
Constant	4.7154	0.000		4.7321	0.001	
Random effects	**σ^2**	**[95% CI]**		**σ^2**	**[95% CI]**	
Health office region	0.4529	.1827	1.1225	.5166	.2159	1.2360

Table A4: sensitivity analysis for individuals with light mental disabilities. The table shows the coefficients and the significance levels of the fixed effects and the 95% confidence interval of the random effect for both the original model and the extended model. These results are produced by a multilevel model. ZZP 1 is used as the reference category. Note- income is measured as additional €500,- income; assets are measured as an additional €1000,- assets.

	Auditory disabilities					
	Original model			Original model + ZZP		
Fixed effects	Coef.	Sig.		Coef.	Sig.	
Age	.0361	0.017		.0394	0.011	
Male	-.0001	0.462		.0150	0.389	
Partner	.0806	0.087		-.0260	0.089	
Income	-.0062	0.220		-.0082	0.176	
Assets	-.0048	0.554		.0046	0.586	
ZZP						
3				3 .3670	0.200	
4				4 .7295	0.120	
Constant	.4574	0.140		.0542	0.062	
Random effects	**σ^2**	**[95% CI]**		**σ^2**	**[95% CI]**	
Health office region	2.405	.8965	6.4495	2.4245	.8946	6.5710

Table A5: sensitivity analysis for individuals with auditory disabilities. The table shows the coefficients and the significance levels of the fixed effects and the 95% confidence interval of the random effect for both the original model and the extended model. These results are produced by a multilevel model. ZZP 2 is used as the reference category. Note- income is measured as additional €500,- income; assets are measured as an additional €1000,- assets.

	Visual disabilities					
	Original model			Original model + ZZP		
Fixed effects	Coef.	Sig.		Coef.	Sig.	
Age	.0145	0.039		.0147	0.020	
Male	.7957	0.017		.8082	0.015	
Partner	-2.1543	0.000		-2.1360	0.000	
Income	-.0103	0.182		-.0105	0.188	
Assets	.0055	0.980		.0049	0.740	
ZZP						
3				3.3604	0.417	
4				4.3560	0.593	
Constant	.6214	0.664		-.1737	0.054	
Random effects	**σ^2**	**[95% CI]**		**σ^2**	**[95% CI]**	
Health office region	3.8055	1.6633	8.7069	3.7917	1.6494	8.7163

Table A6: sensitivity analysis for individuals with visual disabilities. The table shows the coefficients and the significance levels of the fixed effects and the 95% confidence interval of the random effect for both the original model and the extended model. These results are produced by a multilevel model. ZZP 2 is used as the reference category. Note- income is measured as additional €500,- income; assets are measured as an additional €1000,- assets.