Year: 2024

Three Essays on Modeling Long-Term Care of Institutionalized Elderly in Switzerland

SHEMENDYUK Aleksandr

UNIL | Université de Lausanne

FACULTÉ DES HAUTES ÉTUDES COMMERCIALES

DÉPARTEMENT DE SCIENCES ACTUARIELLES

Three Essays on Modeling Long-Term Care of Institutionalized Elderly in Switzerland

THÈSE DE DOCTORAT

présentée à la

Faculté des Hautes Études Commerciales
de l'Université de Lausanne

pour l'obtention du grade de

Doctorat en sciences actuarielles

par

Aleksandr SHEMENDYUK

Directeur de thèse
Prof. Joël Wagner

Jury
Prof. Boris Nikolov, président
Prof. Hansjoerg Albrecher, expert interne
Prof. Michel Vellekoop, expert externe

LAUSANNE
2024

UNIL | Université de Lausanne

FACULTÉ DES HAUTES ÉTUDES COMMERCIALES

DÉPARTEMENT DE SCIENCES ACTUARIELLES

Three Essays on Modeling Long-Term Care of Institutionalized Elderly in Switzerland

THÈSE DE DOCTORAT

présentée à la

Faculté des Hautes Études Commerciales
de l'Université de Lausanne

pour l'obtention du grade de

Doctorat en sciences actuarielles

par

Aleksandr SHEMENDYUK

Directeur de thèse
Prof. Joël Wagner

Jury
Prof. Boris Nikolov, président
Prof. Hansjoerg Albrecher, expert interne
Prof. Michel Vellekoop, expert externe

LAUSANNE
2024

UNIL | Université de Lausanne
Faculté des hautes études commerciales
Internef - 261
CH-1015 Lausanne

IMPRIMATUR

La Faculté des hautes études commerciales de l'Université de Lausanne autorise l'impression de la thèse de doctorat rédigée par

Aleksandr SHEMENDYUK

intitulée

Three Essays on Modeling Long-Term Care of Institutionalized Elderly in Switzerland

sans se prononcer sur les opinions exprimées dans cette thèse.

Lausanne, le 26.06.2024

Professeure Marianne Schmid Mast, Doyenne

Members of the Thesis Committee

Professor Joël Wagner: Thesis supervisor, Full Professor at the Department of Actuarial Science, Faculty of Business and Economics (HEC Lausanne), University of Lausanne and Swiss Finance Institute, Switzerland.

Professor Hansjoerg Albrecher: Internal expert, Full Professor at the Department of Actuarial Science, Faculty of Business and Economics (HEC Lausanne), University of Lausanne, Switzerland.

Professor Michel Vellekoop: External expert, Full Professor at Actuarial Sciences and Mathematical Finance, Faculty of Economics and Business, University of Amsterdam, Netherlands.

Professor Boris Nikolov: Jury president, Full Professor at the Department of Finance, Faculty of Business and Economics (HEC Lausanne), University of Lausanne, Switzerland.

University of Lausanne
Faculty of Business and Economics

PhD in Actuarial Science

I hereby certify that I have examined the doctoral thesis of

Aleksandr SHEMENDYUK

and have found it to meet the requirements for a doctoral thesis.
All revisions that I or committee members
made during the doctoral colloquium
have been addressed to my entire satisfaction.

Signature: ____________________ Date: 03.06.2024

Prof. Joël WAGNER
Thesis supervisor

University of Lausanne
Faculty of Business and Economics

PhD in Actuarial Science

I hereby certify that I have examined the doctoral thesis of

Aleksandr SHEMENDYUK

and have found it to meet the requirements for a doctoral thesis.
All revisions that I or committee members
made during the doctoral colloquium
have been addressed to my entire satisfaction.

Signature: Date: 5. 6. 2025

Prof. Hansjörg ALBRECHER
Internal expert

University of Lausanne
Faculty of Business and Economics

PhD in Actuarial Science

I hereby certify that I have examined the doctoral thesis of

Aleksandr SHEMENDYUK

and have found it to meet the requirements for a doctoral thesis.
All revisions that I or committee members
made during the doctoral colloquium
have been addressed to my entire satisfaction.

Signature: ______________________ Date: 3.6.2024

Prof. Michel VELLEKOOP
External expert

Acknowledgements

A special thanks to my supervisor, Joël Wagner, who conducted my research with wisdom and patience. His teachings about an academic paper's structure and proper story presentation have been essential to shaping my thesis. He demonstrated high clarity, precision, and professionalism in our work, allowing me to learn and implement this mindset into my life.

Thanks to Hansjoerg Albrecher for organizing and accompanying to numerous conferences and events, which set the stage for discussions and exchanges on my research topic. I would also like to thank Michel Fuino for his significant help in getting me started on this work. His assistance in translating all the documentation concerning the data from French and his introduction to the modeling of LTC made it possible. I am also grateful to Martin Bladt, who took the time to explain survival modeling to me. His guidance on how to be quick and efficient in the academic world has been more than valuable in my development as a researcher.

I thank Professor Enkelejd Hashorva, who was always welcoming and kind during the initial period of my stay. Thanks to his support, I adapted and settled into my new environment. Cosimo and Virginia Picci have been supportive with their recommendations, guidance, and direct pieces of advice during the adaptation to Swiss life. Many thanks go to Olga Marksa and Finbarr Murphy for supporting my stay in Switzerland and helping me many times with various problems. Your help was the foundation of my successful journey here.

I am glad to have worked together with the Department of Operations: Valerie Chavez, Marc-Olivier Boldi, Fabien Baeriswyl, Samuel Orso, Thibault Vatter, and Laurent Vuillon. It has been a rewarding experience to work with such dedicated people.

Andrey Ugarte, my academic brother from the very first day of my PhD, with whom we shared many trips and whose never-ending support and energy were unmatched. To my Russian Gs, Nikolai Kriukov, Gregory Yasnovidov, and Pavel Ievlev, thank you for working and training together and deeply discussing mathematical riddles and problems. Your companionship and intellectual exchanges maintained me at a high physical and intellectual level. Dina Finger and Veronika Kalouguina, you are lovely Russian girls, and your presence has been delightful. Laura Aburto, a majestic and altruistic Mexican girl, who is always willing to help and provide support. Alaric Müller, Brandon Garcia Flores, and Sascha Günther, you have been absolute G's with whom to share the most significant travels and experiences in life.

I genuinely appreciate every one of you for making my PhD journey memorable and successful. Thank you for being supportive and helpful.

Summary

This thesis explores the intricate dynamics of long-term care for the elderly in institutional settings, addressing critical aspects of financing, planning, and optimizing care based on health factors. Using comprehensive longitudinal data from nursing homes in the canton of Geneva, Switzerland, the research models the burden of institutional care through multiple perspectives. Firstly, an accelerated failure time model and beta regression are used to assess the duration and intensity of care, respectively, revealing that while age and gender are significant, the underlying diseases and the number of different diagnoses primarily influence care duration. Simultaneously, care intensity is driven by individual levels of dependence and specific limitations. Secondly, applying a spectral clustering algorithm and multinomial logistic regression, the study identifies eight typical health profiles of institutionalized elderly. These profiles help understand the resource allocation and the need for specialized insurance products. Lastly, using a multi-state Markov model, the research analyzes transitions between different care states, illustrating significant variations in care trajectories and costs influenced by demographics, medical diagnoses, and initial care states. The findings highlight the necessity for advanced strategies in managing the financial burden of long-term care, emphasizing that females generally require longer periods with less intensive care, whereas severe conditions escalate quickly to intensive care and incur higher costs. Overall, this thesis provides valuable insights for healthcare planning, infrastructure preparedness, and the design of targeted insurance products, ensuring that the evolving needs of the elderly population are met efficiently and sustainably.

Résumé

Cette thèse explore les dynamiques complexes des soins de longue durée pour les personnes âgées en milieu institutionnel, en abordant les aspects critiques du financement, de la planification et de l'optimisation des soins en fonction des facteurs de santé. En utilisant des données longitudinales complètes provenant des établissements médicaux-sociaux du canton de Genève, en Suisse, la recherche modélise la charge des soins institutionnels sous plusieurs angles. Premièrement, un modèle de temps de défaillance accéléré et une régression bêta sont utilisés pour évaluer respectivement la durée et l'intensité des soins, révélant que, bien que l'âge et le sexe soient significatifs, les maladies sous-jacentes et le nombre de diagnostics différents influencent principalement la durée des soins. Simultanément, l'intensité des soins est déterminée par les niveaux de dépendance individuels et les limitations spécifiques. Deuxièmement, en appliquant un algorithme de regroupement spectral et une régression logistique multinomiale, l'étude identifie huit profils de santé typiques des personnes âgées institutionnalisées. Ces profils aident à comprendre l'allocation des ressources et la nécessité de produits d'assurance spécialisés. Enfin, en utilisant un modèle de Markov à états multiples, la recherche analyse les transitions entre différents états de soins, illustrant des variations significatives dans les trajectoires de soins et les coûts influencés par les données démographiques, les diagnostics médicaux et les états de santé initiaux. Les résultats soulignent la nécessité de stratégies avancées pour gérer la charge financière des soins de longue durée, en mettant l'accent sur le fait que les femmes nécessitent généralement des périodes plus longues avec des soins moins intensifs, tandis que les conditions sévères évoluent rapidement vers des soins intensifs et entraînent des coûts plus élevés. Globalement, cette thèse fournit des informations précieuses pour la planification des soins de santé, la préparation des infrastructures et la conception de produits d'assurance ciblés, garantissant que les besoins évolutifs de la population âgée soient satisfaits de manière efficace et durable.

Contents

List of Figures

List of Tables

Chapter 1

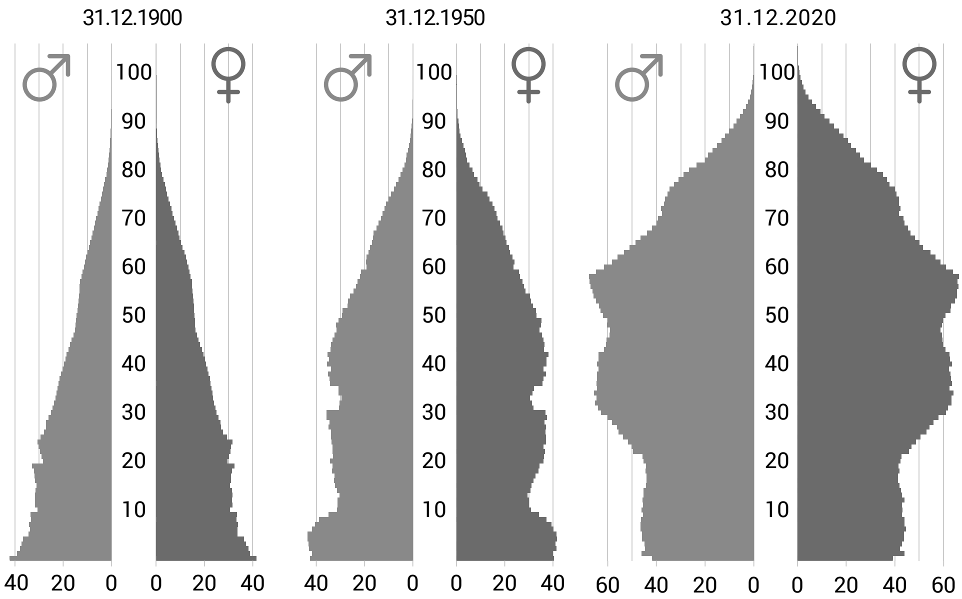
Introduction

The increasing longevity of populations around the world has brought the issue of long-term care (LTC) for the elderly to the forefront of public health and policy discussions. As life expectancy rises, so does the prevalence of chronic conditions and age-related disabilities, necessitating sustained and intensive care. This demographic shift poses significant challenges for LTC systems, which must adapt to meet the growing demand. In many countries, including Switzerland, the need for robust LTC frameworks has become more critical than ever. Effective LTC is essential not only for ensuring the quality of life of the elderly but also for managing the economic and social burdens associated with aging populations. This context highlights the necessity of developing innovative strategies for financing, planning, and delivering LTC services to meet the evolving needs of elderly individuals in institutional settings.

Demographic aging in Switzerland. This long-term process has shaped Switzerland's age structure for over a century and will continue to do so in the future. Rapid aging is expected between 2020 and 2030 as the baby boomer generation reaches retirement age. This shift is driven by several factors, including low fertility rates, reduced mortality, and increased life expectancy. Migration currently helps mitigate the aging effect, but its impact is not sufficient to counterbalance the overall trend. Additionally, rising divorce rates and changing lifestyles, such as the growing number of single parents and childless individuals, contribute to the increasing need for external LTC, as these demographic changes often result in fewer family members available to provide informal care.

Historically, Switzerland's age pyramid has undergone significant changes (Swiss Federal Statistical Office, 2022) as seen from Figure 1.1. In 1900, the pyramid had a broad base, indicating a high birth rate, and a narrow top, reflecting high infant and juvenile mortality. The proportion of individuals under 20 years old decreased from 40.7% in 1900 to 19.9% in 2020 and is projected to be 19.3% by 2050. Conversely, the proportion of people over 64 years old increased from 5.8% in 1900 to 18.8% in 2020, and it is expected to reach 25.6% by 2050. These figures illustrate a significant demographic shift that underscores the urgency of addressing the challenges of LTC for the aging population.

Several key factors contribute to the demographic aging observed in Switzerland (Swiss Federal Statistical Office, 2022). Firstly, the fertility rate has declined significantly, dropping from 3.7 children per woman at the beginning of the 20th century to 1.5 today, which is below the replacement threshold of 2.1. This decline reduces the proportion of young people, leading to



Note: Number of people in 1 000. Source: Swiss Federal Statistical Office (2023).

Figure 1.1: Swiss population pyramid by age and gender.

"aging at the bottom" of the age pyramid. Secondly, increased life expectancy has significantly contributed to "aging at the top" of the age pyramid. Life expectancy has risen dramatically from about 40 years in 1876 to over 80 years today, with current values at 81.0 years for men and 85.1 years for women. Projections suggest further increases by 2050, reaching 87.2 years for men and 89.6 years for women. Lastly, migration plays a significant role in shaping the age structure. Migrants, primarily aged 20-39, help replenish the working-age population. However, since 2015, there has been a noticeable increase in emigration among individuals over 60. While migration currently rejuvenates the population, its future impact may diminish due to the aging European population (Coleman, 2008). These aging factors collectively highlight the growing need for effective LTC strategies to support an increasing elderly population.

Overview of the thesis. The focus on institutional LTC is driven by the significant challenges it poses to financing, infrastructure, and professional caregiver availability, especially in the context of an aging population. Institutional LTC supports elderly individuals who require substantial assistance with activities of daily living, providing comprehensive care that integrates medical, personal, and social services in a single facility. This type of care is essential due to the increasing prevalence of age-related health problems and the need for organized support systems as life expectancy rises (Hirsch, 2005; Okma and Gusmano, 2020). The literature highlights the critical issues of financing (Kitchener et al., 2006; Brown and Finkelstein, 2009), availability of care facilities (Katz, 2011; Cosandey, 2016), and professional caregiver shortages (Nichols et al., 2010; Colombo et al., 2011), which underscore the urgency of effective planning and resource allocation.

This thesis is structured to address these complexities through three main chapters. The first chapter develops models to evaluate the duration and intensity of care required by elderly individuals, highlighting key health indicators that influence these factors. The second chapter identifies typical health profiles using clustering techniques and discusses how these profiles impact resource allocation and the need for specialized insurance products. The third chapter employs a multi-state Markov model to analyze the financial implications of different care paths, focusing on how demographic details and initial health conditions influence LTC costs. Together, these chapters provide a comprehensive examination of institutional LTC, offering insights for improving care strategies, planning infrastructure, and designing targeted insurance products to meet the evolving needs of the aging population.

In the first chapter (see Chapter 2), the objective is to model the duration and intensity of LTC for institutionalized elderly using comprehensive data from Geneva's nursing homes. The study utilizes a longitudinal dataset covering 21 758 individuals over a 22-year period, detailing medical diagnoses, levels of dependence, and physical and psychological impairments. To assess the overall burden of care, two key models are developed: an accelerated failure time (AFT) model with Weibull distribution to estimate the duration of stay in institutional care and a beta regression model to evaluate the weekly intensity of care provided to a person. The findings indicate that, beyond age and gender, underlying diseases significantly impact the duration of stay, with mental and osteoarticular conditions leading to longer stays, whereas tumor-related conditions result in shorter stays due to higher mortality rates. In terms of care intensity, dependence-related limitations, and physical and psychological impairments are the primary determinants. The study reveals that while pathologies affect care duration, they have a less pronounced effect on care intensity compared to limitations and impairments. Finally, the research highlights the significant differences in care needs based on proposed health profiles and underscores the importance of these factors for effective LTC planning and resource allocation in institutional LTC.

The second chapter (see Chapter 3) focuses on identifying typical health profiles of institutionalized elderly individuals using clustering and regression methods. Using the same dataset, the study applies a spectral clustering algorithm to categorize the health characteristics of these individuals. Subsequently, multinomial logistic regression is used to analyze the factors determining membership in these identified health profiles. The analysis reveals eight distinct health profiles, with the largest group comprising individuals with relatively high autonomy, resulting in a longer stay and less need for daily assistance. Conversely, the second largest group consists of individuals with severe health conditions who require substantial daily care. The study finds that gender does not significantly influence profile membership; rather, the combination of limitations and prevalent pathologies are the primary determinants.

The third chapter (see Chapter 4) utilizes a multi-state Markov model to analyze the transitions between different care states and the associated costs for elderly individuals within institutional LTC. By employing the same dataset, the study categorizes care levels into four broad categories, ranging from quasi-autonomy to severe dependency. The model incorporates fixed covariates at admission, such as demographic details, medical diagnoses, and levels of dependence, to forecast care state transitions and their costs. Key findings reveal significant variations in care trajectories and LTC costs across different health profiles. Females typically require longer periods of less intensive care, whereas conditions like severe and nervous diseases lead to quicker progression to intensive care and incur higher initial costs. The study highlights that individuals with cerebrovascular conditions experience slower transitions to severe states, eventually accumulating substantial costs, while those with tumors transition rapidly to death, resulting in lower overall costs due to shorter care durations.

Ideas for further research. While this thesis has uncovered many results regarding the modeling of LTC needs and costs for institutionalized elderly individuals, facilitating optimized resource allocation, and informing healthcare planning and insurance product design, there are some limitations and areas for further investigation. Future research could significantly benefit from incorporating time-varying covariates into the models used to predict transitions and costs in institutional LTC. Allowing variables such as health status, level of dependence, and medical conditions to change over time would offer more accurate dynamics of elderly care needs. Additionally, exploring joint modeling approaches where the evolution of care intensity directly influences survival probabilities could provide a more dynamic understanding of the development of LTC needs. Such models could uncover the interdependencies between care requirements and survival (Hsieh et al., 2006; Piulachs et al., 2015), leading to more effective care planning and potentially improving patient outcomes through more personalized and timely interventions in care strategies. Furthermore, combining the approaches of the second and third chapters, future research could investigate how individuals starting in a particular health profile evolve over time into other health profiles. By considering the eight identified health profiles and allowing for covariates to change over time, it would be possible to study the transitions between different health states. This could lead to a deeper understanding of the progression of health conditions in institutionalized elderly and inform more nuanced and effective care strategies, LTC policies, and insurance products.

Bibliography

Brown, J. R. and A. Finkelstein, 2009, The private market for long-term care insurance in the united states: A review of the evidence, *Journal of Risk and Insurance*, 76(1):5–29.

Coleman, D., 2008, The demographic effects of international migration in Europe, *Oxford Review of Economic Policy*, 24(3):452–476.

Colombo, F., A. Llena-Nozal, J. Mercier, and F. Tjadens, 2011, *Help Wanted? Providing and Paying for Long-Term Care.* OECD Health Policy Studies. OECD Publishing, Paris.

Cosandey, J., 2016, *De Nouvelles Mesures pour les Soins aux Personnes Âgées.* Avenir Suisse, Zurich, Switzerland.

Hirsch, D., 2005, *Facing the Cost of Long-term Care: Towards a Sustainable Funding System.* Joseph Rowntree Foundation.

Hsieh, F., Y.-K. Tseng, and J.-L. Wang, 2006, Joint Modeling of Survival and Longitudinal Data: Likelihood Approach Revisited, *Biometrics*, 62(4):1037–1043.

Katz, P. R., 2011, An International Perspective on Long Term Care: Focus on Nursing Homes, *Journal of the American Medical Directors Association*, 12(7):487–492.e1.

Kitchener, M., T. Ng, N. Miller, and C. Harrington, 2006, Institutional and Community—Based Long-Term Care, *Journal of Health & Social Policy*, 22(2):31–50.

Nichols, B. L., C. R. Davis, and D. R. Richardson, 2010, An Integrative Review of Global Nursing Workforce Issues., *Annual Review of Nursing Research*, 28:113–132.

Okma, K. and M. K. Gusmano, 2020, Aging, Pensions and Long-term Care: What, Why, Who, How? Comment on "Financing Long-term Care: Lessons From Japan", *International Journal of Health Policy and Management*, 9(5):218–221.

Piulachs, X., R. Alemany, M. Guillén, and C. Serrat, 2015, Joint Modeling of Health Care Usage and Longevity Uncertainty for an Insurance Portfolio, In J. Gil-Aluja, A. Terceño-Gómez, J. C. Ferrer-Comalat, J. M. Merigó-Lindahl, and S. Linares-Mustarós, Herausgeber, *Scientific Methods for the Treatment of Uncertainty in Social Sciences*, Seiten 289–297. Springer International Publishing, Cham.

Swiss Federal Statistical Office, 2022, *Portrait démographique de la Suisse.* 21764559. Federal Statistical Office (BFS), Neuchâtel.

Swiss Federal Statistical Office, 2023, Age structure of Switzerland, 1860 - 2050 - 1860-2050 | Diagram.

Chapter 2

Modelling the Burden of Long-Term Care for Institutionalised Elderly Based on Care Duration and Intensity

The financing of long-term care and the planning of care capacity are of increasing interest due to demographic changes and the ageing population in many countries. Since many care-intensive conditions begin to manifest at higher ages, a better understanding and assessment of the expected costs, required infrastructure, and number of qualified personnel are essential. To evaluate the overall burden of institutional care, we derive a model based on the duration of stay in dependence and the intensity of help provided to elderly individuals. This article aims to model both aspects using novel longitudinal data from nursing homes in the canton of Geneva in Switzerland. Our data contain comprehensive health and care information, including medical diagnoses, levels of dependence, and physical and psychological impairments on 21 758 individuals. We build an accelerated failure time model to study the influence of selected factors on the duration of care and a beta regression model to describe the intensity of care. We show that apart from age and gender, the duration of stay before death is mainly affected by the underlying diseases and the number of different diagnoses. Simultaneously, care intensity is driven by the individual level of dependence and specific limitations. Using both evaluations, we approximate the overall care severity for individual profiles. Our study sheds light on the relevant medical, physical and psychological health indicators that need to be accounted for, not only by care providers but also by policy-makers and insurers.

This is a joint work with M. Bladt, M. Fuino, and J. Wagner, published in Annals of Actuarial Science (2023), volume 17, number 1, pp. 83–117.

2.1 Introduction

Population ageing is one of the major challenges faced by the society of most developed countries. As longevity improves, pathologies and dependence that appear at higher ages put a strain on the old-age care systems, their organisation, and financial planning (Hirsch, 2005; Okma and Gusmano, 2020; Waitzberg et al., 2020). At higher ages, it is common that elderly individuals present difficulties in performing activities that are part of their daily lives (see, e.g., Fuino and Wagner, 2018; Vanella et al., 2020). In that sense, care delivered to maintain functional abilities is identified under the name of old-age long-term care (LTC). In most developed countries, the provision of care to elderly people, as well as its financing, are issues present in social policy discussions (Karlsson et al., 2006; Le Corre, 2012; Duell et al., 2019). Many studies have evidenced problems related to handling LTC needs (see, e.g., Pang and Warshawsky, 2010; Shao et al., 2015, 2019). As critical points, they specify that current schemes will soon face a lack of financing (Kitchener et al., 2006; Brown and Finkelstein, 2009), in available care infrastructure (Katz, 2011; Cosandey, 2016), and in professional caregivers (Nichols et al., 2010; Colombo et al., 2011). This stresses the relevance of proper planning and integrates the societal and political evolutions of the scope of handling LTC, both in institutions and at home. Therefore, the emergence of high demand for LTC requires evaluating the capacity of the infrastructure, in particular, the availability of beds and the number of qualified caregivers in specialised institutions. The total care needs set the target for the governments that are ultimately responsible for providing elderly individuals with decent care. Defining an appropriate monitoring for determining the amount of care required is fundamental. The estimation of the overall amount of care also is crucial to secure the financing of care, a concern that involves the government, the insurers and elderly individuals themselves.

In this paper, we study the factors that drive the total care burden of institutionalised elderly individuals. We express the overall burden in terms of the number of hours of care received while living in an institution. We call the *severity of care* the total number of hours. It can be modelled by multiplying the *duration of stay*, i.e., the time spent in dependence in an institution, with the *intensity of care*, i.e., the amount of help, expressed in time units, received per period. The duration of stay indicates the occupancy period of a bed in an LTC institution, while the intensity of care is associated with utilisation of medical and care resources, in particular, the number of minutes of help from nurses. We study both components and investigate the determinants that explain the duration and intensity. Building on longitudinal data, we first derive a model to estimate the number of months that elderly individuals stay in an institution. A second model evaluates the number of minutes of care that persons receive each week along the most influential covariates. Combining both peices of information, we evaluate the overall care severity per elderly individual for different profiles.

The overall burden or severity of LTC can be determined in several ways. On the one hand, the overall institutions' costs stem from the duration in dependence. In fact, factors including the health state, sociodemographic characteristics, and physical and psychological impairments determine the time spent in institutional care (see, e.g., Hedinger et al., 2015; Moore et al., 2019). Moreover, different family situations affect the duration of stay in the institution, as well as the amount of care provided; see, e.g., Pinquart and Sörensen (2011) and Mommaerts (2020). Mortality is another cause that shortens the duration. For example, patients with schizophrenia, mental disorders, tumours, and cognitive impairments suffer from higher mortality rates;

see Campbell et al. (1985), Davidson et al. (1988) and Pack (2009). On the other hand, measuring the LTC severity also requires a metric for the intensity of care delivered by professionals (Carrino et al., 2018). Indeed, cost analysis highlights that most expenses are devoted to the time that caregivers have to spend on each resident (Hu, 1986; Dorr et al., 2005) to such an extent that, within OECD countries, patient profiles are defined in relation to the minutes of care required (Muir, 2017). From a medical perspective, doctors evaluate LTC severity based on medical metrics such as the level of functional limitations and cognitive troubles. Many researchers state that mental and physical diseases can affect functional abilities and therefore entail LTC needs (Anderson et al., 1993; Guibert and Planchet, 2018; Fuino and Wagner, 2020). In this context, the most well-documented pathologies regarding LTC dependence are dementia and Alzheimer's (Arrighi et al., 2010; Koroukian et al., 2016; Farias et al., 2017), heart failure, and high blood pressure (Kuo et al., 2005; Sinclair et al., 2008; Lesman-Leegte et al., 2009), and to some extent cancer (Goodwin, 1991; Avis and Deimling, 2008; Chavan et al., 2017). Therefore, individuals' pathology profiles affect the severity of the dependence and lead to diverse health outcomes and mortality patterns (Tomas and Planchet, 2013; Albarrán et al., 2019; Jennings et al., 2020). Finally, from a patient perspective, becoming care dependent means a change in lifestyle that is difficult to accept. When moving into an institutional setup, lifestyle habits are drastically altered, and elderly individuals feel a loss of intimacy (Hyer et al., 2005). This is reflected in practice by the higher prevalence of depression syndromes among institutionalised elderly individuals (Boyle, 2005; Thakur and Blazer, 2008).

Our study is based on a longitudinal dataset covering the whole institutionalised population of the Geneva canton in Switzerland over a 22-year period, from 1996 to 2018. We build our analysis on the records of 21 758 individuals filled out using the Canadian monitoring method "PLAISIR". The method records a person's pathologies, physical limitations, psychological and sensory impairments, the amount of care provided, and further personal information such as gender, date of birth and date of death. Accounting for the right-censored nature of the data, we model the duration in institutional care using the survival approach, namely, an accelerated failure time model with Weibull distribution, while the intensity of care is modelled using a beta regression.

We find that, after age and gender, the pathologies are the key drivers of the duration of stay. However, despite significantly affecting the intensity of care, diseases do not affect the amount of care provided to elderly individuals as much as dependence-related limitations and physical and psychological impairments. The latter two are the key indicators to describe the intensity of care required by an elderly individual. In contrast, physical limitations are less relevant in describing the duration of stay in dependence. Introducing profiles that relate to different types of health conditions, we find that, in general, women come with the highest total care burden. Furthermore, we show that mental and osteoarticular diseases lead to the highest overall care severity, a finding that results from the higher duration of stay. In contrast, elderly individuals with tumours have the lowest overall care burden, which can be explained by the higher mortality rate, and thus a lower expected duration of stay. Finally, given that the variations in care intensity are relatively small in our data, we find that the overall care severity is mainly shaped by the duration of stay.

The remainder of this paper is organized as follows. In Section 2.2, we lay out the research framework: we review the financing and monitoring of LTC costs in Switzerland and discuss the literature on the variables associated with care duration and intensity. In Section 2.3, we introduce the available dataset, describe the variables, and present descriptive statistics. In Section 2.4 we introduce the model framework, including the accelerated failure time model that lays the basis for the duration analysis and the beta regression model used for the study of the intensity of care. We present and discuss the model results in Section 2.5. For selected profiles of elderly individuals, we evaluate how certain variables affect the overall care severity of an institutionalised elderly individuals. We conclude the paper in Section 2.6.

2.2 Research framework

Our objective is to model the total care burden in terms of the total number of hours of care an institutionalised elderly individual receives. Therefore, our model relies on the time spent in dependence, the amount of help received, and their respective determinants. On the one hand, the duration of stay defines the time of occupancy of a bed in an LTC institution. The contributions of the government directly relate to it, disregarding the specific pathology. On the other hand, the intensity of care relates to the usage of labour from nurses. It strongly depends on the medical condition of elderly individuals. Payments of health insurance are typically associated with the required number of minutes of care. Since our study uses data from Switzerland, we lay out the costs and the financing of the Swiss care system for elderly dependents in this section. Indeed, the costs are directly linked to the duration of stay and the intensity of care. In Section 2.2.1, we describe the organisation and cost monitoring of LTC institutions. In Section 2.2.2, we review the literature on the drivers influencing the care burden.

2.2.1 Financing and monitoring of LTC costs in Switzerland

Switzerland is a federal state consisting of 26 cantons distributed among the German, French and Italian linguistic regions. Rules for the care of elderly individuals and its financing are defined at both the federal and cantonal levels. The federal base framework is tailored along cantonal rules accounting for specific situations. In its broadest definition, LTC denotes care delivered to elderly individuals having difficulties performing daily life activities, often identified through the number of limitations in "activities of daily living" (ADL) and "instrumental activities of daily living" (IADL, see, e.g. Kempen et al., 1995). While this definition, at least in theory, appears valid in most developed countries (see, e.g., Fuino et al., 2020), getting an appropriate definition of LTC in practice is more controversial, in particular, when such a definition influences political and budget decisions and ultimately the amount of care provided and financed by insurers. While in countries such as the US, more than ten LTC systems are listed (Seematter-Bagnoud et al., 2012), LTC in Switzerland is either provided at home or in an institution. Furthermore, we observe three categories of curative LTC treatments: nursing, personal hygiene and ergotherapy (Home Care Association of the Canton of Vaud, 2020). While the first two categories relate to the ability to perform (I)ADL, the third category emphasizes the importance of social aspects beyond the ability to perform specific activities.

The financing of LTC relies on social health insurance, the state government and out-of-pocket payments by the dependent elderly individual. Swiss mandatory health insurance covers all costs defined by the health care benefits ordinance (Swiss Federal Department of Home Affairs, 2021). The contribution to the care costs is defined on a scale along the required number of minutes of care.[1] The state government also participates in funding LTC costs. All Swiss residents

[1]Contributions increase along a scale with 12 levels. The cover amounts to CHF 9.60 per day for up to 20 min-

aged 65+ years in need of LTC are eligible to receive an allowance regulated under the old-age and survivor's insurance law.[2] The predefined amount increases with the acuity level. The state government also indirectly participates in the financing of institutional care, e.g., by constructing new infrastructure and providing further means-tested allowances for those who cannot afford the costs. Finally, households are responsible for a set of noncovered care mostly related to accommodation expenses (lodging, feeding and laundry) in institutional care. Furthermore, since 2011 and to limit the increase in health insurance premiums, copayments of up to 20% of the costs are required from residents (Swiss Federal Social Insurance Office, 2010). In 2016, the overall monthly cost of a stay in a Swiss institution is estimated to be CHF 9 652 (Social Insurance and Accommodation Service of the Canton of Vaud, 2016).

The development of the elderly population in recent decades has increased LTC costs. Against this background, it is essential to assess the overall dynamic to predict the needs of nursing homes and qualified personnel in the future. Based on the findings from Donabedian (1973), an appropriate monitoring method for nursing homes accounts for three dimensions, namely, the patient health condition, the type of service required, and the resources needed (Roussel and Tilquin, 1993). Under these conditions, two types of monitoring have been implemented in Switzerland since the 1990s. The cantons of Vaud, Geneva, Neuchâtel and Jura have implemented the Canadian monitoring method "PLAISIR", which stands for *Planification Informatisée des Soins Infirmiers Requis*,[3] while the other cantons have implemented the American "Resource Utilization Groups" (RUG) monitoring method.[4] Even though significant differences appear in how data are gathered, the results of both methods remain comparable and allow the development of care plans based on estimates of the needs for nursing care and assistance. Indeed, the classifications are articulated around the patient health conditions, the type of care service required and the staff resources needed. Finally, we note that an assessment of the costs of care includes knowledge about the duration of stay and the intensity of care provided.

2.2.2 Review of the determinants of the duration of stay and intensity of care

In our modelling, we separately assess the time spent in dependence and the amount of help received per period. Both dimensions can be investigated through demographic variables and linked to medical diagnoses, the inability to perform (I)ADLs, limitations in physical and cognitive activities, and impairments of psychological and sensory functions. In the following, we discuss a selection of relevant variables outlined in the extant literature.

A vast amount of literature agrees that age and gender are both relevant determinants of the duration in dependency (see Mathers, 1996; Germain et al., 2016; Fong et al., 2017; Fuino and Wagner, 2020) and the intensity of care (see, e.g., de Meijer et al., 2011; Xue, 2011). For example, elderly individuals at high ages are more susceptible to developing multiple types of diseases (van den Akker et al., 1998) that lead to higher mortality rates (Menotti et al., 2001) and reduce the duration of stay in an institution. At the same time, Deeg et al. (2002) find that women have a higher life expectancy than men, regardless of the multimorbidity profile.

utes of daily care and increases by the same amount for each increment of 20 minutes up to a maximum contribution of CHF 115.20 for treatments exceeding 220 minutes per day.

[2]See `www.ahv-iv.ch/en/Social-insurances/Old-age-and-survivorss-insurance-OASI`.

[3]See the Commission intercantonale PLAISIR at `www.ctplaisir.ch`.

[4]See the Centers for Medicare & Medicaid Services at `www.cms.gov`.

Moreover, Rickayzen and Walsh (2002) observe that women are more likely than men to develop a higher dependency from external help across all ages and thus require a higher intensity of care.

The World Health Organization (1980) and the Medicine (1991) introduce the relationships among pathologies, impairments of organ systems and the resulting limitations or disabilities. In general, a disease causes certain organ malfunctions that result in a loss or abnormality of mental, emotional or physiological structures. Furthermore, these impairments lead to functional limitations, i.e., lack of ability to perform an action or activity in a manner considered normal, and overall disability, i.e., limitation in performing socially defined activities and roles. As a consequence, different pathologies affect both mortality and the dependence, directly affecting the duration of stay and the intensity of care, respectively. Furthermore, the influence of pathologies on LTC needs is widely studied by, e.g., Boult et al. (1994), Guccione et al. (1994), Tomiak et al. (2000), Pritchard (2006), Callahan et al. (2012), Biessy (2017) and Rudnytskyi and Wagner (2019). Finally, research suggests accounting for the number of diseases, i.e., multimorbidity (Marengoni et al., 2011; Barnett et al., 2012).

Geriatric syndromes are conditions commonly experienced by older individuals (see Inouye et al., 2007), including visual and hearing impairments, depressive symptoms, low cognitive performance, persistent dizziness or lightheadedness. Branch and Jette (1982) show that similar impairments do not significantly influence the decision to enter a nursing home. However, Koroukian et al. (2016) find that, when explaining the health status of a person, accounting for the co-occurrence of functional limitations and geriatric syndromes is more informative than considering chronic conditions alone. This means that impairments in psychological and sensory functions should add to the explanation of the duration of stay and the intensity of care. Further works on the influence of impairments, limitations, and disabilities and LTC needs are those of Branch and Jette (1982), Miller and Weissert (2000), Tomiak et al. (2000), Rickayzen and Walsh (2002), and de Meijer et al. (2011).

2.3 Data on institutional LTC and descriptive statistics

In the following, we describe the data used in our study. In Section 2.3.1, we provide information on the available data and define the variables used in the analysis. In Section 2.3.2, we report descriptive statistics on the duration of stay in LTC and care intensity. Exploratory data analysis allows us to substantiate the choice of the methodological approach for modelling.

2.3.1 Available data and description of variables

Our study is based on a private dataset containing observations on elderly individuals who have received institutional care in the canton of Geneva in Switzerland during the period from 1996 to 2018. The anonymous individual data stem from the evaluation tool used to assess the care needs (Republic and Canton of Geneva, General Directorate for Health, 2019). The data contain information on individuals, their medical diagnoses and comprehensive details on their limitations and impairments. Furthermore, it provides information on the date of entry into the care institution, the number of minutes of help provided each week and, if applicable, the date of death. For this study, we retain a set characterising 21 758 individuals, focusing on elderly individuals aged 65 years or older.[5] After entering an institution, every person passes an initial medical screening. Various tests examine the overall state of health, pathologies, and physical and mental health disorders. During an observation period, the intensity of care required by the person and expressed as the number of minutes of care per week is recorded. While such tests are typically repeated approximately every one to two years, we focus on the first evaluation made at entry. Of the available information (for the data collection methodology, see Roussel and Tilquin, 1993), and following the literature review in Section 2.2.2, we consider 19 key variables that characterize each record in our data (see Table 2.1).

Variable	Description	Values
Duration and intensity of care		
D	Duration of stay in the institution	positive (in months)
T	Intensity of care provided per week	positive from 0 to 10 080 (in minutes)
C	Right-censoring indicator	yes, no
Demographic variables		
AG	Age at entry in the institution	65, 66, 67, . . . years
GE	Gender	male, female
Medical diagnoses		
$D1$	Main diagnosis	mental, cerebrovascular, nervous, osteo-articular, heart, tumour, other problem
$D2$	Secondary diagnosis	see $D1$, plus "none"
ND	Number of additional diagnoses	0, 1, . . . , 7
Levels of dependence		
DP	Dependence in ADL	four levels: 1–6, 7, 8, 9
PM	Physical mobility limitations	five levels: 1–5, 6, 7, 8, 9
OR	Orientation problems	five levels: 1–4, 5, 6, 7, 8+
OC	Occupational limitations	five levels: 1–5, 6, 7, 8, 9
SI	Social integration limitations	five levels: 1–4, 5, 6, 7, 8+
Impairments of psychological and sensory functions		
RM	Recent memory impairment	adequate, mild, moderate, severe
PA	Perception and attention impairments	adequate, mild, moderate, severe
IM	Impairment in impulses	adequate, mild, moderate, severe
WM	Will and motivation impairment	adequate, mild, moderate, severe
BH	Behavioural impairment	adequate, mild, moderate, severe
VS	Visual impairment	adequate, mild, moderate, severe

Table 2.1: Description of the variables.

Duration and intensity of care. The original data contain the date of admission in the institution and the date of death if applicable. If the person died before the end of the observation period, the difference between the date of death and the date of entry allowed us to calculate the duration of stay D in months.[6] If the date of death was empty, the person was still alive at

[5]The set of data used in this study covers 93.3% of the original data retrieved from the evaluation tool. Thereby, we removed individuals who departed from the institution before death (3.82%), who were younger than 65 years (2.67%), or who presented empty records or corrupt data (0.21%).

[6]In approximately 20% of the records, typically, in older observations, our data do not include the exact date

the date of data extraction. In this case, we calculate the duration D as the difference between the date of entry and the latest date available in the dataset, which is August 21st, 2018. Additionally, we create a separate indicator variable C telling us if the person is alive or dead, i.e., indicating if the data are right-censored or not.

The intensity of care is recorded as the total number of minutes of care T provided to the person per week, i.e., a number between 0 and 10 080, where the upper bound corresponds to the total number of minutes in one week. This number includes the time of care given for respiratory help (respiratory exercises, chest physical therapy), eating and drinking (providing vitamins, verifying the diet), elimination (giving, removing, and emptying urinal, maintaining hygiene and skin integrity), hygiene (personal, hair and beauty care), mobility (pushing wheelchair, getting up or lying down), communication (supportive communication, teaching, group activities), medication needs, intravenous therapy, and other treatments (dressing wounds, blood pressure). The full list and descriptions are available from Roussel and Tilquin (1993).

Demographic variables. Using the date of birth and the date of admission, we calculate the age at entry into institution AG by taking the number of full years that have passed since birth until entry. In our data, the youngest age at entry is 65 years, while the oldest person has entered institutional care at the age of 106. Furthermore, information on the gender GE of the individual is available in the data. It is recorded as a binary factor with levels "male" and "female".

Medical diagnoses. Each observation carries information about the person's disorders. Individuals may have received several medical diagnoses and up to nine are recorded in the data. They are ranked by importance by a doctor. We label the most important ("first") diagnosis as $D1$ and explicitly consider one secondary diagnosis $D2$. The variable ND indicates the number of additional diagnoses beyond the first two. $D1$ and $D2$, with ND, allow us to account for the top two medical conditions and possible interactions, as well as to have information on the number of additional health problems that relate to the overall severity.

Diagnoses are encoded using the International Classification of Diseases.[7] We reduce the number of unique diagnoses by aggregating the diseases into six groups, namely, mental, cerebrovascular, nervous, osteoarticular, heart, and tumour diseases. All other diagnoses are grouped in a category labelled "other".[8] The main diagnosis $D1$ is a factor variable with seven levels. The

of death. In such cases, we rely on information on the period of the year when death has occurred. Indeed, the time of death is available through the period of the year coded through "January–March", "April–May", "June–August", "September–October", and "November–December". This information enables us to approximate the date of death and the duration of stay using the middle point of the period.

[7]See `www.who.int/standards/classifications/classification-of-diseases`. Since the data collection dates back to 1996, earlier diagnoses have been encoded using the old ICD-9 standard. Since 2007, the contemporary ICD-10 classification has been used. To avoid inconsistencies, we map all ICD-9 encodings into ICD-10 using the conversion table provided by the Centers for Medicare & Medicaid Services (2014).

[8]The group of mental diagnoses includes dementia, schizophrenia, depressive disorders, mental retardation, and neurotic disorders. Next, cerebrovascular diagnoses include subarachnoid or intracerebral heamorrhage, strokes, cerebral infarction and other sequelae of cerebrovascular diseases. The group of diagnoses labelled "nervous" include Alzheimer's disease, brain degeneration, epilepsy, extrapyramidal syndromes and movement disorders (e.g., Parkinson's disease), and sclerosis. Osteoarticular diagnoses consist of arthritis, scoliosis, osteochondritis, damage to cervical disks, deformation of the limbs, and osteoporosis. Heart diseases include hypertension, ischaemic heart diseases, myocardial infarction, cardiac arrhythmias, heart failure, diseases of the blood transportation system and others. The group of tumour diagnoses combines all types of tumours, e.g., breast tumours, digestive system tumours, skin tumours, and tumours of the respiratory organs. Finally, the group of other diagnoses comprises endocrine, nutritional, metabolic (including obesity and diabetes), and respiratory diseases.

secondary diagnosis $D2$ is a factor variable with eight levels since we include the possibility of no second diagnosis labelled "none". Note that the same disease group may appear several times, e.g., when a person has several disorders from the same disease group.

Level of dependence. The level of dependence is measured along five dimensions: limitations with ADL, physical mobility, orientation, occupation, and social integration. As with the World Health Organization (1980), the recorded limitations are measured on ordered nine-level scales, where each level corresponds to a particular severity. In Table 2.2, we describe the limitations for the different levels in each dimension (see also Roussel and Tilquin, 1993). Since individuals entering institutional care are mostly moderately or severely dependent, we observe very few records showing lower levels of dependence. Therefore, we aggregate the levels so that they constitute a share of at least approximately 10% to 15% of the data (see Table 2.1 and the descriptive statistics in Section 2.3.2). This allows for a lower number of categories in the further modelling. For example, for the social integration limitations variable SI, we consolidate the levels from 1 to 4 into "1–4", yielding 8.9% of the individuals.

Level	Dependence in ADL, DP	Physical mobility limitations, PM	Orientation problems, OR	Occupational limitations, OC	Social integration limitations, SI
1	Independence	Full mobility	Full orientation	Appropriate occupations	Socially integrated
2	Independence subject to mechanical assistance	Occasionally limited mobility	Fully compensated orientation problems	Intermittent occupations	Inhibited participation (discomfort, shyness)
3	Independence subject to adaptation of environment	Deficient mobility (slowness)	Intermittent orientation disturbances	Occup. limited in scope	Limited participation (type of social activities)
4	Predictable need for help in certain situations	Limited mobility in general	Partially compensated orientation disturbances	Adjusted occupations	Limited relations (only primary and secondary contacts)
5	Predictable need for help up to once a day	Limited to the neighbourhood	Moderate disturbances of orientation	Occup. limited in time	Poor relations (difficulties with secondary contacts)
6	Predictable need for help more than once a day	Limited to the institution	Severe disturbances of orientation	Occup. limited in type	Reduced relations (only primary contacts)
7	Unpredictable or quasi-permanent need for help	Limited to the floor	Deprivation of orientation	Occup. limited in time and type	Disturbed relations (difficulties with primary contacts)
8	Need for help with most ADL	Limited to the room	Disorientation	No occupation	Nonexistent social relations (no contacts due to incapacity)
9	Need for help with all ADL	No mobility (restricted to bed or chair)	Coma or vegetative state	Inappropriate occupations	Social isolation (cut off from the outside)

Table 2.2: Measurement of the level of dependence.

First, the level of dependence in ADL (DP) considers the physical dependence in performing ADL. It refers to the individual's ability to complete, independently, the basic ADL (e.g., personal hygiene, eating, dressing) and the IADL (e.g., housekeeping, cooking). The assessment of a person's abilities does not consider the institutional environment, i.e., it compares the individual's potential to perform (I)ADL to a usual healthy person of the same age and gender. Next, the variable PM measures the limitations of physical mobility, i.e., the ability to move effectively in the surroundings. The evaluation considers the independent use of mechanical aids (e.g., prosthesis, wheelchair, cane) but not the aid given by other persons. The principal indicator is the distance to which the person can move away from the bed or the chair. The capacity for orientation and interactions with the environment is coded in the variable OR. This concept includes the reception of signals from the environment, their assimilation and the formulation of a response. Living and occupations throughout the day are assessed through the limitations in time and type in OC. This concept refers to the person's ability to occupy the time in a manner customary for the age and gender group within the institutional environment. Here, all activities related to employment, recreation, education, creation and customary everyday tasks are included. The difference between the levels “no occupation” and “inappropriate occupations” stems from the ability to perform activities where the first refers to persons who are incapable of sustaining any form of activities, while the second refers to those who do activities without a defined goal. Finally, the social relations and their limitations are recorded in SI. This concept refers to the person’s ability to participate in social activities and maintain adequate social relations, considering life in an institutional setting.

Impairments of psychological and sensory functions. Roussel and Tilquin (1993) propose an ordered four-level scale, with the levels adequate, mild, moderate, and severe, to measure the severity of 16 psychological and sensory function impairments.[9] The evaluation considers any compensation used by the person (glasses, medication that corrects psychological impairments) and compares his or her performance to the average performance of a healthy individual of the same age and gender. For certain functions such as recent memory or sight, it is possible to describe precise definitions for the four levels. For other functions, the person’s state is assessed more qualitatively.

The impairments are closely related to the above-discussed medical diagnoses and levels of dependence. In the forthcoming models, we reduce complexity and keep only those impairments that help explain institutional LTC. Following our model selection (see Section 2.5), we retain six of the 16 impairments available in the data: Limitations in the recent or short-term memory RM refer to the individuals’ ability to store new information. The “adequate” level is assigned to those who have no memory problems, while “severe” refers to those who can name up to one of three objects mentioned or shown five minutes earlier. Perception and attention PA refers to the functions that allow an individual to receive information, process it, and concentrate on certain aspects. Impairments of perception include disturbances of the perception of one’s own body, time, place, hallucinations, and difficulties in differentiating fantasy from reality. Impairments of attention include inattentiveness, distractibility, and inability to change the focus of attention. Impairments in impulses or drives IM refers to the increase, decrease, and change of form of different behaviours related to basic physiological needs or instincts (e.g., anorexia, bulimia, dependence on alcohol or tobacco). Will and motivation impairments WM refer to disturbances in the ability to orient one’s behaviour, control one’s actions and pursue a goal. The evaluation considers, for example, a lack of initiative, overcompliance, excessive cooperation, and compulsion. Behavioural impairments BH refer to patterns of behaviour that interfere with social adjustment and functioning. These patterns may be present since adolescence and throughout adult life or may appear due to neurological or mental illness. They mainly manifest themselves as accentuated character traits (e.g., suspiciousness, excessive shyness, worrying, self-destruction, indecisiveness). Visual impairments VS refer to the person’s ability to see and are assessed considering corrected eyesight, for example, with eyeglasses. The “mild” level corresponds to a person who cannot read regular print but can read large prints. The “moderate” level person is unable to read but can follow an object with the eyes. Finally, the “severe” level relates to blindness.

[9] Recent memory, long-term memory, thinking (content, speed), perception and attention, consciousness and wakefulness, orientation (time/person/space), decision-making, impulses (drives), will and motivation, emotions (including feelings and mood), behaviour, language, sight, hearing, making self understood, and understanding others.

2.3.2 Descriptive statistics

In the following, we present the descriptive statistics for the duration of stay D and the intensity of care T. Recall that the available data cover a fixed period that terminates at the date of data extraction. The data include $n = 21\,758$ persons who entered a care institution: 17 919 (82.4%) of them died in the observation period, while 3 839 (17.6%) were still alive at the time of data extraction. Due to this right-censoring, we cannot directly calculate the mean duration of stay D, and thus, we use survival analysis techniques.

The standard way to obtain median estimates of the duration of stay D is to apply the Kaplan–Meier product-limit estimator, a nonparametric estimator based on the survival curve proposed by Kaplan and Meier (1958). Indeed, the Kaplan–Meier estimate allows for right-censoring and left truncation in seriatim data. To report the median duration of stay D_{med} across multiple factors, we apply Kaplan–Meier estimates on subsets of the data. In Table 2.3, we present the median duration of stay D_{med} and the mean intensity of care T_{avg} for the different variables' categories.[10]

Demographic variables. We divide the age at entry AG into six classes to illustrate the underlying distribution. We observe that the Kaplan–Meier estimates of the median duration of stay D_{med} are decreasing with the age at entry, which is due to increasing mortality rates at higher ages. At the same time, the mean intensity of care T_{avg} provided to the person fluctuates around the same value of approximately 16 hours per week. In groups of persons aged 100 years or more at entry, the intensity of care increases to 20.5 hours per week.

Most of the elderly individuals in our data are women. Men constitute just above a quarter (27.5%) of the data. We note that men stay dependent for a shorter amount of time than women, with their median duration being almost 15 months lower. Furthermore, men require on average 1.5 hours of care more per week. The prevalence and higher median duration of stay of women can be explained by their higher life expectancy; see, e.g., Mathers et al. (2001), Fong et al. (2017), Schünemann et al. (2017), and Fuino and Wagner (2018).

Medical diagnoses. Mental diagnoses are those with the highest prevalence in persons entering institutional care. While they rank first in the main diagnosis $D1$, mental ranks second in the secondary diagnosis $D2$, after the group of other diagnoses. Pathologies of the nervous system and heart problems also show a high prevalence in both the main and secondary diagnoses. We observed similar values for the median duration of stay across the different main diagnoses, except for persons with osteoarticular problems and tumours. Indeed, osteoarticular pathologies are associated with higher median durations of stay by more than half a year (total 44.8 months), while half of the tumour patients die after 8.7 months. In contrast, only the groups with cerebrovascular and nervous pathologies increased the mean intensity of care. Those with heart diseases as the main diagnosis require the least amount of help during the week. It is remarkable that if a person has one sole diagnosis, i.e., the secondary diagnosis $D2$ is "none", the median duration of stay in the institution almost doubles, being slightly above 5 years (62.2 months).

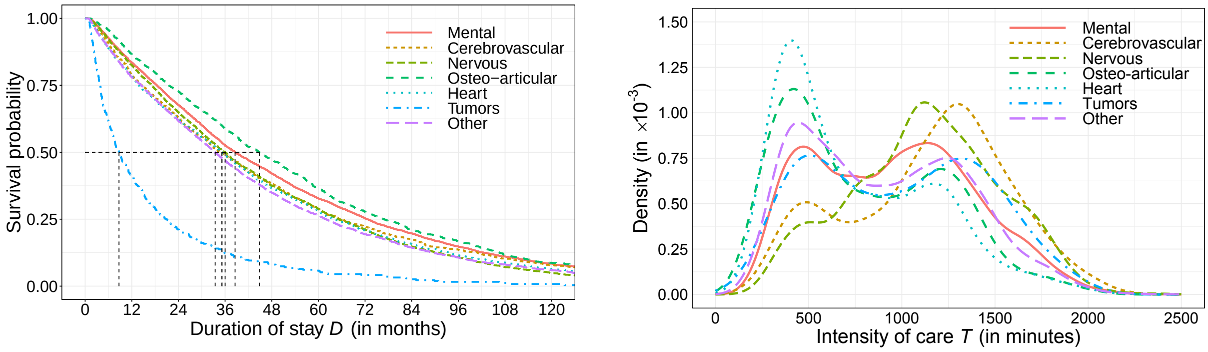
[10] For the lower levels of DP, PM, OR, OC and SI that contain very few observations associated with similar values of D_{med} and T_{avg}, we merge the first four, five or six levels together until the cumulative share reaches approximately 10% to 15% of the data.

	n	%	D_{med}	T_{avg}
Right-censoring C				
Yes	3 839	17.6	–	–
No	17 919	82.4	–	–
Age at entry AG				
65–69	647	3.0	68.6	931
70–79	3 887	17.9	48.0	984
80–89	11 323	52.0	38.3	945
90–99	5 745	26.4	27.0	969
100+	156	0.7	15.9	1 231
Gender GE				
Female	15 776	72.5	40.2	937
Male	5 982	27.5	25.9	1 021
Main diagnosis $D1$				
Mental	7 463	34.3	38.6	958
Cerebrovascular	1 267	5.8	35.2	1 139
Nervous	3 974	18.3	36.0	1 125
Osteoarticular	1 567	7.2	44.8	800
Heart	1 860	8.5	35.2	757
Tumour	390	1.8	8.7	989
Other	5 237	24.1	33.4	910
Secondary diagnosis $D2$				
None	379	1.7	62.2	820
Mental	5 584	25.7	37.6	988
Cerebrovascular	713	3.3	33.3	1 087
Nervous	1 532	7.0	36.3	1 144
Osteoarticular	2 191	10.1	43.9	872
Heart	3 570	16.4	34.5	866
Tumour	345	1.6	12.2	1 012
Other	7 444	34.2	34.1	964
Number of additional diagnoses ND				
0	1 468	6.7	54.5	856
1	2 202	10.1	48.6	876
2	3 007	13.8	43.5	912
3	3 068	14.1	37.4	943
4	2 991	13.7	33.9	956
5	2 454	11.3	33.5	979
6	2 122	9.8	29.6	999
7	4 446	20.4	26.1	1 053
Dependence in ADL DP				
1–6	3 643	16.7	53.7	414
7	8 856	40.7	40.6	780
8	7 623	35.0	27.9	1 274
9	1 636	7.5	17.9	1 686
Physical mobility limitations PM				
1–5	2 256	10.4	61.1	421
6	6 315	29.0	44.1	689
7	5 534	25.4	34.2	970
8	2 195	10.1	28.5	1 052
9	5 458	25.1	24.1	1 449

	n	%	D_{med}	T_{avg}
Orientation problems OR				
1–4	3 574	16.4	52.4	530
5	7 524	34.6	37.3	792
6	5 837	26.8	31.2	1 098
7	2 414	11.1	30.9	1 276
8+	2 409	11.1	28.6	1 469
Occupational limitations OC				
1–5	2 062	9.5	61.0	435
6	5 933	27.3	40.9	706
7	10 226	47.0	31.5	1 068
8	2 748	12.6	27.0	1 392
9	789	3.6	35.2	1 333
Social integration limitations SI				
1–4	1 937	8.9	54.6	516
5	5 221	24.0	42.8	689
6	7 666	35.2	33.5	950
7	5 385	24.7	29.7	1 235
8+	1 549	7.1	29.9	1 519
Recent memory impairment RM				
Adequate	1 554	7.1	59.4	561
Mild	5 974	27.5	41.1	718
Moderate	8 347	38.4	33.5	955
Severe	5 883	27.0	30.2	1 317
Perception and attention imp. PA				
Adequate	1 831	8.4	56.5	528
Mild	7 207	33.1	40.5	738
Moderate	11 710	53.8	30.9	1 116
Severe	1 010	4.6	37.5	1 512
Impulse impairment IM				
Adequate	2 608	12.0	53.2	538
Mild	8 168	37.5	39.0	783
Moderate	9 922	45.6	30.6	1 147
Severe	1 060	4.9	25.0	1 612
Will and motivation imp. WM				
Adequate	1 559	7.2	55.7	505
Mild	6 172	28.4	43.1	682
Moderate	12 039	55.3	32.1	1 068
Severe	1 988	9.1	27.8	1 524
Behavioural impairment BH				
Adequate	1 388	6.4	52.9	542
Mild	6 783	31.2	39.9	735
Moderate	12 734	58.5	32.2	1 089
Severe	853	3.9	41.0	1 502
Visual impairment VS				
Adequate	5 099	23.4	47.5	773
Mild	11 445	52.6	34.4	975
Moderate	4 631	21.3	31.2	1 093
Severe	583	2.7	28.9	1 229

Table 2.3: Descriptive statistics on the median duration of stay D_{med} (in months) and the mean intensity of care T_{avg} (in minutes per week).

Considering the main diagnosis $D1$, Figure 2.1 extends the results of the Kaplan–Meier estimates of the duration of stay D and of the intensity of care T distribution from the descriptive statistics in Table 2.3. From Figure 2.1a we see that the duration of stay D is drastically reduced by a tumour diagnosis, while osteoarticular pathologies come with higher survival rates. The kernel density estimation in Figure 2.1b sheds light on the influence of the main diagnosis on the intensity of care.[11] Overall, we note that the distribution of T is bimodal, with peaks at approximately 450 minutes (7.5 hours) and 1 200 minutes (20 hours) of care per week. We see that the intensity of care in the nervous and cerebrovascular pathologies is left-skewed, which results in higher mean values. The other diagnoses yield distinct bimodal distributions, which raises the hypothesis that diagnoses, on their own, are insufficient to explain the intensity provided to a person.



(a) Kaplan-Meier estimate of the duration of stay.

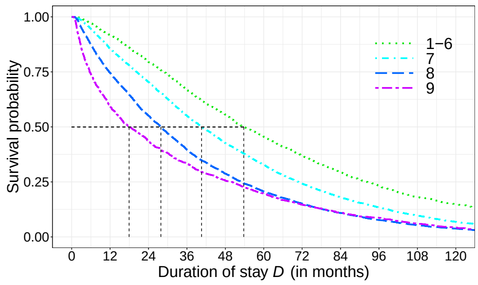
(b) Kernel density of the intensity of care.

Figure 2.1: Kaplan-Meier estimation of the duration of stay D (in months) and kernel density estimation of the intensity of care per week T (in minutes) across main diagnoses $D1$.

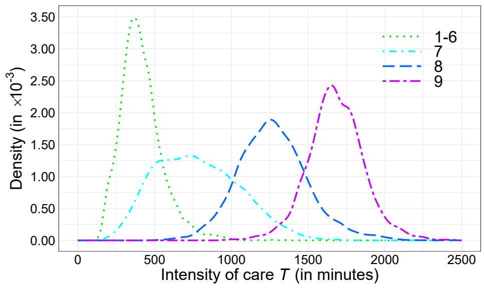
Most dependent persons have multiple diseases with several additional diagnoses ND, with the highest prevalence being found at three and seven additional diagnoses, respectively. The individuals who have seven additional diagnoses are characterized by the lowest median duration of stay (26.1 months) and the highest mean intensity of care (1 053 minutes per week). With an increasing number of additional diagnoses, the median duration of stay decreases and the mean intensity of care slightly increases.

Level of dependence. From Table 2.3 we see that all variables representing the dependence (i.e., dependence in ADL DP, physical mobility limitations PM, orientation problems OR, occupational limitations OC, social integration limitations SI) follow the intuition that the higher the dependence level is, the lower the median duration of stay and the higher the mean intensity of care are. All variables representing limitations affect the median duration of stay D_{med} and the mean intensity of care T_{avg}. The spread between the lowest and the highest levels is up to three years of stay (from 61.1 to 24.1 months in PM) and more than 20 hours of care per week (from 414 to 1 686 minutes in DP).

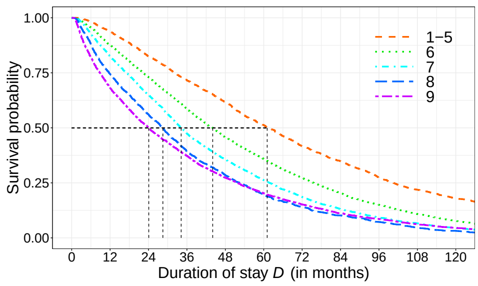
[11]We use the kernel density estimator given by $\hat{f}_h(x) = \frac{1}{nh}\sum_{i=1}^{n} K(\frac{x-T_i}{h})$, where T_i is the intensity of care of the individual i, $n = 21\,758$ is the number of individuals, the kernel $K(z) = (2\pi)^{-1/2}\exp(-z^2/2)$ is the standard normal density function, and $h = 0.9\min(\hat{\sigma}, \text{IQR}/1.34)\, n^{-0.2}$ is a smoothing parameter with sample standard deviation $\hat{\sigma}$ and interquartile range IQR (Silverman, 1986, p. 45).



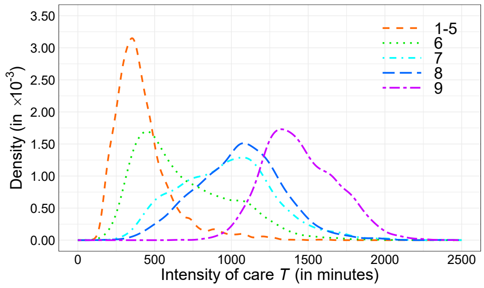
(a) D: Dependence in ADL DP



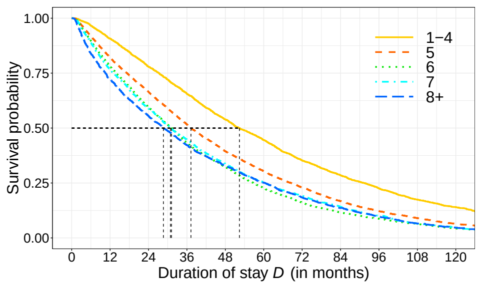
(b) T: Dependence in ADL DP



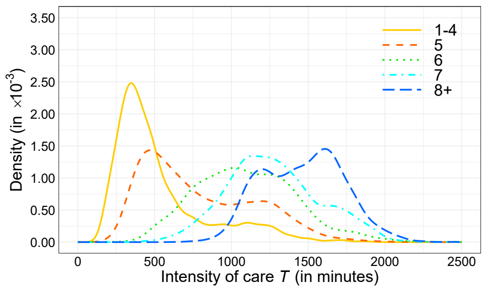
(c) D: Physical mobility limitations PM



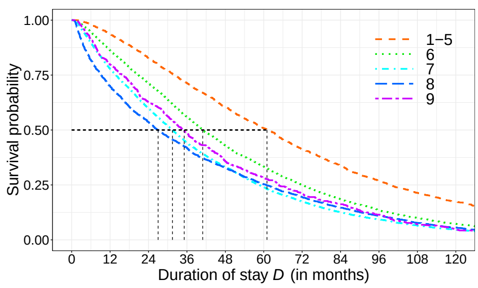
(d) T: Physical mobility limitations PM



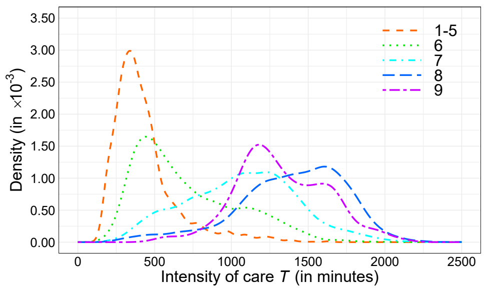
(e) D: Orientation problems OR



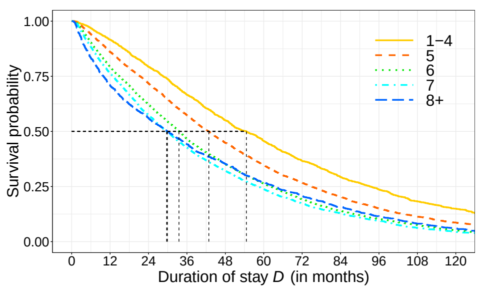
(f) T: Orientation problems OR



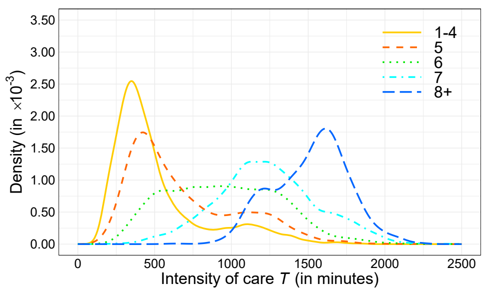
(g) D: Occupational limitations OC



(h) T: Occupational limitations OC

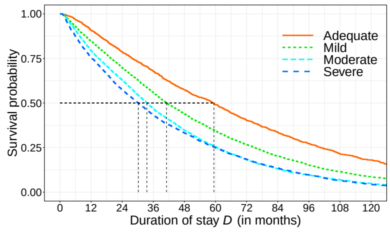


(i) D: Social integration limitations SI

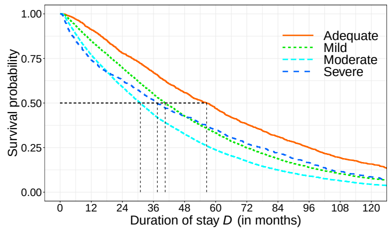


(j) T: Social integration limitations SI

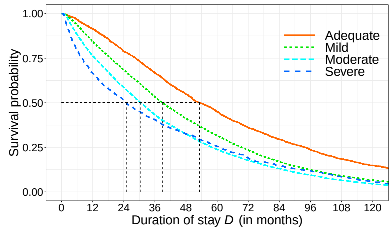
Figure 2.2: Kaplan-Meier estimation of the duration of stay D (in months) and density estimation of the intensity of care per week T (in minutes) across dependence factors.



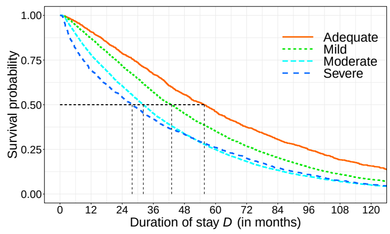
(a) D: Recent memory RM



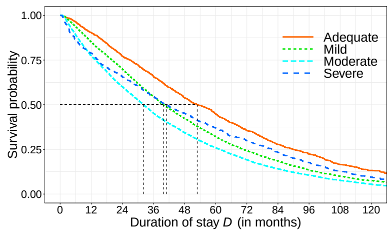
(b) D: Perception / attention PA



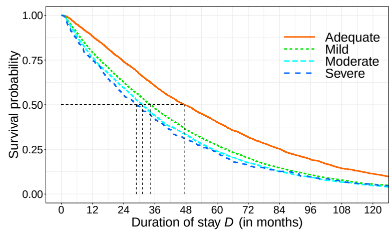
(c) D: Impulses IM



(d) D: Will and motivation WM



(e) D: Behaviour BH



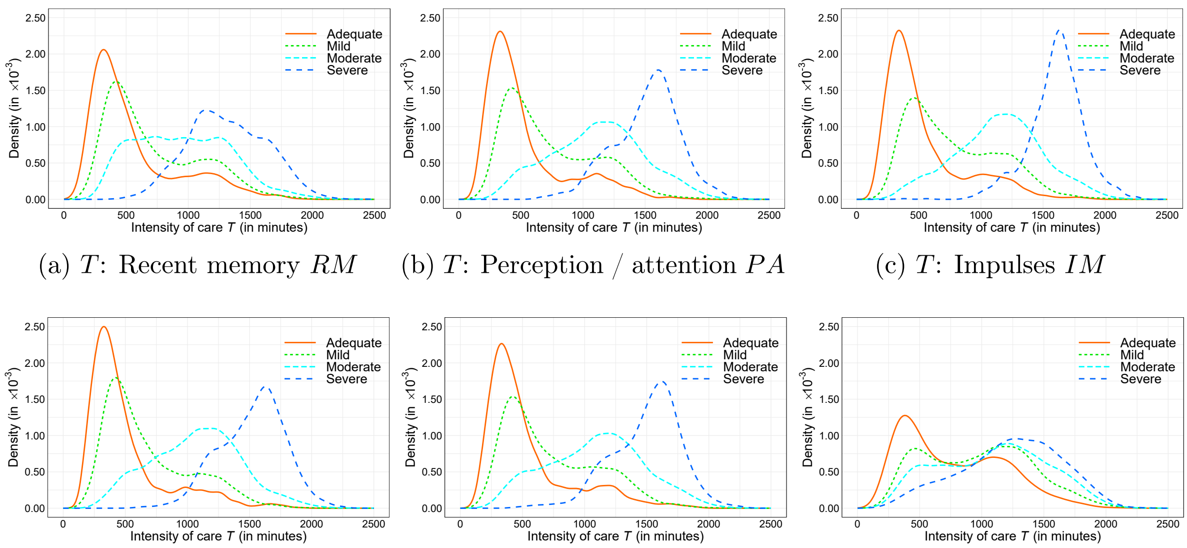
(f) D: Visual VS

Figure 2.3: Kaplan-Meier estimation of the duration of stay D (in months) across psychological and sensory function impairments.

In particular, we note that 35% of the institutionalised elderly individuals (Level 8 in dependence in ADL DP, see Table 2.2) require help for most of their daily needs, and 7.5% require constant aid from the personnel (Level 9 in DP). Almost a quarter of elderly individuals are restricted to a bed or chair in terms of mobility (Level 9 in PM), 10.1% are limited to their room (Level 8 in PM), while the rest can move around in the institution. For both dependence in ADL DP and physical mobility limitations PM, we see a clear distinction in the mean intensity of care between the different severity levels. Simultaneously, we observe 22.2% suffering from severe impairment of orientation or complete disorientation (Levels 7 and 8+ in orientation problems OR). Those individuals, on average, require a higher intensity of care, comparable to those who are highly dependent on ADL or highly limited in physical mobility. The most prevalent level of occupational limitations OC is 7, i.e., occupations limited in time and type, supporting the decision to institutionalise for these elderly individuals. Furthermore, most of the persons socialise only with primary contacts (Level 6 of social integration limitations SI). Indeed, the prevalence of the isolated elderly individuals living in nursing homes is at least twice as high as that of the community-dwelling population (Victor, 2012).

We extend the results obtained in Table 2.3 by plotting the Kaplan–Meier and kernel density estimates for the dependent variables in Figure 2.2. The graphs demonstrate clear differences in the survival probability along D and in the density of T across different levels of dependence. While many curves can be well separated, the representing curves of some levels are intertwined, as with the intensity of care across levels of OC in Figure 2.2h, or are close to each other, as with the curves representing the intensity of care in Levels 7 and 8 (floor and room limitations, respectively) of physical mobility PM.

Impairments of psychological and sensory functions. We observe a similar impact of the impairments (recent memory impairments RM, perception and attention impairments PA, impulse impairments IM, will and motivation impairments WM, behavioural impairments BH, visual impairments VS). As expected, we observe that when the level of psychological or sensory function impairment worsens, the median duration of stay D_{med} decreases, and the mean intensity of care T_{avg} increases. Regarding dependence, impairments importantly affect the median duration of stay D_{med} and the mean intensity of care T_{avg}, with spreads of approximately two and a half years (from 59.4 to 30.2 months for RM) and approximately 18 hours or care per week (from 538 to 1 612 minutes in IM). For all variables, except visual impairments VS, the most prevalent level of psychological and sensory function impairments is the moderate level.



(a) T: Recent memory RM (b) T: Perception / attention PA (c) T: Impulses IM

(d) T: Will and motivation WM (e) T: Behaviour BH (f) T: Visual VS

Figure 2.4: Density estimation of the intensity of care per week T (in minutes) across psychological and sensory function impairments.

We present the Kaplan–Meier and density estimates of the duration of stay D and the intensity of care T, respectively, in Figures 2.3 and 2.4. The "adequate" level of all psychological and sensory impairments is associated with the highest survival probabilities, while the other levels intersect each other. At the same time, for all impairments, except VS, we note a good separation of the distribution of T across the levels. In Figure 2.4f we observe that all distributions of T for visual impairments VS are intertwined. Although the moderate and severe levels of visual impairments are left-skewed, there is no clear separation of the distributions such as, for instance, in Figure 2.4c for impulse impairments IM.

2.4 Modelling framework

Our objective is to fit an explanatory model to calculate the foreseeable need for LTC of a person who has just entered the institution. The overall care need or severity S corresponds to the total number of hours of care elderly individuals receive while sojourning in an institution. Thus, we quantify the overall care severity through the product $S = D \cdot T$, where D stands for the duration of stay and T for the intensity of care.[12] This decomposition allows us to separately investigate the time spent in the institution, i.e., the period where a bed is occupied, and the amount of care

[12] In the original data and in the numerical results the duration of stay, D is expressed in months and the intensity of care T is expressed in minutes per week (see Table 2.1). In Section 2.5.5, we express the numerical results for the care severity S in hours. Therefore, we need to express D in weeks by multiplying with 4.345, the average number of weeks in a months, and T in hours per week by dividing by 60. Thus, taking units into account, the severity S is obtained from $S = D \cdot 4.345 \cdot T/60$.

received, i.e., the usage of caregivers' resources. Indeed, as discussed in Section 2.2, we expect to find different influencing factors for the two dimensions. The overall mean care severity is then given by $\mathbb{E}[S] = \mathbb{E}[D \cdot T]$. In our modelling we consider the simplifying assumption that T and D are independent. Such an approach is commonly accepted, for example, in the practice of actuarial calculations in non-life insurance.[13] We approximate the mean care severity $\hat{S}$ by

$$\hat{S} = \mathbb{E}[S] = \mathbb{E}[D] \cdot \mathbb{E}[T] = \hat{D} \cdot \hat{T}, \tag{1}$$

where $\hat{D} = \mathbb{E}[D]$ and $\hat{T} = \mathbb{E}[T]$ are estimated with two separate models.

In Section 2.4.1 we present a model for the duration of stay D, expressing the number of months an elderly individual spends in an institution until death. In Section 2.4.2, we lay out a model for the intensity of care T, corresponding to the number of minutes of care received per week based on the individual's evaluation at entry.

2.4.1 Duration of stay model

To model the duration of stay D in the institution, we first assess its distribution by fitting the observed durations with distributions commonly used in survival models. We find that the formal hazard proportionality test described in Grambsch and Therneau (1994) is not passed, although the assumption of proportional hazards visually holds when plotting the Cox–Snell residuals. This is commonplace when faced with a large amount of data, and thus, we proceed by considering a different type of model, the accelerated failure time (AFT) model; see Collett (2015). The two model classes intersect when the underlying distribution is Weibull.

To select the underlying distribution for the AFT model, we use the BIC scores of the fitted models with all variables (see Table 2.1) for the exponential, Weibull, Gaussian, logistic, log-normal and log-logistic distributions of D_i. The lowest BIC score is obtained using the Weibull distribution. Thus, we apply the Weibull AFT model to our data.

A standard log-linear form of the AFT model with Weibull distribution is

$$\log D_i = x_i^{\mathrm{T}} \lambda + \sigma \varepsilon_i, \quad i = 1, \ldots, n, \tag{2}$$

where $\lambda = (\lambda_0, \lambda_1, \ldots, \lambda_k)^{\mathrm{T}}$ is a vector of unknown regression parameters, $x_i = (x_{i0}, x_{i1}, \ldots, x_{ik})$ are the observations of known covariates, and n stands for the number of observations. Here, λ_0 corresponds to the intersection term, and hence we have $x_{i0} = 1$, for $i = 1, \ldots, n$. In this form, ε_i does in fact have the standard Gumbel distribution.[14]

In our case, D_i follows a Weibull distribution with scale parameter $\exp(x_i^{\mathrm{T}} \lambda)$ and shape param-

[13] This assumption dates back to Lundberg (1903). The analysis of possible "correlations" between D and T is beyond the scope of the present study. Such analysis could build on a Copula method (see, e.g., Czado et al., 2012) adapted to the case of right-censored variables.

[14] The standard Gumbel distribution with the location parameter 0 and the scale parameter 1 has the survival function $S_{\varepsilon_i}(x) = \exp[-\exp(x)]$. Therefore, the random variable $D_i = \exp(x_i^{\mathrm{T}} \lambda + \sigma \varepsilon_i)$ has the survival function $S_{D_i}(t) = \exp[-\exp(-x_i^{\mathrm{T}} \lambda / \sigma)\, t^{1/\sigma}]$, which is the Weibull survival function with scale parameter $\exp(x_i^{\mathrm{T}} \lambda)$ and shape parameter $1/\sigma$.

eter $1/\sigma$. The mean duration is then expressed as

$$\mathbb{E}[D_i] = \exp(x_i^{\mathrm{T}}\lambda)\,\Gamma\left(1+\sigma\right), \tag{3}$$

where Γ stands for the gamma function, $\Gamma(z) = \int_0^\infty x^{z-1}e^{-x}\,\mathrm{d}x$.

AFT models account for right-censoring, and the coefficients λ are obtained by maximizing the likelihood function (see Klein and Moeschberger, 1997, Chapter 3.5),

$$\mathcal{L} = \prod_{i=1}^{n} \left[f_W(D_i)\right]^{\delta_i} \left[S_W(D_i)\right]^{1-\delta_i}, \tag{4}$$

where f_W is the Weibull density function, S_W is the Weibull survival function, and $\delta_i = 0$ if the data are right-censored and $\delta_i = 1$ otherwise. To fit the model, we applied the `survreg` function from the `survival` package in `R`; see Therneau (2021).

2.4.2 Care intensity model

The intensity of care T provided to a person each week is bounded and takes values in the interval $(0, 10\,080)$. The upper bound is derived from the total number of minutes in one week. Usual practice performs a regression analysis on a transformation of the data so that the modified response variable, say $\tilde{T}$, takes values in the whole real line. Such an approach is in general disadvantageous since we can interpret the resulting analysis only in terms of the mean of $\tilde{T}$, while our interest is on the mean of T. However, a simple linear transformation $\tilde{T} = T/10\,080$ does not obstruct our intentions. Moreover, we see from Figures 2.1, 2.2 and 2.4 that the data seem to be heteroskedastic. Indeed, not only do the means depend on the levels of the predictors, but the variance also changes.

An interpretative model in terms of the mean of T based on the beta distribution, hence, called the beta regression model, has been proposed by Ferrari and Cribari-Neto (2004). Later, Simas et al. (2010) provided an extension of the beta regression model that allows for nonlinearity and variable dispersion. In the latter model, the standard beta density function

$$f(\tilde{T};\, p, q) = \frac{\Gamma(p+q)}{\Gamma(p)\,\Gamma(q)}\tilde{T}^{p-1}(1-\tilde{T})^{q-1}, \quad 0 < \tilde{T} < 1, \tag{5}$$

is parameterized by the mean $\mu = p/(p+q) \in (0,1)$ and the precision parameter $\phi = p+q > 0$, yielding

$$f(\tilde{T};\, \mu, \phi) = \frac{\Gamma(\phi)}{\Gamma(\mu\phi)\,\Gamma\left((1-\mu)\phi\right)}\tilde{T}^{\mu\phi-1}(1-\tilde{T})^{(1-\mu)\phi-1}, \quad 0 < \tilde{T} < 1. \tag{6}$$

While the mean μ relates to the mean of $\tilde{T}$, the numerical value of the precision parameter ϕ does not have a simple interpretation. However, its estimate provides information on the variance of $\tilde{T}$. Indeed, by definition, the variance of a random variable with a beta distribution is $\mathrm{var}(\tilde{T}) = V(\mu)/(1+\phi)$, where $V(\mu) = \mu/(1-\mu)$. Thus, for a given mean μ, the larger the value of ϕ is, the smaller the variance of $\tilde{T}$ and T.

Let $\tilde{T}_i$, $i = 1, \ldots, n$, follow the beta distribution with the above density function. We assume that the mean μ and the precision parameter ϕ characterizing $\tilde{T}_i$ satisfy the following functional relations:

$$g_1(\mu_i) = x_i^{\mathrm{T}}\beta, \quad \text{and} \quad g_2(\phi_i) = x_i^{\mathrm{T}}\theta, \tag{7}$$

where $\beta = (\beta_0, \beta_1, \ldots, \beta_k)^{\mathrm{T}}$ and $\theta = (\theta_0, \theta_1, \ldots, \theta_k)^{\mathrm{T}}$ are vectors of unknown regression parameters, and $2(k+1) < n$. Here, β_0 and θ_0 correspond to the intersection terms, and hence, we have $x_{i0} = 1$, $\forall i = 1, \ldots, n$.

The resulting log-likelihood function has the following form:

$$\ell(\beta, \theta) =$$
$$\sum_{i=1}^{n} \left[\log\Gamma(\phi_i) - \log\Gamma(\mu_i\phi_i) - \log\Gamma\left((1-\mu_i)\phi_i\right) + (\mu_i\phi_i - 1)\log\tilde{T}_i + ((1-\mu_i)\phi_i - 1)\log(1-\tilde{T}_i) \right],$$

where $\mu_i = g_1^{-1}(x_i^{\mathrm{T}}\beta)$ and $\phi_i = g_2^{-1}(x_i^{\mathrm{T}}\theta)$ are defined in Equation (7). There are various approaches to choose the link functions such that $g_1^{-1} : \mathbb{R} \to (0,1)$ and $g_2^{-1} : \mathbb{R} \to \mathbb{R}_+$. It is the best practice to use interpretable link functions, as opposed to data-driven approaches, since only in the former case will the standard errors of the resulting parameter estimates be truthful. In our numerical implementation, we choose the standard transformations

$$g_1(\mu) = \log\left(\frac{\mu}{1-\mu}\right), \quad \text{and} \quad g_2(\phi) = \log(\phi), \tag{8}$$

and, therefore, we have, for $i = 1, \ldots, n$,

$$\mu_i = \frac{1}{1 + \exp(-x_i^{\mathrm{T}}\beta)}, \quad \text{and} \quad \phi_i = \exp(x_i^{\mathrm{T}}\theta). \tag{9}$$

To fit this model, we use the `R` package `betareg`. Details can be found in the original work by Cribari-Neto and Zeileis (2010), and the extended work by Grün et al. (2012).

2.5 Results and discussion

In this section, we apply the econometric models introduced in Section 2.4. In Section 2.5.1 we discuss the specification of the models. We introduce the variable transformations and discuss the selection of the psychological and sensory function impairments, the inclusion of interaction terms between age at entry and gender, and how the variable importance is measured. We also show how the coefficients of the models are interpreted. We present the results of the duration of stay and intensity of care models, respectively, in Table 2.4 and analyse and interpret them in Sections 2.5.2 and 2.5.3. Next, we assess the goodness of fit of both models in Section 2.5.4, and finally we highlight model estimates of the duration of stay, the intensity of care and the overall care severity for selected profiles of the institutionalised elderly individuals in Section 2.5.5.

2.5.1 Specification of the models and results

In Table 2.4, we report the regression results for both the duration of stay (Equation 2) and intensity of care (Equation 6) models. In each model and for each variable, we report the estimates for the regression coefficients with the standard deviation and the significance level. Recall that the original data contain 16 variables related to psychological and sensory function impairments (see Section 2.3.1). To reduce the complexity and improve the scores of the models, we reduce the number of these factor variables using a variable selection procedure based on the Bayesian information criterion (BIC). Overall, we retain six variables associated with psychological and sensory function impairments. Three variables (PA, BH, VS) appear in the duration of stay model, and four (RM, IM, WM, VS) appear in the intensity of care model. All the other covariates summarised in Table 2.1 are included in both models.

Most of the covariates in our data are categorical variables (see Table 2.1). From the descriptive statistics in Table 2.3, we observe that women (72.5%) are more prevalent than men in institutional care, and, therefore, we choose "female" as the baseline for the gender GE variable. For the main diagnosis $D1$, we choose the group of mental pathologies as the baseline since it has the highest prevalence (34.3%). The second diagnosis, $D2$, involves comorbidity and interactions with $D1$. To avoid ambiguous interpretations in the baseline, we assume that elderly individuals have no secondary diagnosis and choose "none" as the baseline for $D2$. Furthermore, for the variables that describe the levels of dependence, we use the group of lowest levels as a baseline. Thereby, we use the groups laid out in the descriptive statistics (see Table 2.3), i.e., levels 1–6 for dependence in ADL DP, 1–5 for physical mobility limitations PM, 1–4 for orientation problems OR, 1–5 for occupational limitations OC, and 1–4 for social integration limitations SI. Finally, we use the "adequate" level (healthy) as the reference category in the impairments of psychological and sensory functions (recent memory impairments RM, perception and attention impairments PA, impulse impairments IM, will and motivation impairments WM, behavioural impairments BH and visual impairments VS).

The set of covariates further includes two numerical variables: the age at entry AG and the number of additional diagnoses ND. While AG starts at 65 years, ND takes integer values from 0 to 7, where zero indicates that the person has no additional diagnoses, i.e., only one or two diagnoses given by $D1$ and $D2$. As we have seen in Table 2.3, LTC prevalence rates and entrance into care institutions expand after the age of 80 years (see also, e.g., Colombo et al., 2011). To account for this, we consider $AG = 80$ years as a reference point and subtract 80 from the AG variable when fitting the models, i.e., we transform the predictor into $(AG - 80)$. Hence, an 80-year-old woman at entry with a mental main diagnosis, without secondary or additional diagnoses, the lowest dependence levels and no other impairments characterises the baseline health profile and corresponds to the intercept term, or baseline, in both models.

In Table 2.4 we also provide intuition for the interpretation of the obtained estimates in the column labelled "Effect". For the categorical variables, the "Effect" measures the increase or decrease of D and T in absolute values when the variable switches from its baseline to the corresponding level, and all other parameters remain the same at the baseline. For numerical variables, we do not report the information. Indeed, since our models are nonlinear, the corresponding effects must be evaluated through Equations (3) and (9), respectively. If several parameters are changed at the same time, the effects also must be calculated using the original equations (see also the model estimations illustrated in Section 2.5.5).

Furthermore, to rank the importance of the variables, we remove each variable from the model and compute the resulting BIC score. Then, we subtract the BIC score of the full model and report the difference in the column labelled "Imp. (rank)" in Table 2.4. If the difference is positive, the reduced model would suffer from information loss, and the variable is important. In contrast, if the difference is negative, the reduced model would benefit from removing the variable.

Since we report the results for all variables, some of them have negative importance values (for example, OR, OC, SI in the duration of stay model), which means that these variables may be omitted. Finally, we order each difference in BIC scores and report the rank in parentheses.

2.5.2 Duration of stay

In the first part of Table 2.4 in the column labelled "Duration of stay D", we present the results of the AFT model (Equation 2) applied to our dataset. The first columns present the fitted coefficients $\hat{\lambda}$ of the model and the corresponding standard deviations $\sigma_{\hat{\lambda}}$. The mean duration of stay for the baseline that can be read from the intercept row in the "Effect" column is 135 months.

Demographic variables. We observe a negative effect of the age at entry AG on the duration of stay with $\hat{\lambda}_{AG} = -0.0354$. This follows the intuition that the later a person enters institutional care, the less time he or she spends there. Our result substantiates the findings on increased mortality rates at higher ages (Mathers, 1996; Deeg et al., 2002; Fong et al., 2017) and, thus, a reduced duration of stay (Colombo et al., 2011; Fuino and Wagner, 2020). At the same time, the coefficient $\hat{\lambda}_{GE} = -0.3884$ yields that males, on average and for the baseline profile, spend 43.4 fewer months than women in the institution. Both variables share first and second place in the importance ranking, with the age at entry AG being almost twice as important as the gender GE in terms of BIC.

Medical diagnoses. As one can observe from the descriptive statistics in Table 2.3 and the survival curve pictured in Figure 2.1a, pathologies are one of the key factors that shape the duration of stay D. In fact, the number of additional diagnoses ND is the third most important variable, followed by the main diagnosis $D1$ (rank four). The secondary diagnosis $D2$ takes eighth place. All main diagnoses significantly reduce the duration of stay compared to the group of mental diagnoses, except for cerebrovascular and osteoarticular pathologies, which appear to be not significant. A tumour in the main diagnosis significantly reduces the baseline duration by 77.4 months on average. In absolute value, the coefficient $\hat{\lambda}_{D1}^{\text{Tumour}} = -0.8512$ is the highest among the $D1$ levels. This result follows from the lower expected lifetime due to the often faster progression of the tumours, which more rapidly leads to death compared to other diseases (Guccione et al., 1994). Next comes the group of heart-related diseases, which reduce the average duration of stay by 17.5 months.

The secondary diagnosis $D2$ does not significantly affect the duration of stay except for tumour diagnoses and, to a lesser extent, heart diseases (compared to the baseline with no secondary diagnosis). We observe that the duration of stay, on average, is reduced by an additional 43.6 months ($\hat{\lambda}_{D2}^{\text{Tumour}} = -0.3899$) regardless of the type of main diagnosis $D1$. Simultaneously, heart disease in $D2$ decreased the mean duration by 9.7 months. In general, the more pathologies a person has, the less time he or she spends in dependence ($\hat{\lambda}_{ND} = -0.0522$). Multimorbidity comes with a higher chance of developing severe conditions along a pathology, which eventually increases the mortality rate, especially at higher ages (see, e.g., Menotti et al., 2001; Deeg et al., 2002; Byles et al., 2005).

Level of dependence. Our regression results show significant differences between the different levels of DP, PM and OC and thus support the clear distinction that we observed between the

	Duration of stay D					Intensity of care T							
	$\hat{\lambda}$	$\sigma_{\hat{\lambda}}$	Sig.	Effect	Imp. (rank)	$\hat{\beta}$	$\sigma_{\hat{\beta}}$	Sig.	Effect	$\hat{\theta}$	$\sigma_{\hat{\theta}}$	Sig.	Imp. (rank)
Intercept	4.9862	(.0498)	***	135.0		−3.4955	(.0166)	***	296.8	5.6313	(.0872)	***	
$\ln \sigma$	−0.2702	(.0058)	***										
AG	−0.0354	(.0009)	***		1527.5 (1)	−0.0014	(.0002)	***		0.0114	(.0015)	***	75.2 (7)
Gender GE (*baseline*: Female)					795.3 (2)								404.5 (3)
Male	−0.3884	(.0131)	***	−43.4		0.0684	(.0033)	***	20.3	−0.0793	(.0220)	***	
Main diagnosis $D1$ (*baseline*: Mental)					304.8 (4)								5.8 (12)
Cerebrovascular	−0.0111	(.0266)		−1.5		0.0336	(.0061)	***	9.8	−0.0811	(.0441)	.	
Nervous	−0.0821	(.0171)	***	−10.6		0.0332	(.0041)	***	9.7	−0.0244	(.0285)		
Osteoarticular	0.0276	(.0241)		3.8		0.0229	(.0067)	***	6.7	−0.1177	(.0411)	**	
Heart	−0.1391	(.0226)	***	−17.5		0.0057	(.0062)		1.7	−0.0385	(.0385)		
Tumour	−0.8512	(.0437)	***	−77.4		0.0328	(.0112)	**	9.6	−0.0171	(.0766)		
Other	−0.1266	(.0162)	***	−16.1		0.0358	(.0041)	***	10.5	−0.0864	(.0270)	**	
Secondary diagnosis $D2$ (*baseline*: None)					41.4 (8)								−82.9 (14)
Mental	0.0099	(.0445)		1.3		−0.0030	(.0135)		−0.9	0.1425	(.0774)	.	
Cerebrovascular	−0.0327	(.0530)		−4.3		0.0048	(.0152)		1.4	0.0952	(.0917)		
Nervous	0.0006	(.0482)		0.1		0.0176	(.0141)		5.1	0.1789	(.0836)	*	
Osteoarticular	0.0761	(.0464)		10.7		−0.0091	(.0140)		−2.6	0.1996	(.0807)	*	
Heart	−0.0747	(.0448)	.	−9.7		−0.0042	(.0137)		−1.2	0.1869	(.0782)	*	
Tumour	−0.3899	(.0618)	***	−43.6		0.0206	(.0175)		6.0	0.1868	(.1087)	.	
Other	−0.0283	(.0440)		−3.8		0.0142	(.0135)		4.1	0.1122	(.0767)		
ND	−0.0522	(.0028)	***		340.1 (3)	0.0130	(.0007)	***		−0.0062	(.0046)		321.1 (5)
Dependence in ADL DP (*baseline*: 1–6)					182.6 (5)								6489.1 (1)
7	−0.0750	(.0211)	***	−9.7		0.4308	(.0066)	***	152.7	−1.0442	(.0339)	***	
8	−0.2532	(.0275)	***	−30.2		0.6946	(.0078)	***	280.6	−0.7241	(.0451)	***	
9	−0.5687	(.0407)	***	−58.5		0.9084	(.0097)	***	408.6	−0.7383	(.0703)	***	
Physical mobility limitations PM (*baseline*: 1–5)					77.1 (6)								4010.2 (2)
6	−0.1407	(.0232)	***	−17.7		0.1756	(.0082)	***	55.0	−0.1266	(.0387)	**	
7	−0.2299	(.0263)	***	−27.7		0.3212	(.0089)	***	107.9	−0.0973	(.0436)	*	
8	−0.2930	(.0308)	***	−34.3		0.3838	(.0098)	***	132.9	−0.0077	(.0509)		
9	−0.2842	(.0301)	***	−33.4		0.5207	(.0094)	***	192.9	0.4890	(.0510)	***	
Orientation problems OR (*baseline*: 1–4)					−17.6 (11)								363.4 (4)
5	−0.0227	(.0247)		−3.0		0.0549	(.0086)	***	16.2	0.0448	(.0432)		
6	0.0125	(.0328)		1.7		0.1570	(.0108)	***	48.7	0.2902	(.0587)	***	
7	0.0460	(.0409)		6.4		0.1699	(.0125)	***	53.1	0.2507	(.0753)	***	
8+	−0.0980	(.0486)	*	−12.6		0.2090	(.0139)	***	66.5	0.2728	(.0891)	**	
Occupational limitations OC (*baseline*: 1–5)					−26.2 (12)								279.8 (6)
6	−0.0736	(.0248)	**	−9.6		0.0917	(.0087)	***	27.6	−0.0689	(.0419)		
7	−0.0993	(.0278)	***	−12.8		0.1235	(.0095)	***	37.7	−0.0924	(.0470)	*	
8	−0.0767	(.0341)	*	−10.0		0.0999	(.0104)	***	30.2	−0.1684	(.0586)	**	
9	−0.0790	(.0436)	.	−10.2		0.2076	(.0126)	***	66.0	−0.3851	(.0742)	***	
Social integration limitations SI (*baseline*: 1–4)					−33.9 (13)								−2.6 (13)
5	0.0212	(.0284)		2.9		−0.0332	(.0096)	***	−9.4	−0.0170	(.0470)		
6	−0.0141	(.0335)		−1.9		−0.0381	(.0109)	***	−10.8	−0.0405	(.0553)		
7	−0.0427	(.0401)		−5.6		−0.0196	(.0121)		−5.6	−0.2120	(.0661)	**	
8+	−0.0132	(.0556)		−1.8		−0.0446	(.0144)	**	−12.6	0.0801	(.0931)		
Recent memory RM (*baseline*: Adequate)													25.5 (10)
Mild						0.0100	(.0098)		2.6	0.1643	(.0459)	***	
Moderate						−0.0300	(.0110)	**	−9.8	0.2677	(.0539)	***	
Severe						−0.0300	(.0122)	**	−9.2	0.3737	(.0675)	***	
Perception and attention PA (*baseline*: Adequate)					16 (9)								
Mild	−0.0175	(.0268)		−2.3									
Moderate	−0.0783	(.0322)	*	−10.2									
Severe	0.1257	(.0473)	**	18.1									
Impairment in impulses IM (*baseline*: Adequate)													26.8 (9)
Mild						0.0469	(.0088)	***	13.8	0.0601	(.0432)		
Moderate						0.0671	(.0098)	***	19.9	0.0825	(.0515)		
Severe						0.0415	(.0124)	***	12.2	−0.2106	(.0856)	*	
Will and motivation WM (*baseline*: Adequate)													15.2 (11)
Mild						0.0195	(.0105)	.	5.7	0.0037	(.0504)		
Moderate						0.0640	(.0117)	***	19.0	−0.0138	(.0582)		
Severe						0.0629	(.0131)	***	18.7	−0.0779	(.0776)		
Behavioural impairment BH (*baseline*: Adequate)					64.6 (7)								
Mild	−0.0455	(.0291)		−6.0									
Moderate	−0.0369	(.0326)		−4.9									
Severe	0.2986	(.0483)	***	47.0									
Visual impairment VS (*baseline*: Adequate)					11.2 (10)								52.3 (8)
Mild	−0.0706	(.0147)	***	−9.2		0.0313	(.0042)	***	9.2	0.0932	(.0250)	***	
Moderate	−0.0212	(.0181)		−2.8		0.0291	(.0049)	***	8.5	0.1275	(.0309)	***	
Severe	0.0834	(.0373)	*	11.7		0.0625	(.0090)	***	18.5	−0.0502	(.0640)		

Note: Significance levels in column "Sig." are reported as follows: p-value < 0.1 . , < 0.05 *, < 0.01 **, < 0.001 ***. The column "Effect" reports the effect related to a category deviating from the baseline (all other parameters remaining at the baseline). The column "Imp. (rank)" reports the effect on the BIC and the corresponding rank of the variable.

Table 2.4: Model results for the duration of stay D and the intensity of care T models.

curves of the different levels in the graphs of Figure 2.2 (see Figures 2.2a, 2.2c, 2.2g, respectively). All levels of dependence in ADL DP, the fifth most important variable, are highly significant and reduce the mean duration of stay by up to 58.5 months. Furthermore, physical mobility PM takes the sixth place in the importance ranking, with all coefficients being highly significant. Increased levels of PM monotonously shorten the duration of stay. Both DP and PM increase the mortality rates, which result in a shorter duration (Rickayzen and Walsh, 2002). Despite its rank at 12 (second to last in the ranking), the occupational limitations variable OC has all its coefficients significantly different from the baseline, although the p-value thresholds are different. For example, Level 7 (confined occupation in terms of time and type) reduces the mean duration of stay the most (12.8 months) with a three-star significance, while the most vulnerable group of unoccupiable elderly individuals (Level 9) yields the least significant coefficient (reduction of 10.2 months).

The overlapping curves for the levels in the variables OR and SI translate into regression coefficients that are not significant. The variable occupational problems OR has only one coefficient $\hat{\lambda}_{OR}^{8+} = -0.0980$ (disorientation or unconscious) that is one-star significant, which reduces the mean duration of stay by 12.6 months compared to the baseline.

Impairments of psychological and sensory functions. The BIC variable selection procedure leaves us with three factors related to the impairments that are included in the duration of stay model: perception and attention PA, behavioural BH, and visual impairments VS. Behaviour BH ranks seventh in the importance ranking, right after the dependence in ADL DP and physical mobility PM variables. Since behavioural impairments manifest themselves as accentuated character traits, elderly individuals with severe levels of BH are cared for more intensely (see Figure 2.4e), which leads to a higher mean duration of stay. The coefficient of the severe level ($\hat{\lambda}_{BH}^{\text{Severe}} = 0.2986$) is the only significant coefficient. It increases the mean duration of stay by 47 months compared to the baseline.

The perception and attention variable PA takes the ninth rank in the importance list and is the second most important variable among psychological and sensory function impairments. We observe two coefficients significantly different from the baseline: $\hat{\lambda}_{PA}^{\text{Moderate}} = -0.0783$ (one star) and $\hat{\lambda}_{PA}^{\text{Severe}} = 0.1257$ (two stars). Surprisingly, they are of the opposite signs. Compared to the adequate level, moderate impairments decrease the mean duration of stay by 10.2 months, while severe impairments increase it by 18.1 months. From Figure 2.4b we deduce that the latter level corresponds to a much higher intensity of care, which through more attentive care results in slower health deterioration and, thus, a higher expected duration (Tombaugh and McIntyre, 1992).

Finally, the mild level in the visual impairments variable VS reduces the duration of stay by 9.2 months, which may be linked to the lower level of help and overconfidence of the person. Indeed, from Figure 2.4f we see that the adequate and mild (and, to some extent, the moderate) levels of VS receive similar intensities of care, while blind people (severe level) receive extra attention. We find that a severe level of sight impairment increases the mean duration of stay by 11.7 months.

2.5.3 Intensity of care

The results of the beta regression model (Equation 6) for the intensity of care are presented in the second part of Table 2.4 under the heading "Intensity of care T". The first two columns provide the β and θ estimates corresponding to the mean and precision parameters of the beta distribution of $\tilde{T}$. The mean intensity of care T provided to the baseline profile is 296.8 minutes per week (see the column labelled "Effect"), corresponding to approximately five hours per week. The other values reported in the "Effect" column relate to increases and decreases in the intensity of care T in the different factors.

Demographic variables. We observe a significant negative, although small, effect of the age at entry AG on the mean intensity of care. The estimate $\hat{\beta}_{AG} = -0.0014$ indicates that older individuals receive, on average, slightly less help for their daily needs. At the same time, the positive three-star significant coefficient $\hat{\theta}_{AG} = 0.0114$ suggests that at higher ages, the variance of the intensity of care is lower compared to the younger elderly individuals, which may result from heterogeneous health conditions and an increase in disability (Fries, 1980; Olshansky et al., 1991). The variable AG ranks seventh in importance. Furthermore, the coefficient $\hat{\beta}_{GE} = 0.0684$ indicates that males receive, on average, more help than females. For the baseline profile, the difference is 20.3 minutes per week. The negative coefficient $\hat{\theta}_{GE} = -0.0793$ indicates that the amount of help received by males has a higher variance, yielding more precise estimations for women than for men. Gender GE is one of the key determinants of the intensity of care, since it takes third place in importance.

Medical diagnoses. As we have observed in Figure 2.1b, the main diagnosis $D1$ is not a strong determinant factor for explaining the intensity of care. Indeed, $D1$ takes only the 12th place in the importance ranking. Nevertheless, all diagnoses' coefficients are significantly (three stars) different from the mental disease baseline, except for tumour (two-star significant) and heart diseases (not significant). Significant differences increase the mean intensity of care by approximately 10 minutes per week. The secondary diagnosis $D2$ is the least important variable in our model. Since none of the $\hat{\beta}_{D2}$ coefficients is significant, there is no benefit in knowing the secondary diagnosis for explaining the intensity of care. However, the positive coefficients $\hat{\theta}_{D2}$ indicate that the variance of the intensity of care evaluation can be reduced by including $D2$. Finally, the number of additional diagnoses ND ranks fifth in importance. The coefficient $\hat{\beta}_{ND} = 0.0130$ is highly significant and has a positive effect on the mean intensity, i.e., the more comorbidities a person has, the more care he or she requires. This finding supplements the results of Barnett et al. (2012) when applied to the intensity of care provided to dependent elderly individuals in an institution. Indeed, the number of pathologies provides more relevant information than the underlying diseases themselves.

Level of dependence. Dependence in ADL DP is the most important variable explaining the intensity of care. Moreover, it comes with the highest values of $\hat{\beta}$ coefficients (all three-star significant) among all variables. Compared to the baseline (levels 1–6), levels 7, 8 and 9 increase the mean intensity of care by 152.7 minutes (2.5 hours), 280.6 minutes (4.7 hours) and 408.6 minutes (6.8 hours) per week, respectively. Thus, expectedly, ADL limitations are a key driver of care intensity. Simultaneously, the coefficients $\hat{\theta}_{DP}$ are negative, which indicates a higher variance of the intensity of care for different levels of DP compared to the baseline.

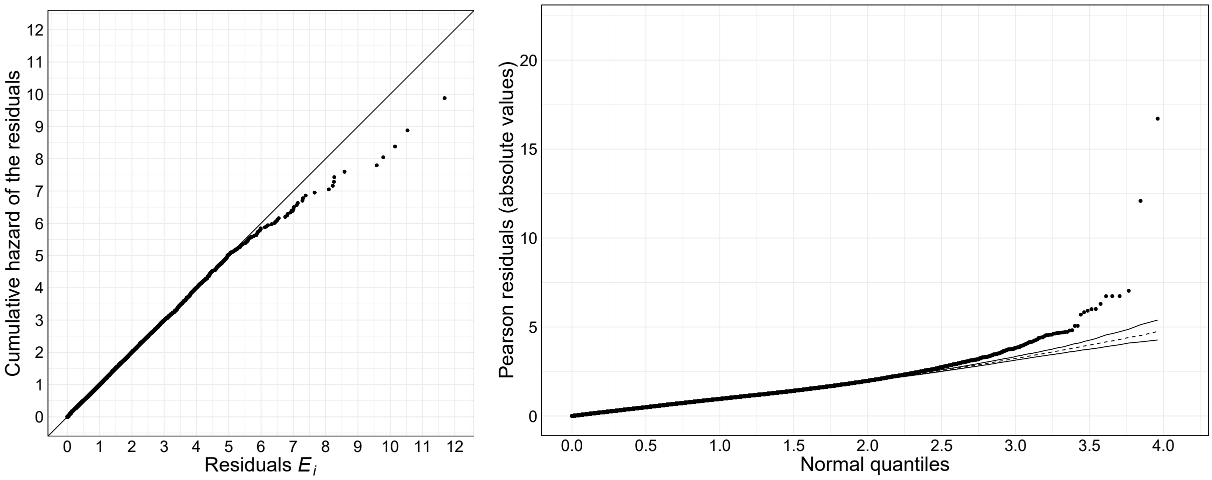
The second most important variable, PM, is associated with physical mobility limitations. All coefficients $\hat{\beta}_{PM}$ are three-star significant and positive, indicating an increasing mean intensity of care compared to the baseline. Moreover, the amount of help increases for the higher levels of PM by up to 192.9 minutes (approximately 3.2 hours) per week for the fully immobile elderly individuals (Level 9). At the same time, the precision coefficient $\hat{\theta}^9_{PM} = 0.4890$ is three-star significant and positive, indicating a lower variance compared to the baseline. In contrast, Levels 6 and 7 lead to a higher variance, which may be explained by the fact that people who ordinarily get around independently inside the institution and their bedroom, respectively, are more exposed to a sudden and unexpected need for help when moving around. For example, when trying to get to another floor, being lost, or forgetting the place of their bedroom (Maresova et al., 2019), it might be the case that these two levels should receive more help than they usually do to reduce the spread and make help requests more predictable.

The variables linked to orientation problems OR and occupational limitations OC take fourth and sixth place in the importance ranking. Like the dependence in ADL DP and physical mobility limitations PM, all $\hat{\beta}$ coefficients are three-star significant and positive, yielding an increased mean intensity of care for the higher levels of dependence. For both OR and OC, the maximum increase is approximately one hour per week (66.5 and 66.0 minutes, respectively). Finally, social integration SI is a much less relevant driver of the intensity of care. Indeed, limitations with physical activities drive the intensity of care much more than the needed help with social contacts. Surprisingly, a reduced level of communication abilities leads to a slightly lower amount of help, which may be explained by the solitary lifestyle of these persons (Simard and Volicer, 2020). Although the coefficients $\hat{\beta}_{SI}$ are small, the highest reduction in mean intensity of care (12.6 minutes per week) is found in the most alienated and abandoned individuals (levels 8+).

Impairments of psychological and sensory functions. Following the BIC variable selection procedure four variables are included in our model: recent memory RM, impairment in impulses IM, will and motivation WM, and visual impairment VS. Recent memory RM is the only factor that sees a slight decrease (approximately 10 minutes per week) in the intensity of care at moderate and severe levels (two stars). In the other variables (IM, WM, VS), all levels are significant and come with an increased intensity of care at the more severe levels. However, the increase remains relatively small and remains below 20 minutes per week. Indeed, in the impairment in impulses IM, the largest increase in the mean care intensity is 19.9 minutes per week at the moderate level. For will and motivation WM impairments, we observe an additional 19 minutes per week at the same level, while severe visual impairments require 18.5 minutes per week more.

2.5.4 Goodness of fit and alternative model specifications

Goodness of fit of the AFT model. In the previous sections, we applied the AFT and beta regression models to the data, and we reported the results for the duration of stay D and the intensity of care T. To assess the quality of the fit of the AFT model (Equation 2) with Weibull distribution, we plot the Cox–Snell residuals (see Klein and Moeschberger, 1997, Chapter 11.2). Therefore, we calculate the cumulative distribution function of the Weibull distribution at the



(a) Plot of the Cox-Snell residuals of the AFT model (Equation 2).

(b) Half-normal plot of the standardized residuals of the beta regression model (Equation 6).

Figure 2.5: Illustration of the goodness of fit.

observed durations of stay,

$$U_i \equiv F_W(D_i;\, \lambda, \sigma) = 1 - \exp\left(-\left(\frac{D_i}{\exp(x_i^{\mathrm{T}}\hat{\lambda})}\right)^{1/\hat{\sigma}}\right), \tag{10}$$

using the coefficient estimates $\hat{\lambda}$ and $\hat{\sigma}$ reported in Table 2.4. Under the correct model, the values U_i should be uniformly distributed on the unit interval. However, recall that 17.6% of the observations are censored. To overcome this, we apply the transform $E_i = -\log(1 - U_i)$, and now the Cox–Snell residuals E_i are expected to constitute a right-censored sample that follows the exponential distribution with unit rate. We compute the Neslon–Aalen estimator of the cumulative hazard rate of E_i without any predictors, which should be approximately equal to the cumulative hazard rate of the unit exponential, i.e., the identity function under the null hypothesis.

We report both quantities in Figure 2.5a and we confirm the required behaviour. Indeed, we see that most of the residuals are concentrated on the diagonal, while only the right tail is slightly below. Note that these are few observations from the whole dataset, which contains 21 758 records. However, standard formal statistical tests reject the null hypothesis, which is not surprising for a dataset of this size. Presently, we are satisfied with the visual agreement of the curve depicted in Figure 2.5a. Different model specifications could correct the slight deviation, but at the potential cost of loss of interpretability.

Goodness of fit of the beta regression model. To assess the goodness of fit of the beta regression model (Equation 6), we proceed by calculating the pseudo R^2 as a global measure of explained variance. It is defined as the square of the sample correlation coefficient between the observed intensity of care and the fitted intensity of care. The resulting pseudo R^2 of our model is 79.31%, which in practice is considered relatively high.

We further follow the approach proposed by Ferrari and Cribari-Neto (2004) to extend our analysis. We define the standardised residuals, also called Pearson residuals, as

$$r_i = \left(\tilde{T}_i - \hat{\mu}_i\right) / \sqrt{\widehat{\text{var}}(\tilde{T}_i)}, \tag{11}$$

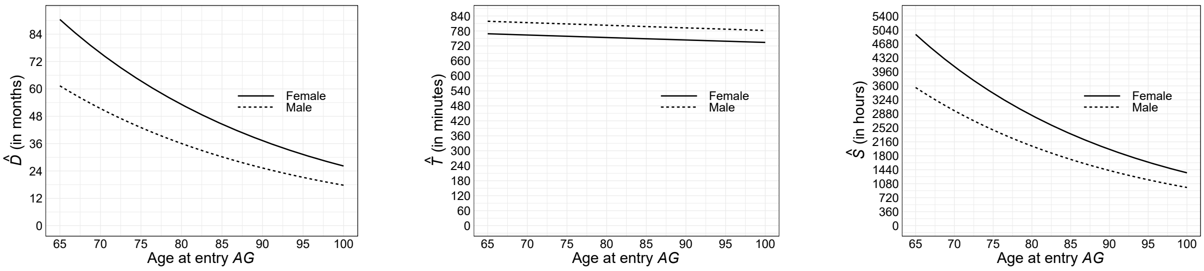
where $\widehat{\text{var}}(\tilde{T}_i) = \left[\hat{\mu}_i(1-\hat{\mu}_i)\right] / (1+\hat{\phi}_i)$, and $\hat{\mu}$ and $\hat{\phi}$ are the estimates of μ and ϕ, respectively. Since the exact distribution of these residuals is not known, half-normal plots with simulated envelopes are a useful diagnostic tool (see Atkinson, 1985; Kutner et al., 2005). The idea is to enhance the standard half-normal plot by adding a simulated envelope that can be used to decide whether the observed residuals are consistent with the fitted model. The construction of a half-normal envelope for the beta regression model is fully described in Ferrari and Cribari-Neto (2004). Under the null hypothesis, the observations should lie inside the envelope a prespecified percentage of times. In Figure 2.5b we draw the envelope (area between both plain curves) and the Pearson residuals using 500 simulations and a 95% confidence interval. We observe three outliers at the top right corner and some observations that lie outside the envelope (see the records starting from 2.2 on the horizontal axis). Overall, 76.3% of the data lie inside the confidence interval. Note that given the large number of observations, the boundaries of the simulated envelope are rather narrow. Thus, we conclude that the intensity of care model achieves satisfactory concordance with the data.

Alternative models. To further investigate the results, we also consider models where the age at entry AG and the number of additional diagnoses ND are coerced into categorical variables, separately and simultaneously, with the levels used in the descriptive statistics reported in Table 2.3. It appears that the resulting BIC values increase importantly, which is due, to a large extent, to the increase in the number of degrees of freedom. Thus, we confirm that AG and ND should be kept as numerical variables. Furthermore, in the extant literature, the interaction term between AG and gender GE is proven to significantly affect LTC usage (see, e.g., von Strauss et al., 2003; Crimmins et al., 2010; Fuino et al., 2020). Indeed, at increasing ages, the duration of stay in an institution and the intensity of care are different for males and females. In our models, however, adding this interaction term yields higher BIC values, and moreover, if added, the coefficients of the interaction terms in both models are not significant for both numerical and categorical definitions of AG.

2.5.5 Estimation of the overall care severity

Using selected profiles of the institutionalised elderly, we estimate the duration of stay, the intensity of care, and the overall care severity. Thereby, the overall mean care severity is estimated by $\hat{S} = \hat{D} \cdot \hat{T}$; see Equation (1), where where $\hat{D} = \mathbb{E}[D]$ and $\hat{T} = \mathbb{E}[T]$ are estimated through Equations (3) and (9), respectively.

Effect of the age at entry and the gender. Our first analysis looks at the care requirements along the age at entry AG and the gender GE. To present the results, we introduce a profile that we call "modal", where for each characteristic other than AG and GE, we take the most prevalent value, i.e., the mode value (see Table 2.3). Hence, the modal profile characterizes an individual with a mental main diagnosis, a secondary diagnosis grouped under "other" and having 7 additional diagnoses. The dependence of the individual is such that he or she needs help with ADL at unpredictable times ($DP = 7$) and has mobility limited to the institution ($PM = 6$), moderate disturbances of orientation ($OR = 5$), occupational limitations in time and



(a) Duration of stay $\hat{D}$. (b) Intensity of care $\hat{T}$. (c) Care severity $\hat{S}$.

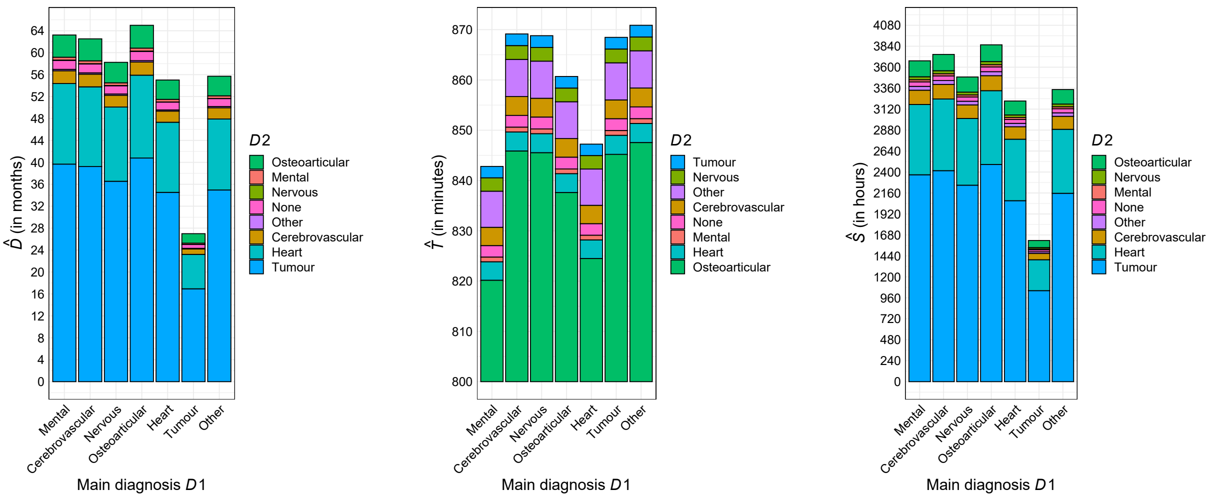
Figure 2.6: Estimated duration of stay, intensity of care and overall care severity for the modal profile.

type ($OC = 7$), and social limitations with only primary contacts ($SI = 6$). Furthermore, the individual has moderate impairments in recent memory RM, perception and attention PA, impulses IM, will and motivation WM, behaviour BH, and, finally, a mild visual impairment VS.

In the graphs of Figure 2.6 we present the estimated duration of stay $\hat{D}$, intensity of care $\hat{T}$ and overall care severity $\hat{S}$ across the age at entry and both genders for the modal profile. We note that throughout all ages, women stay longer in the institution, and they require less help per week. Consequently, the overall care severity $\hat{S}$ of women is larger. In line with their higher life expectancy, for any age at entry, women stay longer in an institution than men (Mathers et al., 2001; Fong et al., 2017; Schünemann et al., 2017). The graph in Figure 2.6a shows that the mean duration of stay when entering an institution at 65 years is 90.5 and 61.3 months for women and men, respectively. At this age, the difference (29.2 months) between the genders is the largest. It decreases as the age at entry AG increases, and the duration of stay shortens. For example, men (women) entering at the age of 80 years are estimated to stay 36 (53) months. These values are comparable with the range of observations reported in (Fuino and Wagner, 2020, Tables 11 and 12). Figure 2.6b indicates that there is only a small difference in the intensity of care between the genders, the intensity yielding 750 (800) minutes per week for men (women). Indeed, we have found that the age at entry is not one of the key determinants of the intensity of care (see Table 2.4). Furthermore, we observe that, for any gender, the difference between the age of 65 and 100 years is only 36 minutes.

With the estimates for the overall care severity $\hat{S}$ in Figure 2.6c, we can observe the total burden of institutional care that comes with men and women entering an institution at different ages. Depending on the age at entry and gender, the care severity can change by a factor of five. Indeed, the estimated values for the modal profile range from 4 925 hours of care for women institutionalized at the age of 65 years to 984 hours of care for men entering the institution at the age of 100 years. We observe a decreasing trend of $\hat{S}$ across the ages at entry that is in line with the trend observed for the duration of stay $\hat{D}$. While the shapes for both genders resemble each other, the care severity for women is approximately 40% higher than that for men (2 840 vs. 2 050 hours at $AG = 80$) but decreases faster. The difference of approximately 1 350 hours at the age of 65 years is only approximately 380 hours at the age of 100 years.

Effect of the main and secondary diagnoses. Considering the modal profile for an 80-year-old woman at entry, we present in Figure 2.7 the estimates for different combinations of the main $D1$ and secondary $D2$ diagnoses, as all other characteristics remain the same. From



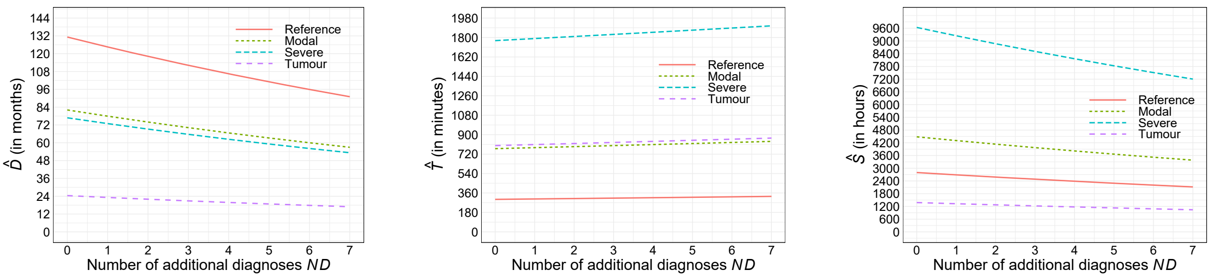
(a) Duration of stay $\hat{D}$. (b) Intensity of care $\hat{T}$. (c) Care severity $\hat{S}$.

Figure 2.7: Estimated duration of stay, intensity of care and overall care severity for the modal profile with different main and secondary diagnoses.

our regression analysis (see Table 2.4) we found that both the main and secondary diagnoses greatly influence the duration of stay, while they have only a small effect on the intensity of care. By estimating the overall care severity, we integrate the effects on both the duration and intensity. We find that the combination of mental and osteoarticular diseases (in any order) leads to the longest estimated duration of stay of approximately 62 months, also triggering the highest overall care severity of approximately 3 650 hours. We observe that a tumour as the main diagnosis is care intensive, with an intensity ranging from 845 minutes per week, in combination with an osteoarticular secondary diagnosis, to 868 minutes per week with a secondary tumour diagnosis. However, the group with a main tumour diagnosis, $D1$, showed the shortest duration of stay (from 17 to 27 months), leading to the lowest overall severity (from 1 040 to 1 620 hours). As with tumours, heart-related diagnoses show a lower estimated duration in both main (from 35 to 55 months) and secondary (from 23 to 56 months) diagnoses. At the same time, they yield one of the lowest intensities of care (between 825 and 845 minutes per week when considering the main diagnosis) after the group of mental diagnoses. Again, the shape of the overall care severity is driven by the duration of stay because pathologies affect the intensity of care less.

Effect of the number of medical diagnoses. To investigate the effect of the number of additional diagnoses ND, we consider three profiles of an 80-year-old woman at entry with a mental main diagnosis and an "other" secondary diagnosis. First, in the "reference" profile, the considered elderly individuals have the lowest dependence levels and no other impairments. Second, in the "modal" profile, dependence and impairments take the mode values as laid out above. Third, in the "severe" profile, all dependence levels and impairments take the highest possible values (i.e., dependence Level 9 and severe impairment). Additionally, we consider a fourth profile focusing on tumours: the "tumour" profile is based on the modal profile but with main and secondary tumour diagnoses. This additional profile is motivated by the observation that a tumour diagnosis noticeably influences the duration of stay (see Figure 2.1a and Table 2.4).

In Figure 2.8, we present the estimated duration of stay $\hat{D}$, intensity of care $\hat{T}$ and overall care severity $\hat{S}$ for the four profiles across the number of additional diagnoses ND. We observe that



(a) Duration of stay $\hat{D}$.　(b) Intensity of care $\hat{T}$.　(c) Care severity $\hat{S}$.

Figure 2.8: Estimated duration of stay, intensity of care and overall care severity along the number of additional diagnoses for different profiles.

with more diagnoses, the duration decreases and the intensity increases for all profiles, which is intuitive. However, each profile has its own character. For example, individuals with the reference profile require the least amount of help with 300 (330) minutes per week for $ND = 0$ ($ND = 7$). However, they stay longer in the institution with a mean duration of 130 (90) months when $ND = 0$ ($ND = 7$). This leads to an overall care severity between 2 800 and 2 120 hours. Individuals with the modal profile, on average, stay in the institution from 82 to 57 months with zero or seven additional diagnoses, respectively. At the same time, the intensity of care ranges from 770 to 840 minutes per week, leading to an overall care severity ranging from 4 480 to 3 380 hours and decreasing with ND.

Individuals with the severe profile stay in the institution slightly less long than the modal profile (range from 77 to 53 months). However, in contrast to the modal profile, individuals with the severe profile are the most demanding for help in their daily needs, with the care intensity ranging from 1 770 to 1 910 minutes per week. Thus, the resulting care severity is almost doubled compared to the modal profile (range from 9 640 to 7 200 hours). Finally, from Figure 2.7b, we note that individuals with the tumour profile require, on average, 30 minutes of care per week less than elderly individuals with the modal profile. However, the duration of stay of these persons is only 24 months if they do not have any additional diagnoses ($ND = 0$). This duration even reduces to 17 months when $ND = 7$. As a result, the overall care severity of the tumour profile is the lowest, ranging from 1 380 to 1 040 hours.

2.6 Conclusion

In this paper, we propose a model to assess the total LTC burden based on the time spent in institutionalised care and the intensity of care provided to elderly individuals. We empirically estimate the model parameters using a private dataset comprising approximately 21 758 individuals from nursing homes in Switzerland. Due to the longitudinal nature of the right-censored data, we relied on survival analysis methods and used an AFT model for the duration of stay. After the age at entry and gender, we found that the pathologies were the key factors affecting the duration of stay in the institution before death. More precisely, individuals with mental and osteoarticular diseases stay the longest, while elderly people with tumours have the shortest duration. Further determinants of the duration are the dependence on ADL and physical mobility limitations. Finally, we find that some mild and moderate levels of physical and sensory function impairments are likely to receive less attention from nurses, which is linked to a reduced duration of stay.

We parameterise a beta regression model for the intensity of care to estimate the mean number of minutes of care per week that a person receives. While we show that pathologies have a minor effect on the amount of help, the key determinants are different limitations in ADL, physical mobility, orientation in space, and occupation. Our results further suggest that psychological and sensory function impairments shape only the distribution of the intensity of care, rather than considerably affecting the mean. Finally, we explore the results by studying selected profiles of the institutionalized elderly individuals. Thereby, we illustrate the overall care severity as the product of the duration of stay and intensity of care. We find that women entering an institution have a higher total care burden than men. We also show that mental and osteoarticular diseases lead to the highest overall severity, mainly resulting from the higher duration of stay. At the same time, tumours lead to the lowest duration of stay, resulting in the lowest care burden.

Our results are directly relevant for policy-makers and the planning of care capacity in institutions. The decomposition of the total number of hours of care in duration and intensity, or, in other words, in the occupancy period of a bed and in the utilisation of care resources, is relevant for deriving actionable policies. On the one hand, the length of stay in an institution drives the number of required places for LTC and the construction of infrastructure. On the other hand, the amount of help needed directly relates to the number of personnel and the education of caregivers. It also is a useful indicator to measure the efficiency of prevention measures, for example, to slow down the aggravation of medical conditions and to contain the increase in required care. Planning the future capacity of institutions and the handling of dependence at large must combine both dimensions of occupancy and prevention while supporting the efforts with policies promoting ageing at home associated with an efficient use of care resources.

In our work, we link demographic factors and medical diagnoses to the care requirements of elderly individuals. The care severity estimate gives an indication of the number of hours of care needed. Hence, it provides an estimate for the future care costs of an elderly individual upon entering an institution. The indicator can help to make the pricing of LTC coverage more precise. For example, innovative insurance contracts could evaluate the one-time premium to guarantee a life annuity underwritten at the moment of entering a care institution. While a large part of the care costs are financed today by health insurers, copayments are required by the elderly individuals to finance their stay in the institution. These may be more important depending on the type of institution (e.g., private and public facilities) and specific types of care (e.g., medical nursing and social company). While the numerical results may vary across countries and populations, we trust that our findings provide relevant indicators when assessing the LTC burden in institutions beyond Switzerland. Indeed, care severity is based on health conditions rather than on country-specific variables.

We provide robust results on institutional LTC estimates solely using information on elderly individuals from the moment when they enter an institution, i.e., in this work, we consider only the first individual health evaluation. During the time in the institution, the health status evolves, and new evaluations are conducted every one or two years. With typically deteriorating health conditions, more information can provide updates on the remaining duration of stay and, more importantly, on the intensity of care, which, on average, increases. Therefore, since our model does not consider the care intensity dynamics, our estimates can potentially be enhanced. Furthermore, the study of the development of the different medical conditions and limitations over time could provide further insight and extend this work. Additionally, it is of interest to derive patterns from the data and to establish key profiles of elderly individuals to further understand the main drivers of the need for care and to better assess the corresponding workload for the personnel. Finally, in this paper, we have approximated the total care burden considering the product of duration and intensity. This approximation holds best if both factors are independent. Further research could study the dependence structure between the two dimensions.

Bibliography

Albarrán, I., P. J. Alonso-González, A. Arribas-Gil, and A. Grané, 2019, How functional data can enhance the estimation of health expectancy: the case of disabled Spanish population, *ASTIN Bulletin*, 49(1):57–84.

Anderson, J. J., J. M. Anthony, Y. Zhang, P. W. F. Wilson, M. Kelly-hayes, P. A. Wolf, B. E. Kreger, and W. B. Kannel, 1993, The Effects of Specific Medical Conditions on the Functional Limitations of Elders in the Framingham Study, *American Public Health Association*, 84(3):351–358.

Arrighi, H. M., T. McLaughlin, and C. Leibman, 2010, Prevalence and Impact of Dementia-related Functional Limitations in the United States, 2001 to 2005, *Alzheimer Disease & Associated Disorders*, 24(1):72–78.

Atkinson, A., 1985, *Plots, Transformations and Regression: An Introduction to Graphical Methods of Diagnostic Regression Analysis.* Oxford science publications. Oxford University Press.

Avis, N. E. and G. T. Deimling, 2008, Cancer Survivorship and Aging, *Cancer*, 113(12):3519–3529.

Barnett, K., S. W. Mercer, M. Norbury, G. Watt, S. Wyke, and B. Guthrie, 2012, Epidemiology of multimorbidity and implications for health care, research, and medical education: a cross-sectional study, *The Lancet*, 380(9836):37–43.

Biessy, G., 2017, Continuous-time semi-markov inference of biometric laws associated with a long-term care insurance portfolio, *ASTIN Bulletin*, 47(2):527–561.

Boult, C., R. L. Kane, T. A. Louis, L. Boult, and D. McCaffrey, 1994, Chronic Conditions That Lead to Functional Limitation in the Elderly, *Journal of Gerontology*, 49(1):M28–M36.

Boyle, G., 2005, The Role of Autonomy in Explaining Mental Ill-Health and Depression Among Older People in Long-Term Care Settings, *Ageing and Society*, 25(5):731–748.

Branch, L. G. and A. M. Jette, 1982, A prospective study of long-term care institutionalization among the aged., *American Journal of Public Health*, 72(12):1373–1379. PMID: 6814269.

Brown, J. R. and A. Finkelstein, 2009, The private market for long-term care insurance in the united states: A review of the evidence, *Journal of Risk and Insurance*, 76(1):5–29.

Byles, J. E., C. D'Este, L. Parkinson, R. O'Connell, and C. Treloar, 2005, Single index of multimorbidity did not predict multiple outcomes, *Journal of Clinical Epidemiology*, 58(10):997–1005.

Callahan, C. M., G. Arling, W. Tu, M. B. Rosenman, S. R. Counsell, T. E. Stump, and H. C. Hendrie, 2012, Transitions in care for older adults with and without dementia, *Journal of the American Geriatrics Society*, 60(5):813–820.

Campbell, A. J., C. Diep, J. Reinken, and L. McCosh, 1985, Factors predicting mortality in a total population sample of the elderly., *Journal of Epidemiology & Community Health*, 39(4):337–342.

Carrino, L., C. E. Orso, and G. Pasini, 2018, Demand of long-term care and benefit eligibility across european countries, *Health Economics*, 27(8):1175–1188.

Centers for Medicare & Medicaid Services, 2014, General Equivalence Mappings (GEMs) – Procedure Codes and Guide. Last accessed: April 11, 2021.

Chavan, P. P., S. K. Kedia, and X. Yu, 2017, Physical and Functional Limitations in US Older Cancer Survivors, *Journal of Palliative Care & Medicine*, 07(04).

Collett, D., 2015, *Modelling Survival Data in Medical Research.* Chapman & Hall/CRC Texts in Statistical Science. CRC Press.

Colombo, F., A. Llena-Nozal, J. Mercier, and F. Tjadens, 2011, *Help Wanted? Providing and Paying for Long-Term Care.* OECD Health Policy Studies. OECD Publishing.

Cosandey, J., 2016, De nouvelles mesures pour les soins aux personnes âgées, *Avenir Suisse*.

Cribari-Neto, F. and A. Zeileis, 2010, Beta regression in R, *Journal of Statistical Software, Articles*, 34(2):1–24.

Crimmins, E. M., J. K. Kim, and A. Solé-Auró, 2010, Gender differences in health: results from SHARE, ELSA and HRS, *European Journal of Public Health*, 21(1):81–91.

Czado, C., R. Kastenmeier, E. C. Brechmann, and A. Min, 2012, A mixed copula model for insurance claims and claim sizes, *Scandinavian Actuarial Journal*, 2012(4):278–305.

Davidson, I. A., M. E. Dewey, and J. R. M. Copeland, 1988, The relationship between mortality and mental disorder: Evidence from the liverpool longitudinal study, *International Journal of Geriatric Psychiatry*, 3(2):95–98.

de Meijer, C., M. Koopmanschap, T. B. d' Uva, and E. van Doorslaer, 2011, Determinants of long-term care spending: Age, time to death or disability?, *Journal of Health Economics*, 30(2):425–438.

Deeg, D. J. H., F. Portrait, and M. Lindeboom, 2002, Health profiles and profile-specific health expectancies of older women and men: The netherlands, *Journal of Women & Aging*, 14(1-2):27–46. PMID: 12537278.

Donabedian, A., 1973, *Aspects of Medical Care Administration.* Harvard University Press.

Dorr, D. A., S. D. Horn, and R. J. Smout, 2005, Cost analysis of nursing home registered nurse staffing times, *Journal of the American Geriatrics Society*, 53(5):840–845.

Duell, D., M. Lindeboom, X. Koolman, and F. Portrait, 2019, Practice Variation in Long-Term Care Access and Use: The Role of the Ability to Pay, *Health Economics*, 28(11):1277–1292.

Farias, S. T., K. Lau, D. Harvey, K. G. Denny, C. Barba, and A. N. Mefford, 2017, Early Functional Limitations in Cognitively Normal Older Adults Predict Diagnostic Conversion to Mild Cognitive Impairment, *Journal of the American Geriatrics Society*, 65(6):1152–1158.

Ferrari, S. and F. Cribari-Neto, 2004, Beta regression for modelling rates and proportions, *Journal of Applied Statistics*, 31(7):799–815.

Fong, J. H., M. Sherris, and J. Yap, 2017, Forecasting disability: application of a frailty model, *Scandinavian Actuarial Journal*, 2017(2):125–147.

Fries, J. F., 1980, Aging, natural death, and the compression of morbidity, *The New England journal of medicine*, 303(3):130–135.

Fuino, M., I. Rudnytskyi, and J. Wagner, 2020, On the Characteristics of Reporting ADL Limitations and Formal LTC Usage Across Europe, *European Actuarial Journal*.

Fuino, M. and J. Wagner, 2018, Long-term care models and dependence probability tables by acuity level: New empirical evidence from switzerland, *Insurance: Mathematics and Economics*, 81:51–70.

Fuino, M. and J. Wagner, 2020, Duration of long-term care: Socio-economic factors, type of care interactions and evolution, *Insurance: Mathematics and Economics*, 90:151–168.

Germain, C. M., E. Vasquez, J. A. Batsis, and D. R. McQuoid, 2016, Sex, race and age differences in muscle strength and limitations in community dwelling older adults: Data from the health and retirement survey (hrs), *Archives of Gerontology and Geriatrics*, 65:98–103.

Goodwin, J. S., 1991, A Population-Based Study of Functional Status and Social Support Networks of Elderly Patients Newly Diagnosed With Cancer, *Archives of Internal Medicine*, 151(2):366.

Grambsch, P. M. and T. M. Therneau, 1994, Proportional hazards tests and diagnostics based on weighted residuals, *Biometrika*, 81(3):515–526.

Grün, B., I. Kosmidis, and A. Zeileis, 2012, Extended beta regression in r: Shaken, stirred, mixed, and partitioned, *Journal of Statistical Software, Articles*, 48(11):1–25.

Guccione, A. A., D. T. Felson, J. J. Anderson, J. M. Anthony, Y. Zhang, P. W. Wilson, M. Kelly-Hayes, P. A. Wolf, B. E. Kreger, and W. B. Kannel, 1994, The effects of specific medical conditions on the functional limitations of elders in the framingham study, *American Journal of Public Health*, 84(3):351–358. PMID: 8129049.

Guibert, Q. and F. Planchet, 2018, Non-parametric inference of transition probabilities based on Aalen–Johansen integral estimators for acyclic multi-state models: application to LTC insurance, *Insurance: Mathematics and Economics*, 82:21–36.

Hedinger, D., O. Hämmig, and M. Bopp, 2015, Social determinants of duration of last nursing home stay at the end of life in Switzerland: A retrospective cohort study Health services research, *BMC Geriatrics*, 15(1):1–8.

Hirsch, D., 2005, *Facing the Cost of Long-term Care: Towards a Sustainable Funding System.* Joseph Rowntree Foundation.

Home Care Association of the Canton of Vaud, 2020, Les tarifs.

Hu, T., 1986, The economic impact of urinary incontinence, *Clinics in geriatric medicine*, 2(4):673—687.

Hyer, L., B. Carpenter, D. Bishmann, and H.-S. Wu, 2005, Depression in Long-Term Care, *Clinical Psychology: Science and Practice*, 12(3):280–299.

Inouye, S. K., S. Studenski, M. E. Tinetti, and G. A. Kuchel, 2007, Geriatric syndromes: Clinical, research, and policy implications of a core geriatric concept, *Journal of the American Geriatrics Society*, 55(5):780–791.

Jennings, L. A., S. Hollands, E. Keeler, N. S. Wenger, and D. B. Reuben, 2020, The Effects of Dementia Care Co-Management on Acute Care, Hospice, and Long-Term Care Utilization, *Journal of the American Geriatrics Society*, Seite jgs.16667.

Kaplan, E. L. and P. Meier, 1958, Nonparametric Estimation from Incomplete Observations, *Journal of the American Statistical Association*, 53(282):457–481.

Karlsson, M., L. Mayhew, R. Plumb, and B. Rickayzen, 2006, Future costs for long-term care: Cost projections for long-term care for older people in the united kingdom, *Health Policy*, 75(2):187–213.

Katz, P. R., 2011, An international perspective on long term care: Focus on nursing homes, *Journal of the American Medical Directors Association*, 12(7):487–492.e1.

Kempen, G. I., A. M. Myers, and L. E. Powell, 1995, Hierarchical Structure in ADL and IADL: Analytical Assumptions and Applications for Clinicians and Researchers, *Journal of Clinical Epidemiology*, 48(11):1299–1305.

Kitchener, M., T. Ng, N. Miller, and C. Harrington, 2006, Institutional and Community—Based Long-Term Care, *Journal of Health & Social Policy*, 22(2):31–50.

Klein, J. D. and M. L. Moeschberger, 1997, *Survival Analysis: Techniques for Censored and Truncated Data*. Statistics for Biology and Health. Springer-Verlag New York.

Koroukian, S. M., N. Schiltz, D. F. Warner, J. Sun, P. M. Bakaki, K. A. Smyth, K. C. Stange, and C. W. Given, 2016, Combinations of Chronic Conditions, Functional Limitations, and Geriatric Syndromes that Predict Health Outcomes, *Journal of General Internal Medicine*, 31(6):630–637.

Kuo, H. K., R. N. Jones, W. P. Milberg, S. Tennstedt, L. Talbot, J. N. Morris, and L. A. Lipsitz, 2005, Effect of Blood Pressure and Diabetes Mellitus on Cognitive and Physical Functions in Older Adults: A Longitudinal Analysis of the Advanced Cognitive Training for Independent and Vital Elderly Cohort, *Journal of the American Geriatrics Society*, 53(7):1154–1161.

Kutner, M. H., C. J. Nachtsheim, J. Neter, and W. Li, 2005, *Applied Linear Regression Models*. McGraw-Hill/Irwin, 5 Auflage.

Le Corre, P.-Y., 2012, *Long-Term Care Insurance: Building a Successful Development*, Seiten 53–72. Palgrave Macmillan UK, London.

Lesman-Leegte, I., T. Jaarsma, J. C. Coyne, H. L. Hillege, D. J. Van Veldhuisen, and R. Sanderman, 2009, Quality of Life and Depressive Symptoms in the Elderly: A Comparison Between Patients With Heart Failure and Age- and Gender-Matched Community Controls, *Journal of Cardiac Failure*, 15(1):17–23.

Lundberg, F., 1903, *Approximerad framställning af sannolikhetsfunktionen. Återförsäkring af kollektivrisker.* PhD thesis, University of Uppsala.

Marengoni, A., S. Angleman, R. Melis, F. Mangialasche, A. Karp, A. Garmen, B. Meinow, and L. Fratiglioni, 2011, Aging with multimorbidity: A systematic review of the literature, *Ageing Research Reviews*, 10(4):430–439.

Maresova, P., E. Javanmardi, S. Barakovic, J. Barakovic Husic, S. Tomsone, O. Krejcar, and K. Kuca, 2019, Consequences of chronic diseases and other limitations associated with old age – a scoping review, *BMC Public Health*, 19(1):1431.

Mathers, C., 1996, Trends in health expectancies in Australia 1981–1993, *Journal of the Australian Population Association*, 13:1–15.

Mathers, C. D., E. T. Vos, C. E. Stevenson, and S. J. Begg, 2001, The burden of disease and injury in australia, *Bulletin of the World Health Organization*, 79(11):1076–1084.

Medicine, I. o., 1991, *Disability in America: Toward a National Agenda for Prevention.* The National Academies Press, Washington, DC.

Menotti, A., I. Mulder, A. Nissinen, S. Giampaoli, E. J. Feskens, and D. Kromhout, 2001, Prevalence of morbidity and multimorbidity in elderly male populations and their impact on 10-year all-cause mortality: The fine study (finland, italy, netherlands, elderly), *Journal of Clinical Epidemiology*, 54(7):680–686.

Miller, E. A. and W. G. Weissert, 2000, Predicting elderly people's risk for nursing home placement, hospitalization, functional impairment, and mortality: A synthesis, *Medical Care Research and Review*, 57(3):259–297. PMID: 10981186.

Mommaerts, C., 2020, Long-term care insurance and the family, Working paper, University of Wisconsin.

Moore, D. C., T. J. Keegan, L. Dunleavy, and K. Froggatt, 2019, Factors associated with length of stay in care homes: a systematic review of international literature, *Systematic Reviews*, 8(1):56.

Muir, T., 2017, Measuring social protection for long-term care.

Nichols, B. L., C. R. Davis, and D. R. Richardson, 2010, An integrative review of global nursing workforce issues, *Annual Review of Nursing Research*, 28(1):113–132.

Okma, K. and M. K. Gusmano, 2020, Aging, Pensions and Long-term Care: What, Why, Who, How? Comment on "Financing Long-term Care: Lessons From Japan", *International Journal of Health Policy and Management*, 9(5):218–221.

Olshansky, S. J., M. A. Rudberg, B. A. Carnes, C. K. Cassel, and J. A. Brody, 1991, Trading off longer life for worsening health: The expansion of morbidity hypothesis, *Journal of Aging and Health*, 3(2):194–216.

Pack, S., 2009, Poor physical health and mortality in patients with schizophrenia, *Nursing Standard*, 23(21):41–45.

Pang, G. and M. Warshawsky, 2010, Optimizing the equity-bond-annuity portfolio in retirement: The impact of uncertain health expenses, *Insurance: Mathematics and Economics*, 46(1):198–209.

Pinquart, M. and S. Sörensen, 2011, Spouses, adult children, and children-in-law as caregivers of older adults: A meta-analytic comparison, *Psychology and Aging*, 26(1):1–14.

Pritchard, D. J., 2006, Modeling disability in long-term care insurance, *North American Actuarial Journal*, 10(4):48–75.

Republic and Canton of Geneva, General Directorate for Health, 2019, EROS/PLAISIR data from 1996-2018.

Rickayzen, B. D. and D. E. P. Walsh, 2002, A multi-state model of disability for the united kingdom: Implications for future need for long-term care for the elderly, *British Actuarial Journal*, 8(2):341–393.

Roussel, B. and C. Tilquin, 1993, *Bio-psycho-social profile of clients in long term care and planning of nursing care required.* Équipe de Recherche Opérationnelle en Santé. Reference manual.

Rudnytskyi, I. and J. Wagner, 2019, Drivers of old-age dependence and long-term care usage in switzerland—a structural equation model approach, *Risks*, 7(3).

Schünemann, J., H. Strulik, and T. Trimborn, 2017, The gender gap in mortality: How much is explained by behavior?, *Journal of Health Economics*, 54:79–90.

Seematter-Bagnoud, L., S. Fustinoni, L. Meylan, S. Monod, A. Junod, C. Büla, and B. Santos-Eggimann, 2012, *Le Resident Assessment Instrument (RAI) et Autres Instruments d'Évaluation, d'Orientation et de Communication Relatifs aux Personnes Âgées dans le Réseau de Soins.* Centre d'Observation et d'Analyse du Vieillissement.

Shao, A. W., H. Chen, and M. Sherris, 2019, To borrow or insure? Long term care costs and the impact of housing, *Insurance: Mathematics and Economics*, 85:15–34.

Shao, A. W., K. Hanewald, and M. Sherris, 2015, Reverse mortgage pricing and risk analysis allowing for idiosyncratic house price risk and longevity risk, *Insurance: Mathematics and Economics*, 63:76–90.

Silverman, B. W., 1986, *Density Estimation for Statistics and Data Analysis.* Chapman & Hall/CRC.

Simard, J. and L. Volicer, 2020, Loneliness and isolation in long-term care and the covid-19 pandemic, *Journal of the American Medical Directors Association*, 21(7):966–967.

Simas, A. B., W. Barreto-Souza, and A. V. Rocha, 2010, Improved estimators for a general class of beta regression models, *Computational Statistics & Data Analysis*, 54(2):348 – 366.

Sinclair, A. J., S. P. Conroy, and A. J. Bayer, 2008, Impact of Diabetes on Physical Function in Older People, *Diabetes Care*, 31(2):233–235.

Social Insurance and Accommodation Service of the Canton of Vaud, 2016, La facture de l'ems.

Swiss Federal Department of Home Affairs, 2021, Ordonnance du DFI sur les Prestations dans l'Assurance Obligatoire des Soins en Cas de Maladie.

Swiss Federal Social Insurance Office, 2010, Nouveau régime de financement des soins.

Thakur, M. and D. G. Blazer, 2008, Depression in Long-Term Care, *Journal of the American Medical Directors Association*, 9(2):82–87.

Therneau, T. M., 2021, *A Package for Survival Analysis in R*. R package version 3.2-10.

Tomas, J. and F. Planchet, 2013, Multidimensional smoothing by adaptive local kernel-weighted log-likelihood: Application to long-term care insurance, *Insurance: Mathematics and Economics*, 52(3):573–589.

Tombaugh, T. N. and N. J. McIntyre, 1992, The mini-mental state examination: A comprehensive review, *Journal of the American Geriatrics Society*, 40(9):922–935.

Tomiak, M., J.-M. Berthelot, E. Guimond, and C. A. Mustard, 2000, Factors Associated With Nursing-Home Entry for Elders in Manitoba, Canada, *The Journals of Gerontology: Series A*, 55(5):M279–M287.

van den Akker, M., F. Buntinx, J. F. Metsemakers, S. Roos, and J. Knottnerus, 1998, Multimorbidity in general practice: Prevalence, incidence, and determinants of co-occurring chronic and recurrent diseases, *Journal of Clinical Epidemiology*, 51(5):367–375.

Vanella, P., M. Heß, and C. B. Wilke, 2020, A Probabilistic Projection of Beneficiaries of Long-Term Care Insurance in Germany by Severity of Disability, *Quality & Quantity*.

Victor, C. R., 2012, Loneliness in care homes: a neglected area of research?, *Aging Health*, 8(6):637–646.

von Strauss, E., H. Agüero-Torres, I. Kåreholt, B. Winblad, and L. Fratiglioni, 2003, Women are more disabled in basic activities of daily living than men only in very advanced ages: A study on disability, morbidity, and mortality from the kungsholmen project, *Journal of Clinical Epidemiology*, 56(7):669–677.

Waitzberg, R., A. E. Schmidt, M. Blümel, A. Penneau, A. Farmakas, Å. Ljungvall, F. Barbabella, G. F. Augusto, G. P. Marchildon, I. S. Saunes, D. Vočanec, I. Miloš, J. C. Contel, L. Murauskiene, M. Kroneman, M. Tambor, P. Hroboň, R. Wittenberg, S. Allin, and Z. Or, 2020, Mapping Variability in Allocation of Long-Term Care Funds Across Payer Agencies in OECD Countries, *Health Policy*, 124(5):491–500.

World Health Organization, 1980, International classification of impairments, disabilities, and handicaps: a manual of classification relating to the consequences of disease, published in accordance with resolution WHA29.35 of the Twenty-ninth World Health Assembly, May 1976.

Xue, Q.-L., 2011, The frailty syndrome: Definition and natural history, *Clinics in Geriatric Medicine*, 27(1):1–15. Frailty.

Chapter 3

On the Factors Determining the Health Profiles and Care Needs of Institutionalized Elders

In many developed countries, population aging raises a number of issues related to the organization and financing of long-term care. While the determinants of the overall burden and cost of care are well understood, the organization of institutionalized long-term care must meet the needs of the elderly. One way to optimize management is to use information on health problems to assess the infrastructure needed, the qualifications of staff, and the allocation of new entrants. In this research, we determine the typical health profiles of institutionalized elderly using novel longitudinal data from nursing homes in the canton of Geneva, Switzerland. Our data contain comprehensive information on health factors such as impairments of psychological and sensory functions, levels of limitations, and pathologies for 21 549 individuals covering the period from 1996 to 2018. First, we perform a spectral clustering algorithm and determine the profiles of the institutionalized individuals. Then, we use multinomial logistic regression to study the effects of the factors that determine these health profiles. Our main findings include eight typical health profiles: the largest group consists of the most "healthy" individuals, who, on average, require the least amount of help with their daily needs and who stay in the institution the longest. We show that, in contrast to age at admission and gender, the limitations and the set of pathologies are relevant factors in determining the profile. Our study sheds light on the typical structures of elderly' health profiles, which can be used by institutions to organize their resources and by insurance companies to derive profile-based products that provide additional insurance coverage in case of special needs.

This is a joint work with J. Wagner, published in Insurance: Mathematics and Economics (2024), volume 114, pp. 223–241.

3.1 Introduction

The aging of the population is a major concern in most developed countries. Improvements in longevity are associated with an increased need for health services for the elderly, placing a significant burden on the old-age care system in the future (OECD, 2017). At higher ages, elderly people are more likely to experience difficulties in performing activities of daily living (ADL, see, e.g., Kempen et al., 1995) and to develop multiple types of diseases (van den Akker et al., 1998), respectively increasing the need for health services (Stark et al., 1995) and the demand for external help (see, e.g., Fuino and Wagner, 2018a; Vanella et al., 2020). In this context, we consider the help provided to elderly individuals in functional abilities, called old-age long-term care (LTC). In most developed countries, the provision of LTC to the elderly is mainly organized along three directions: family care, home care, and institutional care. While family and home care are provided in the person's own home, institutional care refers to persons who require increased assistance with their daily needs and reside in specialized institutions for the elderly. The literature on LTC systems, particularly institutional care, highlights several issues that need to be addressed: financing (Kitchener et al., 2006; Brown and Finkelstein, 2009), availability of care facilities (Katz, 2011; Cosandey, 2016), and availability of professional caregivers (Nichols et al., 2010; Colombo et al., 2011). Institutional LTC has the highest financial and managerial exposure to the coming difficulties. The aim of the present work is to complement the understanding of the care needs of institutionalized elderly individuals in terms of their health profile.

The provision of institutional care requires specialized facilities, trained staff, a strong organization, sustainable financing, and therefore, the inherent involvement of the government, which is responsible for providing the care facilities. Therefore, the increased demand for LTC requires a better assessment of the infrastructure capacity, namely, the number of specialized institutions and the number of available beds, as well as the associated costs, especially with regard to the number and quality of the caregivers. In order to establish an efficient provision of institutional LTC, it is essential to understand the typical demands of the elderly based on their needs. For example, workflow could be facilitated by placing individuals in the same facility or on the same floor who have similar needs, exhibit similar behaviors, or require similar types of care.

From an economic point of view, the management of an LTC facility is more concerned with those individuals who are a greater drain on resources. Thus, on the one hand, the costs of an institution are affected by the length of time that a person stays in the institution. This length of stay is explained by many factors, including age and gender (see, e.g., Mathers, 1996; Deeg et al., 2002; Germain et al., 2016; Fong et al., 2017; Fuino and Wagner, 2020), physical and psychological impairments (Hedinger et al., 2015; Moore et al., 2019), and the spectrum of pathologies (Davidson et al., 1988; Pack, 2009). For example, individuals with musculoskeletal and osteoarticular disorders have lower mortality rates (Makam et al., 2019; Bladt et al., 2023) and therefore longer stay. On the other hand, the amount of daily care provided to an individual adds another dimension to the burden. According to Dorr et al. (2005), the highest costs result from the time that nurses spend with residents. Many researchers state that the pathological profile of a person entails different LTC requirements, which directly affect the level of dependency and, consequently, the amount of help required (see, e.g., Guccione et al., 1994; Fong, 2019). Multimorbidity results in more severe conditions of psychological and sensory functioning, leading to lower levels of autonomy and greater dependence on others (Marengoni et al., 2011; Barnett et al., 2012). In more recent work, Bladt et al. (2023) find that the pathology that most affects an individual is not sufficient to determine the amount of assistance required. In fact, the level of dependency is also highly relevant, a finding supported by the research of, for example, Arrighi et al. (2010); Albarrán et al. (2019); Jennings et al. (2020). Moreover, Koroukian et al. (2016) show that when explaining the health profile of an individual, taking into account geriatric syndromes, e.g., visual hearing impairment, depressive symptoms, low cognitive performance, and dizziness, is more beneficial in determining the burden of care than considering the functional limitations alone.

In this work, we aim to derive typical profiles of the institutionalized elderly in terms of their health status and medical diagnoses. We base our study on a longitudinal data set covering the institutionalized elderly from the canton of Geneva in Switzerland between 1996 and 2018. The analysis is based on 21 549 records reported through the Canadian monitoring system "PLAISIR" (see the manual by Roussel and Tilquin, 1993). The records include information on the person's date of birth, admission to the institution, the date of death (if applicable), and health-related measurements performed by nurses during a one-week observation period: limitations in performing ADL and other activities, the levels of psychological and sensory function impairments, multiple medical diagnoses with their importance, and the amount of care provided per week. To identify typical health profiles, we perform a spectral cluster analysis and use multinomial logistic regression to examine the key factors that influence membership in a particular group.

Our analysis suggests eight health profiles, each characterized by a unique combination of activity limitations, impairments of psychological and sensory functions, and pathologies. We find that the largest group of institutionalized elderly consists of individuals with relatively high autonomy, resulting in less need for assistance and a longer stay. In contrast, the second largest group consists of individuals with the most severe health conditions, who require the highest amount of help (e.g., twice as much daily care as the first group). Using multinomial regression, we find that a person's gender is not a significant factor in grouping. Rather, the relevant profile is determined by the combination of limitations, i.e., the degree of dependence, and the most prevalent type of diagnoses in the pathology profile. These findings expand the current understanding of the needs of institutionalized elderly and the estimation of the associated costs. They allow institutions to optimize their organization and funding bodies, especially insurance companies, to provide adequate coverage (Fuino et al., 2022; Ugarte Montero and Wagner, 2023). This is particularly important, given the escalating demand for LTC in the United States (Institute of Medicine, 2008; Spetz et al., 2015), Europe (Carrino et al., 2018; Fuino and Wagner, 2018b; Spasova et al., 2018) and China (Wong and Leung, 2012; Wang et al., 2018).

The remainder of this paper is organized as follows. In Section 3.2 we introduce the available data set, present the variables, and provide descriptive statistics. In Section 3.3 we present the spectral clustering algorithm and the data transformations required to apply the method. In Section 3.4 we report the results, interpret the health profiles obtained, and explore the determinants of belonging to a particular profile using multinomial regression analysis. In Section 3.5 we conclude our research.

3.2 Data on institutional LTC and descriptive statistics

3.2.1 Available data and variables

Our study is based on the same private data set as that used by Bladt et al. (2023). It contains comprehensive information on the institutionalized elderly in the canton of Geneva for the period from 1996 to 2018. The data are collected using the EROS assessment tool described by Roussel and Tilquin (1993) and include information on age, gender, level of dependence, impairments, and medical diagnoses. It also provides information on the amount of help received from caregivers, the date of entry, and the date of death, if applicable. For this analysis, we retain a subset of data consisting of $N = 21\,549$ elderly individuals and focus on those who entered the institution when they were at least 65 years old.[1] The data consist of 17 890 complete and 3 659 right-censored observations, i.e., 17% of the individuals were still alive in 2018.

Upon entering the facility, each individual undergoes an initial medical examination. Various tests are used to assess general health, medical diagnoses, and more specific limitations and impairments. The assessment also records the amount of help provided to the elderly, expressed in minutes of care per week. We consider 36 key variables that characterize each instance in our data, see Table 3.1. In the following, we provide an overview of the variables, borrowing from the detailed description by Bladt et al. (2023).

Demographic variables. Using the dates of birth and admission to the institution, we calculate the age at entry AG as the number of full years elapsed. We observe the oldest admission to the institution for a 106-year-old person. Information on the gender GE of the individual is recorded as a binary factor with levels "male" and "female".

Medical diagnoses. A person's pathologies include up to nine medical diagnoses, which are recorded and ranked by importance. We label the diagnoses with D_i, where $i = 1, 2, \ldots, 9$, and D_1 denotes the most important diagnosis. If a person has less than nine diagnoses, the D_is are assigned the value "none" for i greater than ND, the total number of diagnoses. Each diagnosis is coded using the International Classification of Diseases, see World Health Organization (2016), and Bladt et al. (2023, Footnote 7). For our analysis, we reduce the number of diagnoses by considering ten groups, namely, the mental, cerebrovascular, respiratory, blood, nervous, osteoarticular, endocrine, heart, and tumors groups. All other diagnoses are grouped in a category labeled "other".[2]

Levels of dependence. Dependence levels are measured along five dimensions: The variable DP takes into account limitations and physical dependence in performing (instrumental) ADL such as eating, dressing, and cooking. Next, the level of physical mobility (PM)

[1] The retained data cover 92.4% of the original data retrieved from the assessment tool. We removed records with incomplete data (1.2%), individuals who left the institution at the time of data extraction (4.0%), and individuals who were younger than 65 years when they entered the institution (2.4%).

[2] For the six groups of mental, cerebrovascular, nervous, osteoarticular, heart, and tumor diseases we use the definitions as in Bladt et al. (2023, Footnote 8). The group of respiratory diagnoses includes chronic respiratory diseases such as bronchitis, emphysema, and asthma. Next, diagnoses of atherosclerosis, aortic aneurysm and dissection, arterial embolism and thrombosis, or capillary disease are classified in the blood disease group. Endocrine diagnoses are thyroid diseases, diabetes, obesity. Finally, the group of other diagnoses consists of nutritional anemia, diseases of the ear and mastoid process, hernias, renal failure, consequences of traumatic injuries, poisoning, and other consequences of external causes.

Variable	Description	Values
Demographic variables		
AG	Age at entry in the institution	in years: 65, 66, 67, ...
GE	Gender	male, female
Medical diagnoses		
ND	Number of diagnoses	between 1 and 9
D_1	Diagnosis of the first importance	mental, cerebrovascular, respiratory, blood, nervous, osteoarticular, endocrine, heart, tumors, other
D_i	Diagnosis of the i-th importance, $i = 2, 3, \dots, 9$	see D_1, plus "none"
Levels of dependence		
DP	Dependence in ADL	nine levels: labeled from 1 to 9
PM	Physical mobility limitations	"
OR	Orientation problems	"
OC	Occupational limitations	"
SI	Social integration limitations	"
Impairments of psychological and sensory functions		
RM	Recent memory	four levels: adequate, mild, moderate, severe
LM	Long-term memory	"
TH	Thinking	"
PA	Perception and attention	"
CW	Consciousness and wakefulness	"
TP	Orientation (time/person/space)	"
DM	Decision making	"
IM	Impulses	"
WM	Will and motivation	"
EM	Emotions, affect, moods	"
BH	Behavioral	"
LG	Language	"
VS	Vision	"
HR	Hearing	"
SU	Making self understood	"
OU	Ability to understand others	"
Duration and intensity of care		
D	Duration of stay in the institution	number of months
T	Intensity of care provided per week	number of minutes (between 0 and 10 080)
RC	Right-censoring indicator	yes, no

Table 3.1: Description of the variables.

measures the ability to move effectively in the environment with the help of mechanical aids, but not with the help of other people. The level of orientation and interaction with the environment (OR) reflects the reception, assimilation, and response to external signals. The level of occupational limitations (OC) shows the person's ability to perform the usual activities in an institution. Finally, the level of social integration (SI) represents the person's ability to participate in social activities and maintain social relationships. In accordance with the World Health Organization (1980), the limitations are recorded on ordered nine-point scales, with each level corresponding to a given severity. A description of the different levels of limitations can be found in Bladt et al. (2023, Table 2).

Impairments of psychological and sensory functions. The data contain medical assessments of 16 impairments of psychological and sensory functions, as listed in Table 3.1. Each impairment is measured on an ordered four-point scale, reaching from adequate to severe, by comparing a person's performance to the average performance of a healthy individual of the same age and sex. While for some functions (e.g., recent memory, and vision) fairly precise descriptions of the four levels are given, for others the condition is assessed qualitatively. A description of the variables and the levels is given in Roussel and Tilquin (1993).

Duration and intensity of care. The dates of admission and death allow the calculation of the duration of stay D expressed in months (see also Bladt et al., 2023, Footnote 6). For right-censored records, the length of stay is evaluated with the time span between admission and the latest date available in the data (August 21st, 2018). These records are flagged with the indicator RC. The intensity of care corresponds to the number of weekly minutes of care T, a number between 0 and 10 080. It includes care provided for breathing assistance, eating and drinking, elimination, hygiene, mobility, communication, medication needs, intravenous therapy, and other treatments.

Comparison to selected other data sets. In the context of LTC, other data sets are commonly used in the literature. Data sets such as the Health and Retirement Study in the United States (HRS), the Survey of Health, Ageing and Retirement in Europe (SHARE), and the China Health, Aging, and Retirement Longitudinal Study (CHARLS) are attractive to researchers because of their accessibility, longitudinal structure, and robustness.[3] These data sets are collected through national surveys and provide valuable information on the dynamics of aging, health, and retirement. Their comparable structures allow researchers to conduct comprehensive studies of aging using various common factors. Recent articles in the actuarial and health literature examining these data sets include areas such as the dynamics of dependency and health (Wu et al., 2018; Fong, 2019; Fu et al., 2022), LTC insurance (Gottlieb and Mitchell, 2020; Sherris and Wei, 2021), and mortality modeling (Crimmins et al., 2019; Xu et al., 2019).

Surveys are weighted to obtain balanced samples within the study population. For example, according to Johnson, 2019, Table 1, approximately 4% of individuals tracked by HRS who are 65 years of age or older receive institutional care. Similarly, in our data set, we observed 3 659 people receiving institutional LTC at the time of data extraction, representing approximately 4.5% of the population aged 65 years and older in the Canton of Geneva in 2018 (Swiss Federal Statistical Office, 2021). However, these studies typically do not follow up with respondents who begin receiving institutional care due to the difficulty in conducting the same surveys online or in person. As a result, research on older people in nursing homes is limited.

Although these data sets provide valuable insights into various aspects of aging, the survey-based approach often fails to capture an individual's health status in a comprehensive manner. Standard questions in surveys about medical conditions follow a structure similar to HRS: "Has a doctor ever told you that you have had a heart attack, coronary heart disease, angina, congestive

[3]The HRS data set is available at `https://hrs.isr.umich.edu/`, originally reviewed by Juster and Suzman (1995) and later by Sonnega et al. (2014); Fisher and Ryan (2017); the SHARE data set can be found at `https://share-eric.eu/` and is presented by Börsch-Supan et al. (2013); and the CHARLS data set from `https://charls.pku.edu.cn/en/` is explained by Zhao et al. (2012).

heart failure, or other heart problems?" (HRS Codebook, 2020, Section C, Question 36). The answers to such questions generate responses that can be used later in data analysis, for example as dummy variables. Our data expand the knowledge of the person's set of pathologies by medical assessments of the importance of diagnoses, allowing for a more detailed analysis. Similarly, five variables on the level of dependence provide extended information on the person's dependence on external help, as well as their social interactions. In addition, most of the variables related to impairments of psychological and sensory functions can be adapted to these national-level data sets. On the downside, our data do not provide information about a person's education, economic status, or prior life experiences.

3.2.2 Descriptive statistics

In the following, we discuss the descriptive statistics of the data focusing on the variables related to the demographics, the number of pathologies, and the limits relating to the levels of dependence. In Table 3.2, we report, beyond the distribution of the records, the median duration of stay in the institution in months and the intensity of care expressed in minutes per week. Due to the right-censoring of the data, the mean length of stay cannot be calculated, so we use survival analysis techniques to present the median length of stay. Therefore, we use the Kaplan-Meier product-limit estimator (Kaplan and Meier, 1958). We construct this non-parametric estimator based on the survival curve, along the subsets of data along the categories of each variable.

Demographic variables. To report the distribution of the age at entry AG, we have divided the range of age values into five categories. We observe that the majority (52.1%) of the admitted individuals are in the age group "80–89", followed by the groups "90–99" (26.5%) and "70–79" (17.8%). The youngest observed group "65–69" contains only 2.9% of the individuals. As expected, the median length of stay is highest in the youngest group (70.5 months) and decreases to 16.7 months in the "100+" group. At the same time, the mean intensity of care is rather stable over the age classes (935 to 984 minutes per week, i.e., about 16 hours per week) with a peak of 1 241.1 minutes or 20.7 hours per week in the "100+" group. Given their higher life expectancy, we observe a higher prevalence of institutionalized women (72.5% of our data). They also have a higher median length of stay (41.8 months) compared to men (26.9 months).

Medical diagnoses. In our data 20.6% of the individuals have nine different diagnoses, while only 1.7% and 4.9% have one or two diagnoses, respectively. The rest of the data is relatively evenly distributed between $ND = 3, 4, \ldots, 8$ (see Table 3.2). Consistent with Bladt et al. (2023), we observe that pathologies have a significant impact on the length of stay, but less so on the intensity of care. In fact, the median length of stay strongly decreases and the average intensity of care slightly increases with the number of diagnoses.

In Figure 3.1 we illustrate the frequency and the ranking of pathologies. The most common diagnosis D_1 is "mental" problems (34.4%), followed by "other" (19.0%) and "nervous" diseases (18.3%). The second most important diagnosis D_2 relates to "other" in 28.2% of the cases, followed by the "mental" (25.8%) and "heart" (16.3%) groups. We observe that the label "other" appears across all importance positions, indicating that it is likely for an elderly individual to have at least one diagnosis of this group. Similar observations can be made for the "heart", "osteoarticular" and, to some extent, "mental" categories. Details on the number of records in each rank and diagnosis with information on the median duration and average intensity of care

	n	(%)	D_{med}	T_{avg}
Right-censoring				
Yes	17 890	(83.0)	–	–
No	3 659	(17.0)	–	–
Age at entry AG				
65–69	627	(2.9)	70.5	935
70–79	3829	(17.8)	49.5	984
80–89	11 227	(52.1)	39.7	944
90–99	5 710	(26.5)	28.2	969
100+	156	(0.7)	16.7	1 231
Gender GE				
Female	15 631	(72.5)	41.8	937
Male	5 918	(27.5)	26.9	1 021
Number of diagnoses ND				
1	368	(1.7)	62.3	822
2	1 060	(4.9)	52.7	865
3	2 157	(10.0)	49.4	876
4	2 960	(13.7)	44.1	914
5	3 032	(14.1)	38.3	941
6	2 972	(13.8)	35.1	956
7	2 441	(11.3)	35.6	976
8	2 121	(9.8)	32.4	999
9	4 438	(20.6)	28.4	1 052

	n	(%)	D_{med}	T_{avg}
Dependence in ADL DP				
1–6	3605	(16.7)	56.0	414
7	8763	(40.7)	42.0	780
8	7571	(35.1)	29.0	1 274
9	1610	(7.5)	18.8	1 688
Physical mobility limitations PM				
1–5	2 231	(10.4)	62.4	422
6	6 268	(29.1)	45.2	689
7	5 469	(25.4)	35.5	971
8	2 186	(10.1)	30.0	1 051
9	5 395	(25.0)	24.8	1 450
Orientation problems OR				
1–4	3 506	(16.3)	53.2	529
5	7 471	(34.7)	38.8	791
6	5 809	(27.0)	32.6	1 098
7	2 376	(11.0)	31.9	1 276
8–9	2 387	(11.1)	30.0	1 469
Occupational limitations OC				
1–5	2 025	(9.4)	61.5	435
6	5 899	(27.4)	42.5	705
7	10 142	(47.1)	33.0	1 069
8–9	3 483	(16.2)	29.5	1 380
Social integration limitations SI				
1–4	1 895	(8.8)	55.5	515
5	5 170	(24.0)	44.1	688
6	7 619	(35.4)	35.0	950
7	5 334	(24.8)	31.2	1 234
8–9	1 531	(7.1)	30.5	1 520

Table 3.2: Descriptive statistics on the median duration of stay D_{med} (in months) and the mean intensity of care T_{avg} (in minutes per week).

are reported in Table 3.5 in Appendix 3.6.1.

Levels of dependence. The lower levels of all limitations variables refer to an independent and healthy individual. As expected, we find that institutionalized individuals tend to fall into the higher levels of dependence. In analogy to Bladt et al. (2023), we report the distribution of records after aggregating the first or last consecutive level to avoid groups containing less than 5% of the sample. Individuals who are assisted quasi-permanently (DP level 7) or who require assistance with most of their needs (DP level 8) are most prevalent in our data, with shares of 40.7% and 35.1%, respectively. Furthermore, in terms of physical mobility, 29.1% and 25.4% of the individuals are restricted to the facility (PM level 6) or to one floor (PM level 7), respectively. At the same time, 25% (PM level 9) are completely immobile, unable to get out of bed or a chair on their own. In general, for all variables DP, PM, OR, OC, and SI we observe that with increasing levels, the median length of stay decreases and the mean intensity of care increases. For example, the duration decreases by 13 months between levels 7 and 8 of depen-

	Mental	Cerebrovascular	Respiratory	Blood	Nervous	Osteoarticular	Endocrine	Heart	Tumors	Other	None
D_1	34.4%	5.8%	1.6%	0.4%	18.3%	7.2%	3.0%	8.6%	1.8%	19.0%	0.0%
D_2	25.8%	3.3%	1.5%	0.5%	7.0%	10.1%	3.9%	16.3%	1.6%	28.2%	1.7%
D_3	14.7%	2.7%	1.4%	0.7%	4.0%	11.1%	4.7%	20.2%	1.4%	32.5%	6.6%
D_4	8.4%	2.1%	1.0%	0.7%	2.5%	10.2%	3.9%	19.3%	1.1%	34.1%	16.6%
D_5	5.3%	1.6%	0.9%	0.6%	1.8%	8.3%	3.0%	15.3%	1.1%	31.7%	30.4%
D_6	3.2%	1.3%	0.7%	0.7%	1.2%	6.2%	2.6%	11.2%	0.8%	27.7%	44.4%
D_7	2.0%	1.1%	0.4%	0.5%	0.9%	4.8%	1.8%	7.2%	0.6%	22.6%	58.2%
D_8	1.2%	0.7%	0.2%	0.4%	0.7%	3.3%	1.1%	4.7%	0.5%	17.7%	69.6%
D_9	0.8%	0.5%	0.2%	0.3%	0.4%	2.3%	0.7%	2.8%	0.4%	12.1%	79.4%

%
[0,10]
(10,20]
(20,30]
(30,40]
(40,50]
(50,60]
(60,70]
(70,80]

Note: For each D_i, the sum across all diagnoses equals 100%.

Figure 3.1: Prevalence of diagnoses across the nine levels of importance D_i.

dence in ADL, while the intensity of care increases by more than 8 hours (494 minutes) per week.

Impairments of psychological and sensory functions. As a consequence of the diseases, functional impairments also affect the length of stay and the intensity of care. While we report full descriptive statistics for the 16 impairments in Table 3.6 in the Appendix 3.6.1, we visualize in Figure 3.2 the pairwise distributions of the six impairments that have the greatest impact (see Bladt et al., 2023): recent memory RM, perception and attention PA, impairment of impulses IM, will and motivation WM, behavior BH, and vision VS. On the main diagonal of the figure we report the histograms of each variable along the four levels, and in the upper triangle we present pairwise distributions of any two impairments, where the size of a rectangle corresponds to the proportion of individuals. From the histograms, we conclude that there is only a minority of individuals who have an "adequate" (lowest) level of any impairment, except for vision VS. In fact, from Table 3.6 we see that the lowest level is more common for language (39.7%), hearing (30.6%), and vision (23.1%) impairments. In general, most individuals have "mild" or "moderate" impairments, while only recent memory limitations are severe for a larger number of individuals (27.1%).

The pairwise distributions also show that the higher the level of one variable, the higher the level of another impairment in most cases (see, for example, the pairs RM and PA, RM and IM, and IM and WM). A counterexample can be observed for the vision impairment VS, which does not show any particular pattern with any other variable. In general, this means that if a person has at least one "moderate" or "severe" impairment, it is likely that other psychological

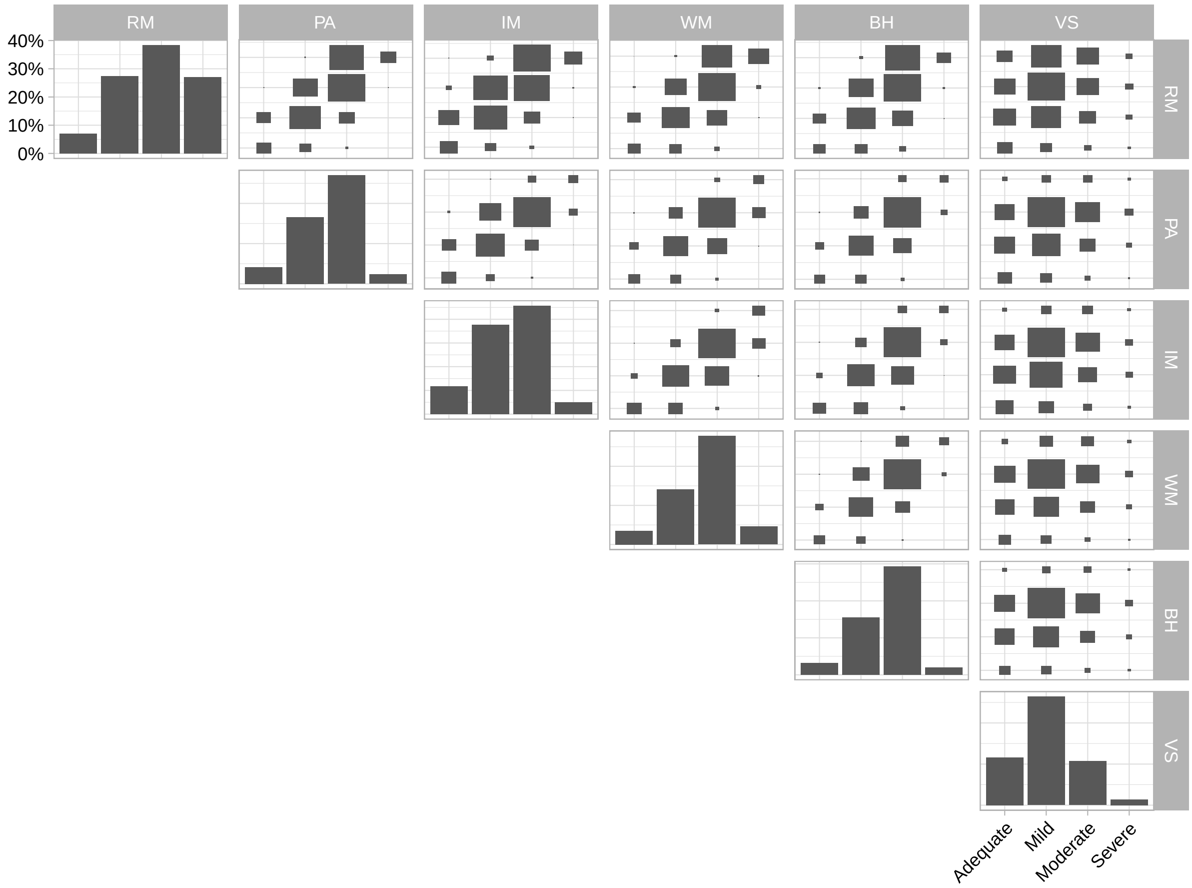


Figure 3.2: Pairwise distribution of the six most relevant impairments of psychological and sensory functions.

and sensory functions are also affected.

3.3 Spectral clustering method and data transformation

3.3.1 Method overview

To derive relevant profiles of elderly individuals from our data, we resort to spectral clustering, a widely used data separation method proposed by Ng et al. (2001). In this method, the data with N observations are treated as connected non-oriented weighted graphs whose vertices are data instances. The weight of an edge represents a similarity measure S between two observations s_i and s_j, $i, j \in \{1, \ldots, N\}$, which is usually taken as a Gaussian kernel, i.e.,

$$S_{ij} \equiv S(s_i, s_j) = \exp(-\|s_i - s_j\|^2/2\sigma^2), \tag{12}$$

where, $\|\cdot\|$ is the Euclidean distance measure,[4] and the scaling parameter σ controls how quickly the similarity decreases as the distance between the two observations increases. To specify this hyper-parameter, we use a standard automatic estimation of an appropriate value using the heuristic procedure implemented in the `spectralcluster` function of The MathWorks

[4]In our analysis, we have tested several distance measures, including the Manhattan, Euclidean, cosine, and Spearman distances. We retained the Euclidean distance because it is the only one that provides consistent and interpretable clusters.

Inc. (2022).

From the similarity matrix S, using the complete linkage method, we construct the k-nearest neighbor graph, a similarity graph using the k-nearest neighbors method, so that the vertices of the graph are data instances, and any two vertices are connected with an edge if at least one of the vertices has the other vertex in its k-neighborhood.[5] The corresponding edge weight is the similarity measure S_{ij} between the two observations s_i and s_j. For practical applications, Brito et al. (1997) suggest using k of the order of $\log N$ to have a connected similarity graph. The resulting similarity graph has a sparse weighted adjacency matrix W, which by definition has non-zero elements,

$$W_{ij} \equiv S_{ij} = \exp(-\|s_i - s_j\|^2/2\sigma^2), \quad i \neq j, \tag{13}$$

and the diagonal elements set to zero $W_{ii} = 0$.

Then, the normalized Laplacian matrix of the similarity graph is computed as

$$L_{\text{rw}} = D^{-1}(D - W) = I - D^{-1}W, \tag{14}$$

where D is a diagonal degree matrix, i.e., $D_{ii} = \sum_{j=1}^{N} W_{ij}$, and I is the identity matrix. Compared to the standard Laplacian matrix $L = D - W$, this normalization is closely related to a random walk on the graph, see Chung (1997), and is suggested for applications by von Luxburg (2007) as it gives the most consistent results.

One of the properties is that the eigenvalues of the matrix L_{rw} are non-negative. The algorithm finds the smallest K eigenvalues, and the corresponding eigenvectors $u_1, u_2, \ldots, u_K$, which form a new matrix $U = [u_1, u_2, \ldots, u_K] \in \mathbb{R}^{N\times K}$ by stacking the eigenvectors in columns. The rows are then normalized, yielding the matrix $\bar{U}_{ij} = U_{ij}/(\sum_{j=1}^{K} U_{ij}^2)^{1/2}$. By treating the rows of $\bar{U}$ as points in $\mathbb{R}^{N\times K}$, the algorithm clusters them into K clusters using the K-means algorithm. Finally, we assign the original observation s_i to cluster l if row i of the matrix $\bar{U}$ is assigned to the cluster l.

3.3.2 Application and data transformation

In the following, we outline the necessary transformations of the data set to apply the clustering algorithm introduced in Section 3.3.1. Our goal is to cluster institutionalized elderly individuals with similar health profiles into distinct groups. Therefore, the clustering algorithm will rely on demographic variables, medical diagnoses, levels of dependence, and impairments of psychological and sensory functions. On the other hand, the length of stay D and the intensity of care T are not included, because these variables do not represent the physical or psychological conditions of the individual.

As seen before, the clustering method relies on a distance or similarity measure between any two instances in the data. For this reason, numerical variables such as the age at entry AG and the number of diagnoses ND are suitable and can remain unchanged. However, categorical variables must be converted to numeric type. For example, gender GE is transformed with

[5]In his tutorial, von Luxburg (2007) also explores other ways of constructing the similarity graph, e.g., by using the ε-neighborhood graph, the mutual k-nearest neighbor graph, and the fully connected graph. The k-nearest neighbor graph is suggested as a general recommendation and it is the only method that gives consistent results.

one-hot encoding, i.e., the variable becomes 1 if the person is male and 0 if the person is female.

To convert the medical diagnoses contained in D_i into numerical variables, we do not use one-hot encoding, as this approach would result in 89 dummy variables. To avoid such complexity and to use the importance rank of the diagnosis, we create a score for each of the ten disease groups (see the possible values for diagnoses in D_1 reported in Table 3.1) according to the formula

$$\text{Score}(d) = \sum_{i=1}^{9} (10 - i) \cdot \mathbb{I}(D_i = d). \tag{15}$$

Here, $d \in \{\text{mental, cerebrovascular}, \dots, \text{tumors, other}\}$ is one of the ten disease groups, and $\mathbb{I}(\cdot)$ stands for the indicator function. So if a disease d is ranked first ($i = 1$), it contributes to the score with a weight of 9, if it is ranked second ($i = 2$), it contributes with a weight of 8, and so on. If a disease group appears more than once in the diagnoses D_i, the contributions of each rank are accumulated.

Variables related to the limitations and impairments of individuals are ordinal, i.e., categorical with ordered levels. We transform the dependence levels, i.e., DP, PM, OR, OC, and SI, into integer variables by using the values corresponding to the level labels ranging from 1 to 9. Variables related to the impairments of psychological and sensory functions usually have additive effects on the physical quality of life (Khil et al., 2015). By considering multiple sensory function impairments, Correia et al. (2016) prove the concept of a global sensory impairment using a structural equation model. Thus, in order to reduce the number of variables and to take into account the severity of each impairment, after assigning an integer value IMP_m to each psychological and sensory function impairment m depending on its level, i.e., 1 for adequate, 2 for mild, 3 for moderate, and 4 for severe, we take the sum over all 16 variables, i.e.,

$$IMP = \sum_{m} IMP_m, \tag{16}$$

where $m \in \{RM, LM, TH, \dots, SU, OU\}$. Transformations associated with medical diagnoses and impairments of psychological and sensory functions are related to the recent concept of intrinsic capacity introduced by World Health Organization (2015).[6]

With the above transformations, we retain a data set of 21 549 observations with 19 variables: two features related to demographic variables (age at entry and gender), 11 features related to medical diagnoses (number of diagnoses and scores of the ten diseases), five variables related to the levels of dependence, and one feature (IMP) related to the impairments of psychological and sensory functions. Before applying the spectral clustering algorithm, we standardize the variables, i.e., we subtract the mean and divide by the standard deviation (except for gender GE, which remains one-hot encoded).

[6]Although different approaches are used to measure the intrinsic capacity score (see, e.g., Aliberti et al. 2022; Beard et al. 2022), a review of the literature conducted by López-Ortiz et al. (2022) indicates the five dimensions of locomotion, vitality, sensation, cognition, and psychology. In addition, Si et al. (2023) examined early-life factors that influence the intrinsic capacity score, which is essentially the sum of the health dimensions (Zhou and Ma, 2022). Our approach is consistent with this concept by aggregating an individual's medical diagnoses and summing various impairments.

3.4 Results

In the following, we present the results of the spectral clustering algorithm applied to our data. First, in Section 3.4.1, we determine the optimal number of clusters and provide interpretations of the detected profiles. Second, in Section 3.4.2, we aim to determine the key factors that influence an elderly person to belong to a certain group. To do this, we introduce, run, and report the results of a multinomial logistic regression model.

3.4.1 Detected profiles of elderly people

As a first step in running the spectral clustering algorithm, we set the number of clusters we are looking for to 15. Next, we derive the optimal number of clusters from the so-called "eigengap" heuristic, i.e., the idea is to find K such that the first eigenvalues $\lambda_1, \ldots, \lambda_K$ of the Laplacian matrix L_{rw} are small, and λ_{K+1} is relatively large, see, e.g., Ng et al. (2001); von Luxburg (2007). In Figure 3.3 we show the first 15 eigenvalues of the standardized Laplacian matrix L_{rw}. We see three gaps in the values, namely, between the first and the second, between the 8th and the 9th, and between the 14th and the 15th eigenvalues. The first gap is not meaningful, since it suggests the use of only one cluster, i.e., no partitioning of the data. The third gap implies a relatively high number of clusters, which would lead to a cumbersome interpretation of the profiles with less distinction between them. Therefore, we continue our analysis with $K = 8$ clusters.

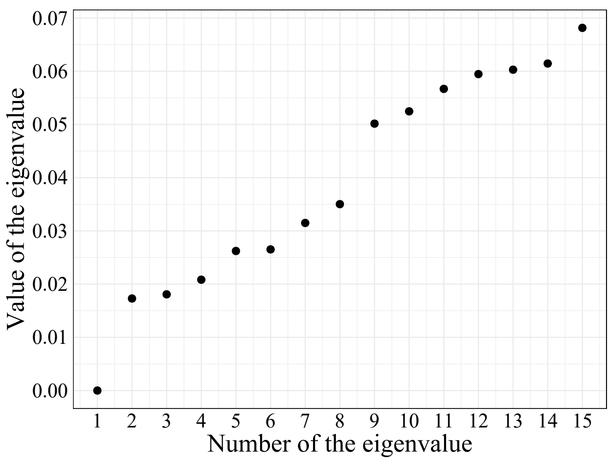


Figure 3.3: Values of the first 15 eigenvalues of the normalized Laplacian matrix of the spectral clustering algorithm.

Our presentation of the eight profiles is organized according to the following exhibits. In Table 3.3, we present the within-cluster statistics. For each group, from the largest to the smallest, we report the number of individuals, demographic statistics, the number of medical diagnoses and the pathology scores, the levels of dependence, the total score of psychological and sensory function impairments, the median duration, the average intensity of care, and the number of right-censored individuals. Several graphs illustrate the results. In Figure 3.4 we present boxplots of the age at entry (Fig. 3.4a) and the number of diagnoses (Fig. 3.4b) across the profiles. Figure 3.5 highlights the boxplots of the dependence levels for each profile, while in Figure 3.6 we show the prevalence of the pathologies in the main diagnosis across the profiles. Finally, the survival curves and the distributions of the intensity of care across the profiles are shown in Figures 3.7a and 3.7b, respectively. Further results of the spectral clustering across pathology scores and the impairments of psychological and sensory functions are shown in Figures 3.10 and 3.11 in the Appendix 3.6.2.

Profile		1 Baseline health profile		2 General severe conditions		3 Moderate-severe conditions with nervous diseases		4 Moderate conditions with endocrine diseases		5 Moderate conditions with cerebrovascular diseases		6 Moderate conditions with respiratory diseases		7 Moderate conditions with blood diseases		8 Moderate conditions with tumor diseases	
Individuals	[#[a] (%[b])]	5 673	(26.3)	4 086	(19.0)	3 929	(18.2)	2 857	(13.3)	2 764	(12.8)	1 267	(5.9)	738	(3.4)	235	(1.1)
Demographic variables																	
Age at entry	[avg (med)]	86.1	(87)	87.0	(88)	83.0	(84)	83.7	(84)	84.0	(85)	83.8	(84)	85.3	(86)	83.9	(84)
	[range]	82	91	83	92	78	88	79	89	80	89	80	89	81	90	80	89
Gender (female)	[#[a] (%[c])]	4 395	(77.5)	3 168	(77.5)	2 731	(69.5)	2 062	(72.2)	1 836	(66.4)	846	(66.8)	470	(63.7)	123	(52.3)
Medical diagnoses																	
Number of	[avg (med)]	5.7	(6)	5.7	(6)	5.6	(5)	6.3	(6)	6.2	(6)	6.5	(7)	6.9	(7)	7.1	(8)
diagnoses	[range]	4	8	4	8	4	8	5	8	5	8	5	9	6	9	6	9
Scores of the diagnoses		avg	(med)	avg	(med)	avg	(med)	avg	(med)	avg	(med)	avg	(med)	avg	(med)	avg	(med)
– mental		6.0	(6)	11.2	(9)	6.6	(8)	6.6	(8)	5.9	(7)	6.8	(7)	5.5	(5)	4.2	(0)
– cerebrovascular		0.2	(0)	0.1	(0)	0.1	(0)	0.2	(0)	8.3	(8)	0.6	(0)	1.4	(0)	0.7	(0)
– respiratory		0.0	(0)	0.0	(0)	0.0	(0)	0.0	(0)	0.1	(0)	7.7	(8)	0.4	(0)	0.3	(0)
– blood		0.0	(0)	0.0	(0)	0.0	(0)	0.0	(0)	0.0	(0)	0.1	(0)	6.5	(6)	0.2	(0)
– nervous		0.6	(0)	0.1	(0)	9.5	(9)	1.9	(0)	3.7	(0)	1.8	(0)	1.9	(0)	1.4	(0)
– osteoarticular		5.6	(5)	3.9	(0)	2.8	(0)	3.3	(0)	2.2	(0)	3.1	(0)	2.9	(0)	1.6	(0)
– endocrine		0.2	(0)	0.2	(0)	0.3	(0)	7.8	(7)	1.2	(0)	1.2	(0)	1.9	(0)	0.9	(0)
– heart		7.4	(7)	5.7	(6)	4.3	(4)	6.9	(7)	6.1	(6)	6.4	(6)	7.7	(7)	3.9	(4)
– tumors		0.9	(0)	0.1	(0)	0.2	(0)	0.2	(0)	0.2	(0)	0.4	(0)	0.3	(0)	17.0	(17)
– other		14.3	(14)	13.7	(13)	10.6	(10)	10.9	(10)	9.8	(9)	10.7	(9)	11.6	(11)	10.2	(9)
Levels of dependence																	
Dependence in	[avg (med)]	6.7	(7)	7.8	(8)	7.7	(8)	7.2	(7)	7.6	(8)	7.2	(7)	7.2	(7)	7.4	(7)
ADL	[range]	6	7	7	8	7	8	7	8	7	8	7	8	7	8	7	8
Physical mobility	[avg (med)]	6.2	(6)	7.8	(8)	7.4	(7)	7.0	(7)	7.5	(7)	7.0	(7)	7.0	(7)	7.3	(7)
limitations	[range]	6	7	7	9	6	9	6	8	6	9	6	8	6	8	6	9
Orientation	[avg (med)]	4.7	(5)	6.4	(6)	6.4	(6)	5.5	(5)	5.9	(6)	5.4	(5)	5.4	(5)	5.4	(5)
problems	[range]	4	5	6	7	5	7	5	6	5	7	5	6	5	6	5	6
Occupational	[avg (med)]	5.9	(6)	7.3	(7)	7.2	(7)	6.6	(7)	6.9	(7)	6.6	(7)	6.5	(7)	6.8	(7)
limitations	[range]	6	7	7	8	7	8	6	7	6	7	6	7	6	7	6	7
Social integration	[avg (med)]	5.1	(5)	6.6	(7)	6.5	(7)	5.8	(6)	6.2	(6)	5.8	(6)	5.7	(6)	5.9	(6)
limitations	[range]	5	6	6	7	6	7	5	7	5	7	5	6	5	6	5	7
Impairments of psychological and sensory functions																	
Level *IMP*	[avg (med)]	31.4	(32)	45.7	(45)	44.8	(45)	38.1	(39)	41.5	(43)	37.3	(38)	37.7	(38)	38.3	(39)
Duration of stay	[(med)]		(46.6)		(32.4)		(37.7)		(40.8)		(35.1)		(29.0)		(28.6)		(8.5)
Intensity of care	[avg (med)]	620	(523)	1 183	(1 189)	1 140	(1 143)	933	(937)	1 112	(1 166)	935	(922)	933	(915)	1 022	(1 026)
	[range]	383	794	955	1 401	858	1 415	573	1 248	764	1 420	550	1 272	531	1 272	648	1 341
Right-censored	[#[a] (%[c])]	1 022	(18.0)	635	(15.5)	710	(18.1)	541	(18.9)	446	(16.1)	175	(13.8)	120	(16.3)	10	(4.3)

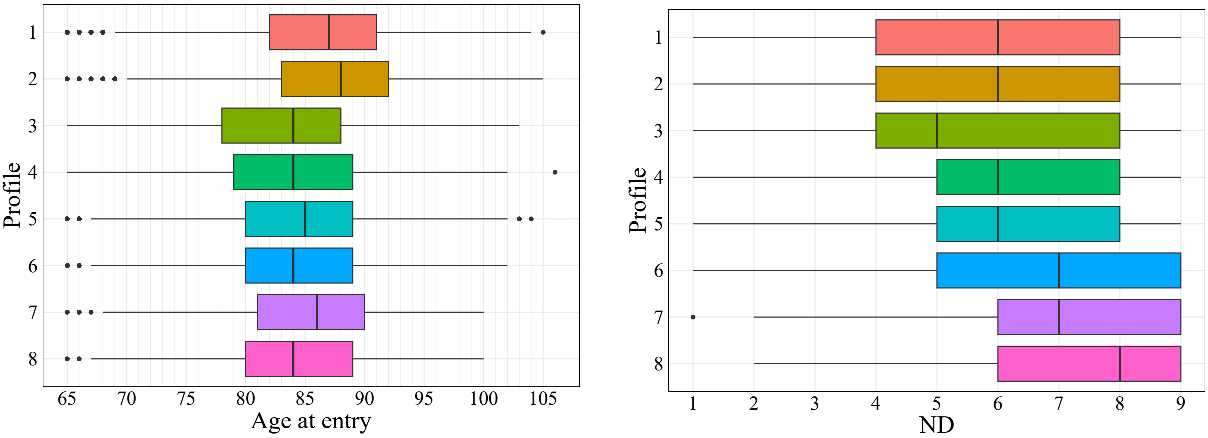
Notes: [a]The "#"-sign refers to the number of records, [b]the "%"-sign refers to the share with respect to the whole data set, [c]the "%"-sign refers to the share of individuals within a profile group, "avg (med)" refers to the average and median values, and "range" indicates the 25th and 75th percentile values of a profile group.

Table 3.3: Descriptive statistics of the eight profiles derived from the spectral clustering.

Profile 1: "Baseline health profile". The largest group contains 5 673 individuals (26.3% of the data), 77.5% of whom are women. The age at entry into the institution varies from 82 (first quartile) to 91 (third quartile), with a median age of 87, see Figure 3.4a.

As shown in Figure 3.4b, the middle 50% of the individuals in profile 1 have between four and eight diagnoses. The latter are distributed among the pathology groups "other" (median score 14), "heart" (7), "mental" (6), and "osteoarticular" (5); boxplots of the scores are available in Figure 3.10. The score for the "other" group is greater than nine, indicating that individuals in this group have, on average, two "other" pathologies. From Figure 3.6 we see that the main diagnosis belongs mostly to the "mental" (31%) or the "other" group (30%). Furthermore, from Table 3.3 we conclude that the "osteoarticular" group of diagnoses appears with a non-zero median score only in the "baseline health profile", although the average score of the "osteoarticular" group is consistently strictly positive across all profiles. Therefore, a higher score of "osteoarticular" pathologies is more frequent in people with the first profile.

The elderly individuals in this group are characterized by low levels of dependence compared to



(a) Boxplot of the age at entry.

(b) Boxplot of the number of diagnoses.

Notes: The box ranges from the first (Q_1) to the third quartile (Q_3) with the line in the box representing the median; using the interquartile range $\mathrm{IQR} = Q_3 - Q_1$, the line outside the box indicates the range between $\max\{\text{minimum value in the data}, Q_1 - 1.5 \cdot \mathrm{IQR}\}$ and Q_1, respectively between Q_3 and $\min\{\text{maximum value in the data}, Q_3 + 1.5 \cdot \mathrm{IQR}\}$; outliers are plotted as dots.

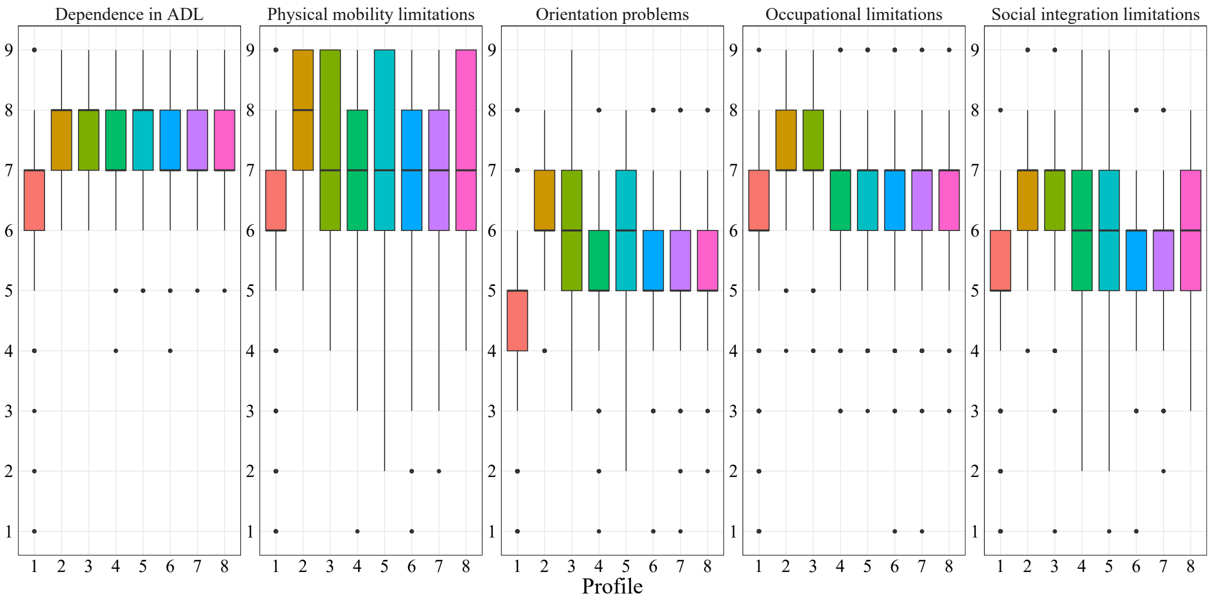
Figure 3.4: Boxplots of the age at entry AG and the number of diagnoses ND across the profiles.

the other profiles, i.e., the average values of the levels of dependence in ADL (6.7), the physical mobility limitations (6.2), the orientation problems (4.7), the occupational limitations (5.9), and the social integration limitations (5.1) are below the corresponding values found in the other profiles, see Table 3.3. This profile contains individuals with rather "mild" levels of psychological and sensory function impairments (average level of 31.4), see also Figure 3.11. Nevertheless, given their dependence in ADL level, the group members are in quasi-permanent need of assistance. However, they are typically able to move freely in the facility or on their floor, have partially compensated or moderate disorientation, have limited occupations in type and perhaps in time, and have poor or reduced relationships with others (cf. the ranges reported in Table 3.3 and the meaning of the values laid out in Bladt et al., 2023, Table 2).

Finally, we note that individuals in this profile have the highest median length of stay (46.6 months, i.e., almost 4 years) but require the least amount of weekly help from caregivers, with an interquartile range between 383 and 794 minutes per week (i.e., between 6 and 13 hours per week). These values are expected from the above and are consistent with the findings of Bladt et al. (2023) that healthier individuals live longer and are less dependent on others.

Profile 2: "General severe conditions". The second largest group that we identify contains 4 086 individuals (19% of the data). Although the set of medical diagnoses is similar to that of the first profile, we observe an increased score in the "mental" group of pathologies, while the score of "ostearticular" diagnoses is reduced (cf. Table 3.3). In Figure 3.6, the "mental" group of diagnoses occupies the largest share (68.2%) of the most important diagnosis D_1; its score is the highest among all profiles (see also Figure 3.10).

Furthermore, the second profile is characterized by severe levels of dependence, the highest among the profiles, see Figure 3.5. In particular, each level of dependence is at least one unit higher than in profile 1. At the same time, the level of impairments of psychological and sensory



Notes: See Figure 3.4.

Figure 3.5: Boxplots of the levels of dependence across the profiles.

functions IMP is 50% higher compared to the "baseline health profile" (average and median levels are 45.7 and 45, to be compared to 31.4 and 32, respectively). This is due to the mostly "moderate" and "severe" levels of impairments, see Figure 3.11. Finally, the median length of stay of 32.4 months (i.e., less than 3 years) is reduced by almost one year compared to profile 1. At the same time, the average intensity of care is almost doubled to 1 183 minutes of care per week, or about 20 hours.

Profile 3: "Moderate-severe conditions with nervous diseases". The third group contains 3 929 individuals with an average age at entry of 83 years, the lowest average value found in all profiles and more than 3 years lower than that in the "baseline health profile". The profile is characterized by a uniquely high score in the "nervous" diseases. In fact, according to Figure 3.6, 71.4% of the individuals have a "nervous" pathology as their main diagnosis. Individuals within this group have slightly lower levels of dependence compared to profile 2, but similar levels of psychological and sensory function impairments. The median length of stay is about 3 years (37.7 months), and the average intensity of care is comparable to that of profile 2 (1 140 minutes per week).

Profile 4: "Moderate conditions with endocrine diseases". In contrast to the other groups, where endocrine pathologies are rare, we observe a significant presence of "endocrine" diagnoses with a mean score of 7.8. However, according to Figure 3.6, only 19.2% of the individuals have "endocrine" as the most important diagnosis D_1, which is second only to the more prevalent group of "mental" diagnoses (34.6%), see also Table 3.7. In terms of levels of dependence and of impairments of psychological and sensory functions, this profile is intermediate between the baseline health profile (profile 1) and profile 2, which refers to general severe conditions. Finally, we note that the elderly in this group have the second highest median length of stay (40.8 months), about half a year less than in profile 1; at the same time, their care requires an average of 933 minutes per week, which is about 5 hours per week more than in profile 1.

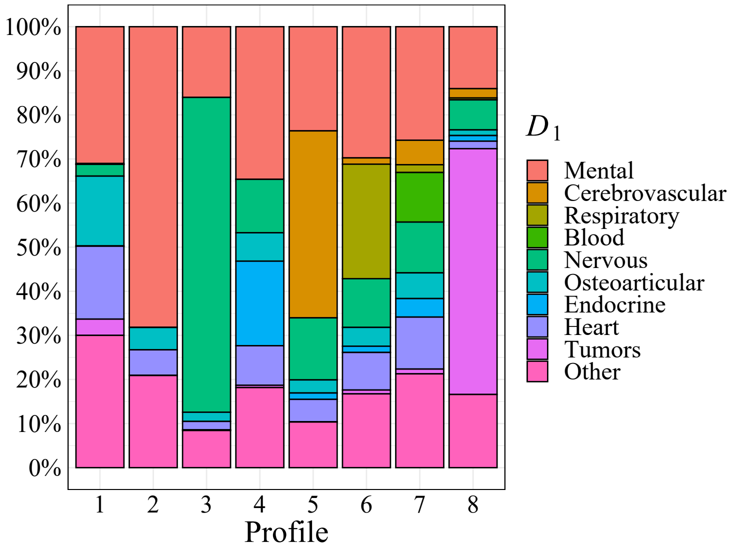
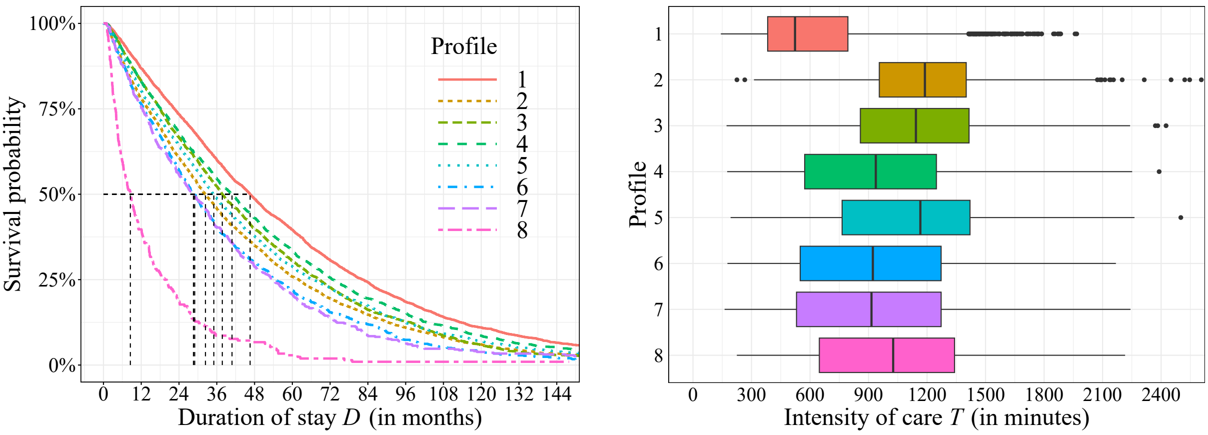


Figure 3.6: Prevalence of the pathologies in the most important diagnosis D_1 across the profiles.



(a) Kaplan-Meier estimate of the duration of stay.

(b) Boxplot of the intensity of care per week.

Notes: See Figure 3.4.

Figure 3.7: Kaplan-Meier estimate of the duration of stay (in months) and boxplot of the intensity of care per week (in minutes) across the profiles.

Profile 5: "Moderate conditions with cerebrovascular diseases". This group contains 2 764 individuals and is characterized by a significant presence of the "cerebrovascular" group of diseases, as indicated by the mean score 8.3 of related diagnoses. In fact, 42.4% of the individuals have a "cerebrovascular" diagnosis D_1 (cf. Figure 3.6). This profile also shows an elevated mean score for diagnoses related to "nervous" diseases (mean score of 3.7), suggesting that both pathologies co-occur. Overall, people in this group are characterized by slightly higher levels of dependence and impairments of psychological and sensory functions than those in profile 4. We find a median length of stay of less than three years (35.1 months), while the average intensity of care reaches 1 112 weekly minutes, one of the highest values among the profiles.

Profile 6: "Moderate conditions with respiratory diseases". The last three groups make up to about 10% of the data. In profile 6 we cluster 1 267 individuals (5.9%). As a common characteristic, we find a significant presence of diagnoses from the "respiratory" diseases group with a mean score of 7.7. In fact, 26% of the individuals have a respiratory disease as the most important diagnosis D_1, which is second in prevalence after mental illness (29.8%), see Figure 3.6. The people in this group are characterized by "moderate" levels of limitations, comparable to those from profile 4, characterized by endocrine disorders. This profile is associated with a low median length of stay (29 months), which is only less than two-thirds of the baseline health profile.

Profile 7: "Moderate conditions with blood diseases". Individuals belonging to this profile (3.4% of the data) experience a significant presence of a diagnosis from the group of "blood" diseases. The mean score of this diagnosis is 6.5. However, only 11.2% of the individuals have the blood-related disease as the most important diagnosis D_1. It appears more often on the third (19.2%), fourth (20.9%), or fifth (17.9%) rank of importance, see Table 3.7. We also observe that this profile is associated with the highest average score (7.7) for a "heart" disease diagnosis among all others, indicating that a higher score for "heart" diseases is often accompanied by a higher score for "blood" diseases, see also Figure 3.10. In general, persons in this group are characterized by "moderate" levels of limitations, as found in the profiles 4 and 6. Furthermore, the median length of stay is rather low (28.6 months) and comparable to that of profile 6. This similarity between profiles 6 and 7 also holds for the intensity of care, with average values of 935 and 933 minutes per week, respectively.

Profile 8: "Moderate conditions with tumor diseases". The last group contains the remaining 235 individuals (1.1% of the data). It contains only 52.3% of females, a rate that is significantly lower than in the other profiles (for comparison, profile 1 has a rate of 77.5% of females). Furthermore, and in contrast to the other profiles, we see a clear presence of the "tumors" group of diseases with a mean score of this diagnosis of 17. This is the highest score of any diagnosis among the profiles. In fact, 55.7% of the individuals have a tumor pathology in their main diagnosis D_1, see Figure 3.6. It is also the most common pathology in the second (D_2) and third (D_3) most important diagnoses, see Table 3.7. Finally, persons in this profile have the lowest median length of stay (8.5 months), which is, for example, more than five times shorter than in the baseline health profile (profile 1) and about three times shorter than the next lowest value observed in profile 7. At the same time, the number of minutes of help per week (1 022 minutes) is close to the values observed in the profiles 2 to 7.

Comparison to other studies. A cluster analysis based on the medical records of 98 elderly in a geriatric outpatient clinic was performed by Fattori et al. (2014). The authors found three significant clusters: (1) individuals with good functional and cognitive health but a high prevalence of diseases, requiring more medical attention and support despite maintaining independence in (I)ADL; (2) older, mostly female individuals with an intermediate number of diseases. They suffer from cognitive and functional decline, while retaining some ADL functionality; and (3) elderly with poor cognitive performance but fewer conditions, who maintain independence in both ADLs and IADLs.

Another study that examined the health profiles of institutionalized elderly people was conducted by Tobis et al. (2021). Using the K-means clustering method, they identified three groups of individuals in their study: (1) those without dementia, who were independent in their daily activities and showed no signs of depression; (2) individuals with symptoms of depression and lower scores on cognitive and functional assessments; (3) participants with the lowest scores on cognitive and functional assessments. However, this study was limited by having only 242 residents, and their needs were assessed using the Camberwell Assessment of Need for the Elderly (CANE), which is based on self-reported responses and may be subject to response bias.

In analyzing the English Longitudinal Study of Ageing data set (ELSA), Khan et al. (2023) found 5 clusters. Although it is a study of the whole population of England, the authors found a group that was associated with a higher risk of nursing home admission. It is characterized by a dominance of all social care needs: 99% likelihood of ADL difficulties, 98% likelihood of mobility difficulties, and 80% likelihood of health conditions that limit earning capacity. The group represented a specific combination of multiple long-term conditions, including arthritis, mental health disorders, cardiovascular disease, and hypertension.

Comparison between current findings and those obtained from studies using the HRS, SHARE, CHARLS or similar data sets is limited. As noted above, these data sets are based on surveys, which means that most of the variables are self-reported and may not be as accurate as medical assessments. In addition, surveys often do not include follow-up data on institutionalized persons, making it difficult to study this particular group of respondents. To the authors' knowledge, no study has focused on the health profiles of institutionalized older adults. In contrast, our data set allows us to follow individuals from the time they enter the nursing home, providing valuable information about their health status.

3.4.2 Determinants of belonging to a profile

In this section, we want to discover the key health factors that determine the profile to which an individual belongs. To do so, we assume that the data are indeed divided into eight groups according to our spectral clustering results. We apply a multinomial logistic regression model to our data with health factors as independent variables and consider the profile number (between 1 and 8, cf. Table 3.3) as the predicted class. We use the same variables as reported in Table 3.1, except for the variables that rank the diagnoses by importance. In fact, we replace $D_1, \ldots, D_9$ with the pathology scores defined in Equation (15), omitting the variable related to the score of the "other" diagnoses group to avoid a linear dependency between the explanatory variables. Furthermore, we do not consider the duration of stay D and the right-censoring indicator RC in the regression analysis, since these variables are not yet known when the person enters the institution. Finally, we do not consider the intensity of care T, which is estimated for the first time soon after admission to the institution. In fact, this variable is more a consequence of the person's state of health.

Let $Y_i \in \{1, 2, \ldots, 8\}$, $i = 1, \ldots, N$, denote the health profile of the i-th individual, and $\mathbf{X}_i$ be the vector of covariates. Then, the standard multinomial logistic regression with eight possible outcomes has the form

$$
\begin{aligned}
\ln \frac{\mathbb{P}(Y_i = 2 \,|\, \mathbf{X}_i)}{\mathbb{P}(Y_i = 1 \,|\, \mathbf{X}_i)} &= \vec{\lambda}_2 \cdot \mathbf{X}_i, \\
\ln \frac{\mathbb{P}(Y_i = 3 \,|\, \mathbf{X}_i)}{\mathbb{P}(Y_i = 1 \,|\, \mathbf{X}_i)} &= \vec{\lambda}_3 \cdot \mathbf{X}_i, \\
&\cdots \\
\ln \frac{\mathbb{P}(Y_i = 8 \,|\, \mathbf{X}_i)}{\mathbb{P}(Y_i = 1 \,|\, \mathbf{X}_i)} &= \vec{\lambda}_8 \cdot \mathbf{X}_i,
\end{aligned}
\tag{17}
$$

where $\vec{\lambda}_k$ is a vector of regression coefficients related to the k-th health profile. Here, the first group $Y_i = 1$, i.e., the "baseline health profile", is taken as the reference or baseline group. Since all probabilities must add up to one, we can derive the following explicit formulas:

$$
\begin{aligned}
&\mathbb{P}(Y_i = 1 \,|\, \mathbf{X}_i) = [1 + \textstyle\sum_{j=2}^{8} \exp(\vec{\lambda}_j \mathbf{X}_i)]^{-1}, \\
&\mathbb{P}(Y_i = k \,|\, \mathbf{X}_i) = \exp(\vec{\lambda}_k \mathbf{X}_i) \cdot \mathbb{P}(Y_i = 1 \,|\, \mathbf{X}_i), \quad k = 2, \ldots, 8.
\end{aligned}
\tag{18}
$$

To fit the multinomial logistic model, we use the `multinom` function from the R package *nnet* (Venables and Ripley, 2002).

To have a clear interpretation of the intercept of the model, we set a reference individual characterized by the modal value of each variable (cf. the distribution information contained in Table 3.2 in Section 3.2.2, and Tables 3.5 and 3.6 in Appendix 3.6.1). Thus, our reference individual is an 87-year-old woman with 9 medical diagnoses, where her primary pathology D_1 is "mental" and the remaining eight pathologies $D_2, \ldots, D_9$ are marked as "other".[7] She is in quasi-permanent need of assistance ($DP = 7$), with mobility limited to the institution ($PM = 6$), and has moderate disorientation ($OR = 5$), occupational limitations in time and type ($OC = 7$), and only primary contacts ($SI = 6$). Her impairments of psychological and sensory functions are "moderate" in all dimensions, except for the following six dimensions, which are classified as "mild": long-term memory LM, consciousness and wakefulness CW, orientation (time, person, space) TP, language LG, vision VS, and hearing HR.

We prune the number of psychological and sensory function impairments to reduce the complexity of the model and improve the Akaike Information Criterion score (AIC, see Akaike, 1974). Thus, we build a baseline model that includes age at entry, gender, medical diagnoses, and level of dependence variables, and then consider models extended by adding all possible combinations of the 16 variables of psychological and sensory function impairments. We choose the model with the lowest AIC score, which is the baseline model plus the variables for consciousness and wakefulness, language, vision, and hearing.[8]

Consequently, we build the multinomial logistic regression model described in Equation (17) using the full sample of 21 549 observations and 21 variables. Although the nine levels (labels from 1 to 9) that define dependence and the four levels (adequate, mild, moderate, severe) that

[7] According to Table 3.5 in Appendix 3.6.1, the mode values of D_6 through D_9 are "none". However, since the mode number of diagnoses ND is nine, for consistency we fill the four last ranked diagnoses with the second most common category "other".

[8] The AIC score of the baseline model is 7 888.5, and its accuracy, or percentage of correctly identified profiles, is 94.19%. The model that also includes CW, LG, VS, and HR results in the lowest AIC score of 7 754.8 and an accuracy of 94.43%. However, we note that according to the Bayesian Information Criterion, which penalizes the number of parameters in the model, see Schwarz (1978), the lowest score is achieved by the baseline model.

define impairments of psychological and sensory functions make the associated variables categorical; the levels are in fact ordered factors. To reduce the number of coefficients in the model, we make an approximation and treat the levels as integers. Nevertheless, we will be cautious in our interpretations. Therefore, all predictors except gender are treated as numeric values. Finally, note that we shift the values taken in the variables by subtracting the corresponding mode values, so that the intercept of the model corresponds to the reference individual. We present the results of the model fit in Table 3.4.

Profile	2 General severe conditions		3 Moderate-severe conditions with nervous diseases		4 Moderate conditions with endocrine diseases		5 Moderate conditions with cerebrovascular diseases		6 Moderate conditions with respiratory diseases		7 Moderate conditions with blood diseases		8 Moderate conditions with tumor diseases	
	$\vec{\lambda}_2$	Sig.	$\vec{\lambda}_3$	Sig.	$\vec{\lambda}_4$	Sig.	$\vec{\lambda}_5$	Sig.	$\vec{\lambda}_6$	Sig.	$\vec{\lambda}_7$	Sig.	$\vec{\lambda}_8$	Sig.
Intercept	-1.1687	***	-3.8592	***	-4.5665	***	-6.2006	***	-6.7943	***	-7.8340	***	-5.0050	***
Demographic variables														
Age at entry	0.0173	**	0.0053		-0.0216	*	-0.0296	**	-0.0587	***	-0.0367	*	-0.0305	*
Gender (baseline: *Female*)														
Male	0.0528		-0.0876		0.0045		-0.0716		-0.1222		-0.5690	*	-0.2720	
Medical diagnoses														
Number of diagnoses	-0.1409	***	-0.1383	***	-0.2011	***	-0.3531	***	-0.3255	***	-0.5298	***	0.0317	
Scores of the diagnoses														
– mental	0.1246	***	0.0370	***	0.0167		0.0234	.	0.0187		0.0674	***	0.0185	
– cerebrovascular	-0.3373	***	-0.3536	***	-0.0604		1.2374	***	0.4953	***	0.6680	***	0.1984	***
– respiratory	-0.1781	*	-0.4282	***	-0.1359		0.4999	***	1.5515	***	0.6155	***	0.3458	***
– blood	0.0381		-0.0424		-0.1613		0.5033	***	0.3993	*	2.2763	***	0.5143	**
– nervous	-0.4016	***	0.7857	***	0.1939	***	0.3138	***	0.2103	***	0.3077	***	0.1133	***
– osteoarticular	-0.0472	***	-0.0698	***	-0.0594	***	-0.0457	**	-0.0205		-0.0042		-0.0321	
– endocrine	-0.2698	***	0.0773	.	1.3140	***	0.4197	***	0.4790	***	0.6143	***	0.2351	***
– heart	-0.0211	**	-0.0153		-0.0036		0.0223	.	0.0283	.	0.0414	*	-0.0293	
– tumors	-0.8877	***	-0.5095	***	-0.5520	***	-0.5650	***	-0.3393	***	-0.5110	***	0.4356	***
Levels of dependence														
Dependence in ADL	1.4905	***	0.9187	***	0.5033	***	0.5436	***	0.6682	***	0.5544	*	0.1474	
Physical mobility limitations	0.6349	***	0.1392	*	0.0028		0.2453	***	0.0614		0.1647		-0.1325	
Orientation problems	1.2300	***	0.9525	***	0.6016	***	0.8567	***	1.3229	***	0.8144	***	0.3969	*
Occupational limitations	0.9011	***	0.5990	***	0.3156	***	0.3893	***	-0.0267		0.4059	**	0.2359	.
Social integration limitations	0.6321	***	0.6149	***	0.5165	***	0.6694	***	0.0771		0.3608	.	0.1659	
Impairments of psychological and sensory functions														
Consciousness and wakefulness	0.6223	***	-0.0724		0.1844		-0.1502		0.1788		0.0748		-0.5042	*
Language	0.0016		0.1194		-0.1059		0.0435		-0.5060	***	-0.1730		0.2218	
Vision	0.0063		0.0834		-0.0271		0.0453		-0.1810		-0.1718		-0.0640	
Hearing	0.1836	**	0.0922		0.1819	.	0.0726		0.1512		0.3004	.	0.3601	*
Probability of reference individual belonging to profile (in %)	22.98		1.56		0.77		0.15		0.08		0.03		0.50	

Notes: The "baseline health profile" (profile 1, see Table 3.3) composes the reference group. The probability that the reference individual belongs to the first group is 73.94%. The significance levels reported in column "Sig." are coded as follows: p-value < 0.1 . ; < 0.05 *; < 0.01 **; < 0.001 ***.

Table 3.4: Results of the multinomial logistic model along the profiles.

In Table 3.4 we present the estimated coefficients $\vec{\lambda}_k$, $k = 2, \ldots, 8$, and the corresponding significance levels based on their p-values. The interpretation of the intercept values follows from the second equality in Equation (18), which for the reference individual reduces to:

$$\mathbb{P}(Y_{\text{ref}} = k \,|\, \mathbf{X}_{\text{ref}}) = \exp(\lambda_k^{\text{Intercept}}) \cdot \mathbb{P}(Y_{\text{ref}} = 1 \,|\, \mathbf{X}_{\text{ref}}). \tag{19}$$

At the same time, the first equality in Equation (18) gives us:

$$\mathbb{P}(Y_{\text{ref}} = 1 \,|\, \mathbf{X}_{\text{ref}}) = [1 + \exp(\lambda_2^{\text{Intercept}}) + \ldots + \exp(\lambda_8^{\text{Intercept}})]^{-1} \approx 73.94\%.$$

Thus, the probability that the reference individual belongs to profile 1, i.e., the "baseline health profile", is 73.94%. We then use Equation (19) to evaluate the probability that the reference individual belongs to profile k, $k = 2, \ldots, 8$. We report the values in the last row of Table 3.4.

The coefficient of each numerical variable indicates the increase/decrease in the log odds of belonging to profile k relative to profile 1, holding other variables constant.[9] For example, increasing dependence in ADL (DP) by one unit increases the logarithmic odds of being in profile 2 ("general severe conditions") by

$$\ln \frac{\mathbb{P}(Y_i = 2 \mid \mathbf{X}_i^{DP+1})}{\mathbb{P}(Y_i = 1 \mid \mathbf{X}_i^{DP+1})} - \ln \frac{\mathbb{P}(Y_i = 2 \mid \mathbf{X}_i^{DP})}{\mathbb{P}(Y_i = 1 \mid \mathbf{X}_i^{DP})} = \lambda_2^{DP} = 1.4905,$$

where $\mathbf{X}_i^{DP+1}$ and $\mathbf{X}_i^{DP}$ are vectors of i-th person covariates that have the same values except for the level of DP, which is increased by one unit in $\mathbf{X}_i^{DP+1}$ compared to $\mathbf{X}_i^{DP}$.

In general, the definition of a multinomial regression does not allow for a straightforward interpretation of the resulting coefficients except for the intercept. Therefore, the only information that can be extracted directly from Table 3.4 is the sign of a coefficient, – a positive sign indicating an increase in the log odds, a negative sign a decrease, – and the significance, – indicating whether the model coefficient is non-zero, i.e., there is a statistically significant difference when comparing the profile to the "baseline health profile," – and the absolute value of a coefficient, – giving some indication of the amplitude at which it affects the log odds.

Regarding demographic variables, we conclude from Table 3.4 that age at entry AG has a small but significant effect on logarithmic odds, except for the third profile. In contrast, gender GE does not seem to be a significant factor, except for profile 7. With respect to medical diagnoses, we find that the number of diagnoses ND seems to be three-star significant for all profiles, except for profile 8 ("moderate conditions with tumor diseases"). All coefficients are negative, indicating that the more diagnoses a person has, the more likely he or she is to belong to the reference group, i.e., the "baseline health profile". This fact is counterintuitive at first, but it can be explained by combining it with the omitted score of the "other" group of pathologies. Increasing the number of diagnoses (ND) by one unit, maintaining all other variables in the model fixed, is possible by adding a pathology from the "other" group of diseases. It implies that the person has no more than eight diagnoses, so it can always be placed in the least important position. This increases the Score(Other), which, as we can see from Table 3.3 and Figure 3.10 in Appendix 3.6.2, is more typical for the "baseline health profile". Similarly, increasing the score for "cerebrovascular" diseases has the greatest effect on the fifth profile; "respiratory" diseases – on the sixth profile; "blood" diseases – on the seventh profile; "nervous" diseases – on the third profile; "endocrine" diseases – on the fourth profile; and "tumors" – on the eighth profile. As we can see from Figure 3.10 in Appendix 3.6.2, even though the scores of "mental", "osteoarticular" and "heart" diseases are usually similar in all profiles, we see some significant coefficients in the model among these pathology scores. In particular, as expected from Table 3.3, the score of "mental" diagnoses affects the second profile with a three-star significant coefficient $\lambda_2^{\text{Mental}} = 0.1246$. Although of small magnitude, it has significant effects on profiles 3 and 7 that were not detected before. The score of "osteoarticular" diagnoses seems quite significant for profiles 2 to 5, but its low absolute values have a small effect compared to those of other variables. The score of "heart" diseases seems to be significant only for profiles 2 and 7, while the absolute values remain low.

[9] In this model, we also have a two-level factor variable, gender GE. While the logic remains the same, we compare a man to a woman (baseline) who have the same values of the other variables.

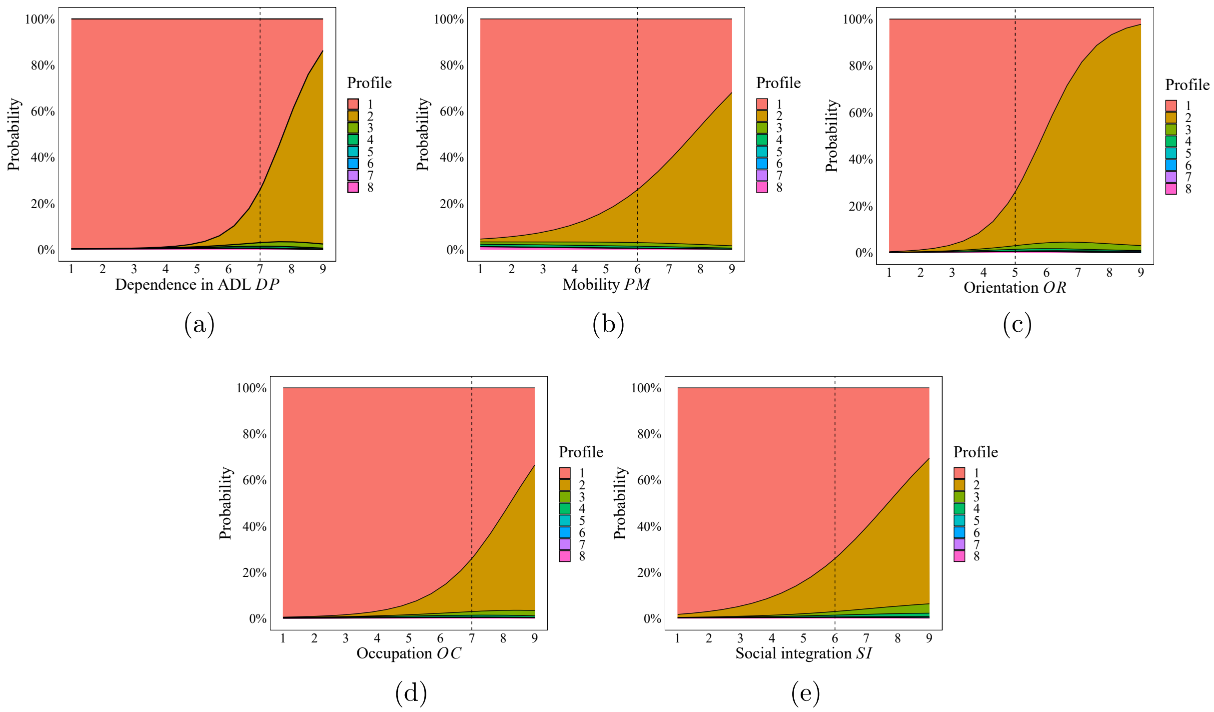
Next, an increase in any level of dependence, if significant, leads to an increase in the logarithmic odds. For example, among all the coefficients, the strongest effect on the probability of belonging to profile 2 is produced by the dependence in ADL ($\lambda_2^{DP} = 1.4905$) and orientation problems ($\lambda_2^{OR} = 1.23$). We observe that the variable OR is significant among all profiles, while the dependence in ADL is also significant, except in profile 8. Furthermore, physical mobility limitations PM is significant only for profiles 2, 3, and 5. In other words, the other profiles contain individuals with PM levels similar to the "baseline health profile".

The impairments related to consciousness and wakefulness and hearing are found to be significant in the "general severe conditions" and have a positive coefficient. Language is only significant in the sixth profile with a three-star negative coefficient, meaning that the individuals who have difficulty verbally expressing themselves are more likely to be in the "baseline health profile" than in the "moderate conditions with respiratory diseases". Similarly, the one-star negative coefficient $\lambda_8^{CW} = -0.5042$ indicates that individuals with impaired lucidity are less likely to belong to profile 8 compared to the baseline profile.

To extend the interpretation of the model coefficients, we vary one of the variables while holding the others fixed and plot the corresponding probabilities predicted by the model according to Equation (18). Therefore, we take the reference individual and vary her five levels of dependence, see the plots in Figure 3.8, and the scores of six pathology groups "cerebrovascular", "respiratory", "blood", "nervous", "endocrine", and "tumors", see the plots in Figure 3.9. We omit the pathology groups "mental", "osteoarticular", and "heart" because they do not yield significant changes in probabilities compared to the others. The vertical dashed lines correspond to the reference individual and the values on these lines reflect the baseline probabilities from Table 3.4.

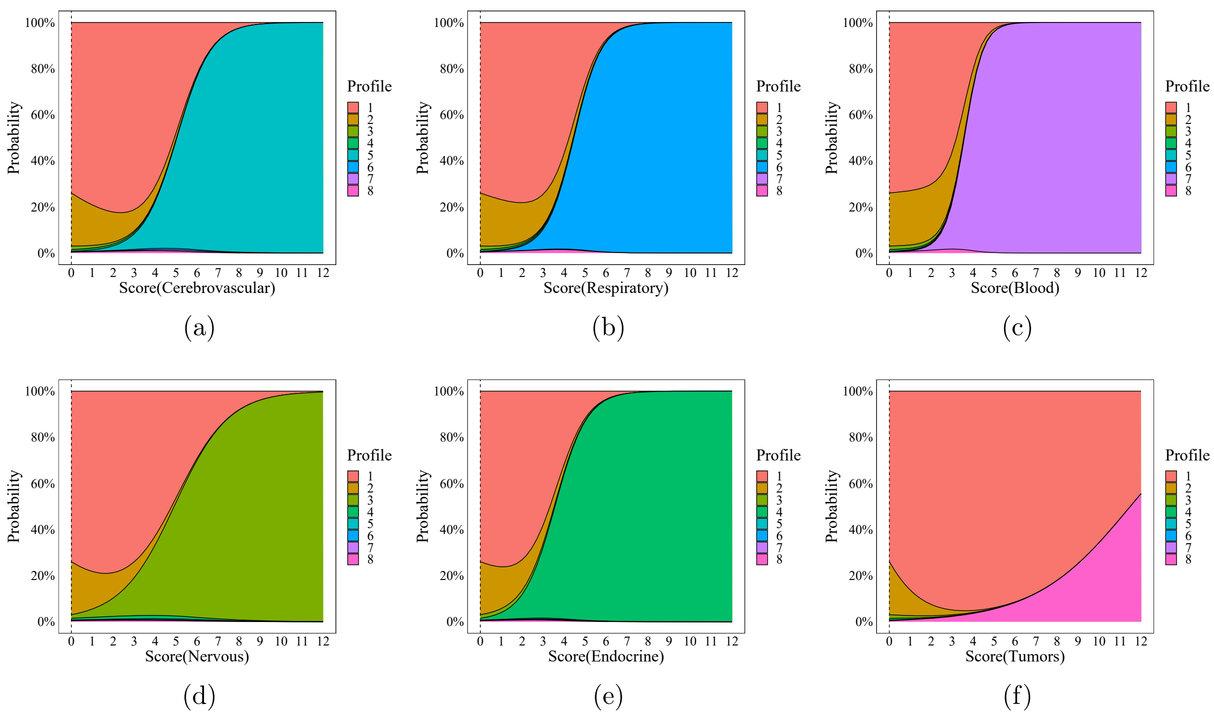
From Figure 3.8 we see that for all types of dependence, the probability of belonging to the "baseline health profile" is highest for low levels. On the other hand, as the level of dependence increases, a person is more likely to belong to the "general severe conditions" profile, which becomes dominant. This is consistent with the observations from Figure 3.5, where the first profile generally contains individuals with lower levels of dependence, while profile 2 refers to more severely dependent individuals. The rate at which the probability of belonging to the second profile increases is higher for dependence in ADL ($\lambda_2^{DP} = 1.4905$) and orientation problems variables ($\lambda_2^{OR} = 1.23$) compared to physical mobility ($\lambda_2^{PM} = 0.6349$), occupational ($\lambda_2^{OC} = 0.9011$) and social integration limitations ($\lambda_2^{SI} = 0.6321$).

In Figure 3.9 we can clearly see that each of the six pathology scores influences the more pathology-specific profiles 3 through 8. Recall that the "general severe conditions" profile (profile 2) is indeed mostly characterized by severe levels of dependence rather than the scores of the pathologies. Since the coefficients of "cerebrovascular" ($\lambda_5^{\text{Cerebrovascular}} = 1.2374$), "respiratory" ($\lambda_6^{\text{Respiratory}} = 1.5515$) and "endocrine" diseases ($\lambda_4^{\text{Endocrine}} = 1.3140$) are close, the probability behavior is similar – at first the weight of the "baseline health profile" increases, but after the score exceeds a value of about 3, the probability of the corresponding profile starts to dominate. The coefficient $\lambda_7^{\text{Blood}} = 2.763$ produces a more rapid increase in the probability of belonging to the "moderate conditions with blood diseases" profile, and on the contrary, the values $\lambda_3^{\text{Nervous}} = 0.7857$ and $\lambda_8^{\text{Tumors}} = 0.4356$ produce more flat rates.



Note: The vertical dashed lines correspond to the reference individual.

Figure 3.8: Probability of belonging to a profile across different levels of dependence.



Note: The vertical dashed lines correspond to the reference individual.

Figure 3.9: Probability of belonging to a profile across different scores of diagnoses.

3.5 Conclusion

In this paper, we examine the health profiles of elderly individuals at the time they enter institutional care. We base our study on a private data set containing 21 549 individuals from nursing homes in Switzerland with comprehensive information on their medical diagnoses, level of dependence, and impairments of psychological and sensory functions. Before proceeding, we transformed the data to account not only for the type of diagnoses a person has, but also for the importance rank as rated by a physician. By running a spectral clustering algorithm, we found eight groups of individuals characterized by different health profiles. Further, assuming that the elderly are indeed grouped along these eight profiles, we built a multinomial regression model to find the key health factors that determine which group a person belongs to.

Among the eight typical health profiles, the two largest groups include two opposite health states: on the one hand, individuals who are relatively healthy, require only a minimum amount of daily help from caregivers, and stay in institutional care the longest; and on the other hand, individuals whose health conditions are more severe, require the most help with their daily needs, and whose length of stay in the institution is shorter. The third largest group lies between the health profiles that are characterized by the degree of dependency and the profiles that are derived primarily from a set of pathologies. In particular, the prevalence of “nervous” diagnoses in the third health profile is associated with levels of dependence and impairments of psychological and sensory functions that are similar to those in the second profile. The other five typical health profiles include individuals with, on average, moderate levels of dependence and impairments of psychological and sensory functions, but their sets of medical diagnoses are different. These profiles are characterized primarily by the prevalence of one of the following disease groups: “cerevrovascular”, “respiratory”, “blood”, “endocrine” or “tumors”.

Using a multinomial regression model, each of the groups is compared to a “baseline health profile” corresponding to the typical (modal) healthy individual with mild levels of dependence and impairments of psychological and sensory functions. We find that the sex of the individual is not important, while the age at admission appears to be significant in four groups. However, the effect of the age at entry is relatively small, so that each profile is rather characterized more by the general health status of the persons. Three groups of diseases, i.e., “mental”, “osteoarticular” and “heart” diseases, appear consistently in each profile and therefore cannot be used to differentiate between the health profiles. In contrast, the other six disease groups, i.e., “cerebrovascular”, “respiratory”, “blood”, “nervous”, “endocrine”, and “tumors” diseases, exclusively define their own profile. We then show that dependence in ADL, physical mobility, orientation problems, and occupational and social integration limitations are the key factors that determine membership in the second profile, i.e. with the most severe health conditions. We also show that only four out of 16 impairments of psychological and sensory functions are relevant to the model: consciousness and wakefulness, language, vision, and hearing. The first and the last are significant in discriminating between the “baseline health profile” and the “general severe conditions” profile. While language is a relevant factor for the respiratory profile, the visual impairments seem to be insignificant for all profiles.

The approach used in this work is also related to the recent concept of intrinsic capacity (World Health Organization, 2015). Although we are not able to use all the variables proposed by López-Ortiz et al. (2022), we propose a method to include the medial diagnoses and impairments of psychological and sensory functions that are ranked and evaluated by nurses. Another limitation of the current work is related to our data set, which only includes elderly people in institutional care in the canton of Geneva, Switzerland. On the one hand, this comprehensive data set allows us to thoroughly examine the health parameters of the elderly in institutional care. Assuming similar demographic and financial conditions, our results can be applied to nursing homes in other countries and provide insights into the overall health status of the institutionalized elderly population. On the other hand, it makes it difficult to compare our results with the existing literature, which focuses mainly on self-reported surveys and insufficiently covers institutional LTC.

Our results are directly relevant to institutional LTC providers and can be used by policy makers. Understanding the typical health profiles of the institutionalized elderly is essential for proper staffing and management, which can reduce logistical costs and increase the efficiency of the care provided. At the same time, understanding the general trends in the predicted amount of help needed (number of minutes of care per week) and the expected length of stay for different profiles allows for more detailed classification and risk analysis. This expands the estimation of total costs and the scope of actuarial applications, enabling, for example, the development of new insurance solutions to meet the financial needs. Our analysis provides insightful results using only the initial health assessment recorded at the time of admission to an institution. However, such assessments are typically performed periodically, e.g., every one to two years, which introduces a temporal evolution of each person's health profile. Therefore, studying the evolution of sets of medical diagnoses, levels of dependence, and impairments of psychological and sensory functions can further enrich current research.

3.6 Appendix

3.6.1 Additional descriptive statistics

	n	(%)	D_{med}	T_{avg}
*D*1				
Mental	7 417	(34.4)	40.5	958.5
Cerebrovascular	1 247	(5.8)	36.5	1 137.5
Respiratory	344	(1.6)	24.3	915.9
Blood	83	(0.4)	26.3	896.6
Nervous	3 933	(18.3)	37.3	1 124.7
Osteoarticular	1 553	(7.2)	46.1	801.3
Endocrine	644	(3.0)	36.9	895.7
Heart	1 844	(8.6)	36.0	756.6
Tumors	384	(1.8)	9.1	991.5
Other	4 100	(19.0)	35.3	913.6
*D*2				
Mental	5 555	(25.8)	39.5	988.8
Cerebrovascular	705	(3.3)	34.3	1 085.2
Respiratory	316	(1.5)	29.4	905.1
Blood	111	(0.5)	26.8	932.4
Nervous	1 518	(7.0)	37.0	1 144.7
Osteoarticular	2 180	(10.1)	45.4	871.4
Endocrine	848	(3.9)	40.1	994.2
Heart	3 522	(16.3)	35.5	864.7
Tumors	342	(1.6)	12.5	1 011.4
Other	6 084	(28.2)	35.1	963.5
None	368	(1.7)	62.3	822.0
*D*3				
Mental	3 166	(14.7)	38.3	997.8
Cerebrovascular	580	(2.7)	34.4	1 052.8
Respiratory	303	(1.4)	29.6	952.2
Blood	143	(0.7)	27.0	904.6
Nervous	860	(4.0)	35.5	1 142.3
Osteoarticular	2 402	(11.1)	42.2	905.7
Endocrine	1 003	(4.7)	37.9	983.6
Heart	4 358	(20.2)	35.1	913.5
Tumors	296	(1.4)	16.2	992.5
Other	7 010	(32.5)	35.8	978.3
None	1 428	(6.6)	54.7	853.6
*D*4				
Mental	1 800	(8.4)	37.0	1 002.7
Cerebrovascular	443	(2.1)	34.0	1 027.2
Respiratory	213	(1.0)	33.3	1 021.9
Blood	155	(0.7)	35.2	942.9
Nervous	546	(2.5)	35.0	1 090.4
Osteoarticular	2 207	(10.2)	39.5	939.7
Endocrine	849	(3.9)	38.5	1 010.1
Heart	4 165	(19.3)	33.1	968.2
Tumors	242	(1.1)	18.1	1 000.3
Other	7 344	(34.1)	35.0	973.4
None	3 585	(16.6)	51.2	867.3
*D*5				
Mental	1 132	(5.3)	33.0	1 005.6
Cerebrovascular	346	(1.6)	31.8	1 038.5
Respiratory	195	(0.9)	27.0	945.1
Blood	138	(0.6)	27.0	991.0
Nervous	393	(1.8)	31.5	1 091.7
Osteoarticular	1 793	(8.3)	37.8	947.2
Endocrine	649	(3.0)	36.5	991.7
Heart	3 295	(15.3)	30.8	987.7
Tumors	236	(1.1)	20.1	1 044.0
Other	6 827	(31.7)	34.0	993.0
None	6 545	(30.4)	47.5	888.3
*D*6				
Mental	690	(3.2)	31.8	1 025.5
Cerebrovascular	278	(1.3)	33.3	975.8
Respiratory	152	(0.7)	28.7	1 025.9
Blood	142	(0.7)	26.8	990.9
Nervous	262	(1.2)	33.1	1 091.6
Osteoarticular	1 326	(6.2)	34.5	978.8
Endocrine	570	(2.6)	31.2	1 013.4
Heart	2 412	(11.2)	29.6	1 011.8
Tumors	171	(0.8)	22.8	982.7
Other	5 969	(27.7)	32.6	1 000.2
None	9 577	(44.4)	44.5	905.1
*D*7				
Mental	422	(2.0)	31.5	1 031.0
Cerebrovascular	227	(1.1)	29.5	1 020.6
Respiratory	85	(0.4)	35.2	966.5
Blood	105	(0.5)	28.7	962.3
Nervous	196	(0.9)	35.5	1 097.2
Osteoarticular	1 040	(4.8)	33.3	1 002.0
Endocrine	379	(1.8)	34.1	1 007.5
Heart	1 545	(7.2)	28.1	1 046.1
Tumors	135	(0.6)	28.6	950.9
Other	4 866	(22.6)	30.9	1 015.3
None	12 549	(58.2)	42.1	917.2
*D*8				
Mental	254	(1.2)	31.2	1 084.3
Cerebrovascular	153	(0.7)	32.8	1 011.1
Respiratory	43	(0.2)	46.1	834.5
Blood	84	(0.4)	20.0	1 026.2
Nervous	149	(0.7)	29.9	1 082.6
Osteoarticular	716	(3.3)	32.4	1 038.7
Endocrine	229	(1.1)	27.9	1 050.0
Heart	1 006	(4.7)	24.0	1 063.9
Tumors	105	(0.5)	30.2	968.2
Other	3 820	(17.7)	29.9	1 025.8
None	14 990	(69.6)	40.9	927.0
*D*9				
Mental	167	(0.8)	25.7	1 083.0
Cerebrovascular	118	(0.5)	35.1	1 001.2
Respiratory	40	(0.2)	30.7	882.5
Blood	60	(0.3)	18.6	1 022.4
Nervous	88	(0.4)	32.9	1 112.8
Osteoarticular	503	(2.3)	28.4	1 043.8
Endocrine	153	(0.7)	30.0	1 089.4
Heart	606	(2.8)	26.4	1 073.1
Tumors	86	(0.4)	24.1	1 103.1
Other	2 617	(12.1)	29.0	1 046.3
None	17 111	(79.4)	39.8	935.9

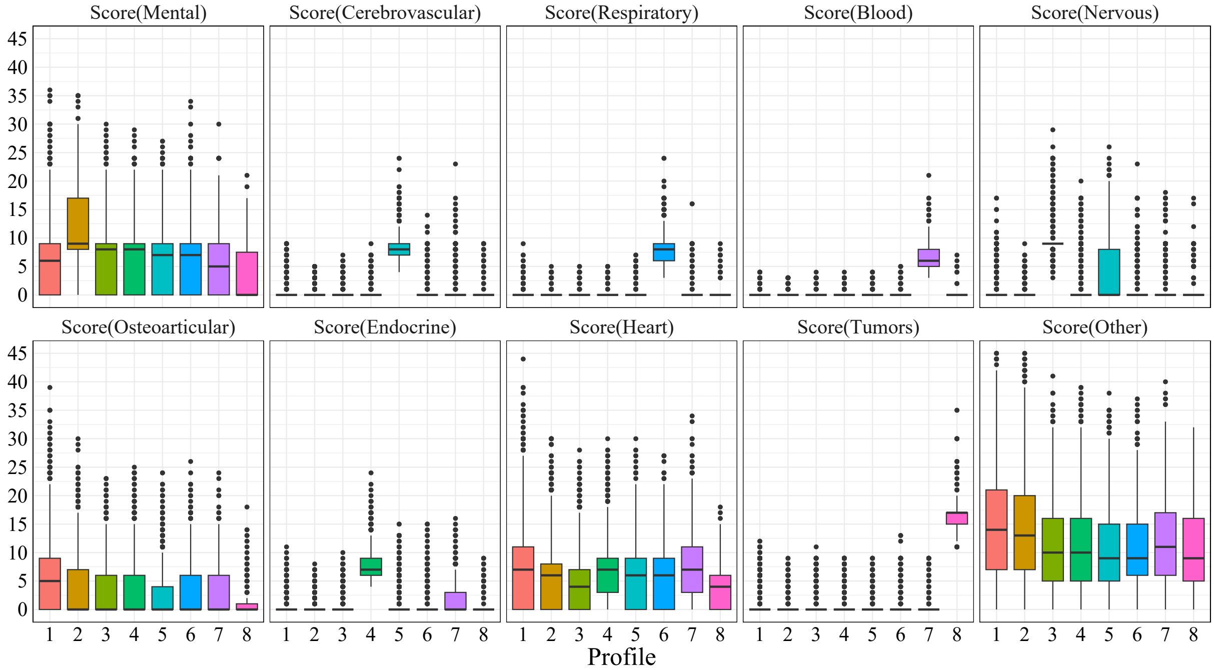
Table 3.5: Descriptive statistics on the median duration of stay D_{med} (in months) and the mean intensity of care T_{avg} (in minutes per week) along the diagnoses ranked by importance.

	n	(%)	D_{med}	T_{avg}
Recent memory				
Adequate	1 503	(7.0)	59.5	558.4
Mild	5 921	(27.5)	42.6	717.8
Moderate	8 285	(38.4)	35.0	954.2
Severe	5 840	(27.1)	31.5	1 316.6
Long-term memory				
Adequate	3 715	(17.2)	49.5	602.5
Mild	8 759	(40.6)	38.5	822.7
Moderate	6 596	(30.6)	32.0	1 157.7
Severe	2 479	(11.5)	31.5	1 453.4
Thinking (content, speed)				
Adequate	1 366	(6.3)	55.8	525.5
Mild	6 441	(29.9)	41.6	708.0
Moderate	10 480	(48.6)	35.0	1 026.4
Severe	3 262	(15.1)	30.4	1 425.2
Perception and attention				
Adequate	1 785	(8.3)	57.0	524.5
Mild	7 136	(33.1)	41.6	737.7
Moderate	11 634	(54.0)	32.5	1 115.5
Severe	994	(4.6)	37.4	1 514.3
Consciousness and wakefulness				
Adequate	2 967	(13.8)	52.8	569.2
Mild	9 416	(43.7)	39.0	815.2
Moderate	9 127	(42.4)	31.2	1 233.9
Severe	39	(0.2)	62.5	1 466.3
Orientation (time/person/space)				
Adequate	2 874	(13.3)	52.2	569.4
Mild	8 205	(38.1)	40.1	767.6
Moderate	8 077	(37.5)	32.4	1 145.7
Severe	2 393	(11.1)	30.6	1 460.7
Decision making				
Adequate	1 181	(5.5)	58.5	507.8
Mild	5 307	(24.6)	44.3	669.1
Moderate	10 221	(47.4)	35.5	964.7
Severe	4 840	(22.5)	29.9	1 378.6
Impulses (drives)				
Adequate	2 541	(11.8)	53.8	535.4
Mild	8 102	(37.6)	40.3	781.7
Moderate	9 859	(45.8)	32.3	1 146.2
Severe	1 047	(4.9)	25.2	1 613.2

	n	(%)	D_{med}	T_{avg}
Will and motivation				
Adequate	1 517	(7.0)	56.3	501.4
Mild	6 099	(28.3)	44.3	680.4
Moderate	11 961	(55.5)	33.6	1 067.3
Severe	1 972	(9.2)	28.5	1 525.1
Emotions				
Adequate	894	(4.1)	57.3	510.7
Mild	6 278	(29.1)	42.8	709.7
Moderate	13 698	(63.6)	33.6	1 076.7
Severe	679	(3.2)	39.5	1 506.8
Behavior				
Adequate	1 355	(6.3)	54.6	539.6
Mild	6 703	(31.1)	41.0	733.6
Moderate	12 648	(58.7)	33.6	1 088.5
Severe	843	(3.9)	41.0	1 504.1
Language				
Adequate	8 548	(39.7)	44.0	745.5
Mild	8 709	(40.4)	35.0	992.1
Moderate	3 325	(15.4)	29.9	1 276.6
Severe	967	(4.5)	31.5	1 474.9
Vision				
Adequate	4 985	(23.1)	48.5	772.0
Mild	11 378	(52.8)	35.8	974.8
Moderate	4 607	(21.4)	32.3	1 092.3
Severe	579	(2.7)	30.2	1 229.9
Hearing				
Adequate	6 590	(30.6)	47.5	815.9
Mild	10 249	(47.6)	35.9	988.0
Moderate	4 494	(20.9)	28.7	1 095.7
Severe	216	(1.0)	26.5	1 187.5
Making self-understood				
Adequate	2 421	(11.2)	50.7	552.2
Mild	7 823	(36.3)	40.6	752.5
Moderate	8 863	(41.1)	33.3	1 114.3
Severe	2 442	(11.3)	28.7	1 467.5
Understanding others				
Adequate	2 010	(9.3)	52.8	543.8
Mild	7 343	(34.1)	42.4	740.0
Moderate	10 640	(49.4)	32.9	1 108.2
Severe	1 556	(7.2)	30.6	1 520.3

Table 3.6: Descriptive statistics on the median duration of stay D_{med} (in months) and the mean intensity of care T_{avg} (in minutes per week) along the impairments of psychological and sensory functions.

3.6.2 Spectral clustering results



Notes: See Figure 3.4.

Figure 3.10: Boxplots of the pathology scores across the profiles.

Bibliography

Akaike, H., 1974, A New Look at the Statistical Model Identification, *IEEE Transactions on Automatic Control*, 19(6):716–723.

Albarrán, I., P. J. Alonso-González, A. Arribas-Gil, and A. Grané, 2019, How Functional Data Can Enhance the Estimation of Health Expectancy: The Case of Disabled Spanish Population, *ASTIN Bulletin*, 49(1):57–84.

Aliberti, M. J., L. Bertola, C. Szlejf, D. Oliveira, R. D. Piovezan, M. Cesari, F. B. de Andrade, M. F. Lima-Costa, M. R. Perracini, C. P. Ferri, and C. K. Suemoto, 2022, Validating Intrinsic Capacity to Measure Healthy Aging in an Upper Middle-Income Country: Findings from the ELSI-Brazil, *The Lancet Regional Health - Americas*, 12:100284.

Arrighi, H. M., T. McLaughlin, and C. Leibman, 2010, Prevalence and Impact of Dementia-related Functional Limitations in the United States, 2001 to 2005, *Alzheimer Disease & Associated Disorders*, 24(1).

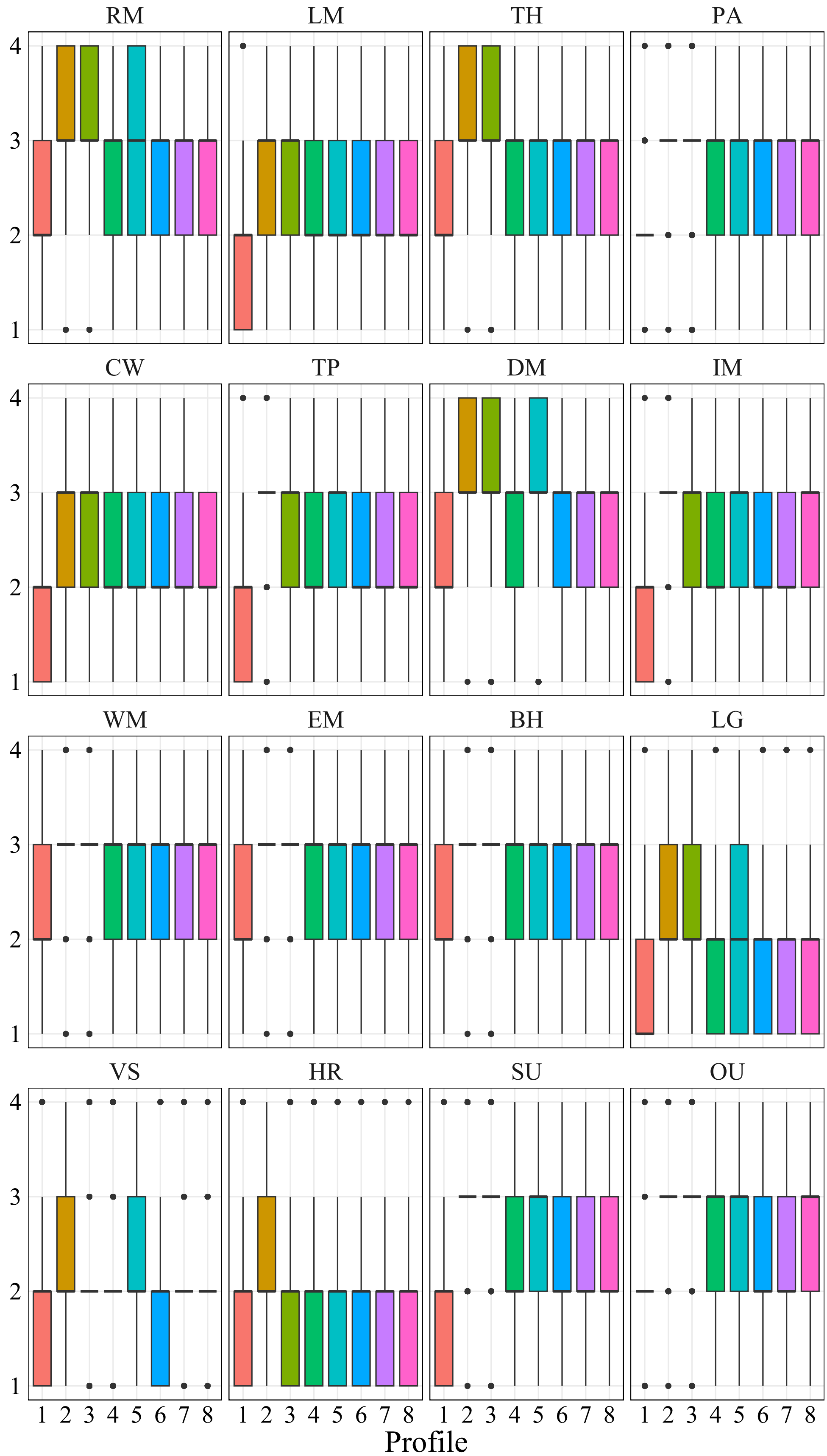
Barnett, K., S. W. Mercer, M. Norbury, G. Watt, S. Wyke, and B. Guthrie, 2012, Epidemiology of Multimorbidity and Implications for Health Care, Research, and Medical Education: A Cross-Sectional Study, *The Lancet*, 380(9836):37–43.

Beard, J. R., Y. Si, Z. Liu, L. Chenoweth, and K. Hanewald, 2022, Intrinsic Capacity: Validation of a New WHO Concept for Healthy Aging in a Longitudinal Chinese Study, *The Journals of Gerontology: Series A*, 77(1):94–100.

Profile	Rank	Mental	Cerebro-vascular	Respi-ratory	Blood	Nervous	Osteo-articular	Endo-crine	Heart	Tumors	Other	None
	D_1	31.0	0.2	0.0	0.0	2.7	15.8	0.1	16.5	3.7	30.0	0.0
	D_2	19.7	0.2	0.0	0.0	1.1	16.6	0.1	21.7	2.2	36.2	2.2
	D_3	11.3	0.3	0.0	0.0	1.0	16.3	0.3	23.4	2.0	37.5	8.0
	D_4	7.5	0.6	0.0	0.0	1.3	12.4	0.2	18.9	1.7	37.4	20.0
1	D_5	4.8	0.8	0.2	0.0	1.3	9.8	0.6	14.3	1.5	32.7	34.0
	D_6	2.8	1.0	0.4	0.1	0.9	6.6	1.5	10.0	1.2	27.6	47.8
	D_7	1.9	0.8	0.4	0.3	0.7	4.7	1.7	6.2	0.8	21.5	61.1
	D_8	1.0	0.7	0.3	0.4	0.5	3.1	0.9	4.4	0.6	16.4	71.9
	D_9	0.7	0.5	0.3	0.2	0.3	2.4	0.6	2.7	0.3	10.4	81.6
	D_1	68.2	0.0	0.0	0.0	0.0	5.1	0.0	5.8	0.0	20.9	0.0
	D_2	34.8	0.0	0.0	0.0	0.0	11.7	0.0	15.5	0.1	35.1	2.8
	D_3	17.8	0.0	0.0	0.0	0.0	12.2	0.1	19.7	0.1	40.3	9.8
	D_4	9.0	0.0	0.0	0.0	0.1	12.5	0.3	18.7	0.3	37.6	21.5
2	D_5	5.2	0.5	0.0	0.0	0.6	8.6	0.4	14.4	0.5	33.4	36.4
	D_6	2.8	0.9	0.3	0.0	0.7	5.8	1.4	9.8	0.5	27.8	50.0
	D_7	1.6	1.0	0.2	0.3	0.6	5.4	1.2	5.8	0.3	21.4	62.1
	D_8	1.1	0.5	0.1	0.3	0.5	3.3	0.9	3.9	0.3	17.1	72.1
	D_9	0.6	0.6	0.2	0.3	0.4	2.2	0.6	2.8	0.3	12.0	80.0
	D_1	16.0	0.0	0.0	0.0	71.4	2.1	0.0	1.9	0.2	8.4	0.0
	D_2	36.0	0.0	0.0	0.0	20.8	6.6	0.3	10.4	0.5	22.7	2.7
	D_3	18.5	0.0	0.0	0.0	11.9	9.1	0.6	16.2	0.7	32.6	10.3
	D_4	9.5	0.1	0.0	0.0	6.1	9.7	1.1	15.9	0.5	34.8	22.3
3	D_5	5.0	0.4	0.1	0.0	3.1	8.0	1.4	12.4	0.9	31.5	37.2
	D_6	2.8	0.9	0.2	0.0	1.4	6.5	1.6	9.3	0.6	26.1	50.6
	D_7	1.4	1.0	0.2	0.4	0.9	4.3	1.5	5.5	0.5	21.5	62.9
	D_8	0.9	0.6	0.2	0.2	0.7	3.0	0.6	3.7	0.4	16.1	73.6
	D_9	0.6	0.4	0.1	0.1	0.4	1.9	0.7	2.2	0.3	11.6	81.8
	D_1	34.6	0.0	0.0	0.0	12.1	6.4	19.2	9.0	0.5	18.2	0.0
	D_2	22.0	0.0	0.0	0.0	3.8	8.7	23.7	18.4	0.4	22.8	0.2
	D_3	12.4	0.2	0.0	0.0	2.5	9.1	26.7	21.3	0.4	25.3	2.1
	D_4	6.6	0.7	0.0	0.0	2.0	8.3	20.9	22.5	0.5	28.9	9.6
4	D_5	4.6	1.2	0.1	0.0	1.2	7.3	13.7	18.0	0.5	31.0	22.4
	D_6	3.5	1.4	0.5	0.0	1.4	6.1	6.7	13.6	0.8	28.9	37.2
	D_7	2.0	1.1	0.5	0.4	1.1	4.8	2.7	7.8	0.8	24.9	53.9
	D_8	1.1	0.6	0.2	0.4	0.7	3.5	1.4	4.6	0.4	19.6	67.7
	D_9	0.9	0.7	0.1	0.4	0.5	2.6	0.8	2.3	0.3	12.1	79.4
	D_1	23.6	42.4	0.0	0.0	14.1	3.0	1.4	5.1	0.1	10.3	0.0
	D_2	19.2	23.3	0.0	0.0	15.9	4.3	2.7	12.9	0.3	20.9	0.5
	D_3	15.3	18.7	0.1	0.0	7.4	6.4	4.4	19.7	0.4	24.7	3.0
	D_4	9.3	12.7	0.4	0.0	4.6	7.0	4.1	21.8	0.6	29.0	10.5
5	D_5	6.2	7.3	0.7	0.0	3.5	6.8	2.5	18.1	0.8	29.8	24.2
	D_6	3.8	2.5	0.6	0.1	2.3	5.2	3.0	14.7	0.5	27.9	39.4
	D_7	2.3	1.6	0.5	0.6	1.6	4.2	1.7	10.1	0.5	22.1	54.8
	D_8	1.4	1.4	0.2	0.5	1.2	3.1	1.2	5.6	0.6	18.1	66.6
	D_9	1.0	0.4	0.3	0.4	0.7	2.2	0.9	3.1	0.6	13.6	77.0
	D_1	29.8	1.4	26.0	0.0	11.0	4.3	1.4	8.5	0.9	16.7	0.0
	D_2	22.3	1.6	24.6	0.0	4.3	6.8	2.8	16.6	0.6	20.4	0.1
	D_3	15.3	1.4	22.7	0.0	2.5	8.1	2.6	20.8	0.9	24.5	1.3
	D_4	10.1	1.1	15.5	0.0	1.6	9.3	2.6	20.0	0.7	31.6	7.5
6	D_5	7.1	1.0	12.2	0.2	1.6	8.7	3.4	16.1	1.2	29.9	18.6
	D_6	4.3	1.2	5.4	0.6	1.2	6.6	4.6	11.7	0.5	29.0	34.9
	D_7	2.9	1.0	1.1	0.3	0.9	6.9	2.4	9.1	0.9	24.6	49.7
	D_8	1.9	0.6	0.2	0.6	0.9	3.9	1.6	6.0	0.6	22.3	61.3
	D_9	1.2	0.9	0.1	0.4	0.4	2.7	0.8	4.1	0.6	15.5	73.2
	D_1	25.7	5.6	1.8	11.2	11.5	5.8	4.2	11.8	1.1	21.3	0.0
	D_2	18.3	3.9	0.4	15.0	4.6	6.2	5.0	19.6	0.8	25.9	0.1
	D_3	10.3	2.7	1.2	19.2	2.6	8.8	6.0	22.0	0.3	25.9	1.1
	D_4	5.7	2.2	0.4	20.9	2.4	7.2	3.7	23.6	0.5	29.8	3.7
7	D_5	5.7	1.9	0.5	17.9	1.4	6.9	4.5	19.5	0.3	28.6	12.9
	D_6	4.2	3.0	0.5	16.7	1.6	6.5	2.6	12.7	0.4	27.0	24.8
	D_7	3.7	1.5	0.3	3.9	1.2	4.5	2.2	12.3	0.7	29.7	40.1
	D_8	2.0	1.1	0.3	1.2	0.9	5.0	2.3	9.2	0.8	22.1	55.0
	D_9	1.2	0.8	0.4	0.1	0.4	3.4	1.2	4.2	0.9	15.2	72.1
	D_1	14.0	2.1	0.4	0.0	6.8	1.3	1.3	1.7	55.7	16.6	0.0
	D_2	11.5	0.9	0.4	0.0	1.7	1.3	0.9	3.8	68.9	10.6	0.0
	D_3	8.9	1.3	1.3	0.4	3.4	5.1	0.4	6.0	50.6	22.1	0.4
	D_4	8.5	2.6	0.4	0.4	3.0	5.5	3.8	12.8	29.4	30.2	3.4
8	D_5	7.2	1.3	0.9	1.3	3.8	5.1	3.4	18.3	17.0	29.4	12.3
	D_6	6.8	2.1	2.1	0.9	0.0	3.0	3.4	17.4	6.0	34.5	23.8
	D_7	4.3	0.9	0.9	0.0	1.3	5.1	2.1	13.6	1.7	31.9	38.3
	D_8	3.0	0.9	0.0	0.9	0.9	7.7	2.1	10.2	1.3	23.4	49.8
	D_9	1.3	0.9	0.0	0.0	0.9	3.8	0.4	6.8	1.3	22.6	62.1

Note: For each D_i, the shares across all diagnoses (including the category "none") sum up to 100%.

Table 3.7: Prevalence of pathology groups (in %) along nine importance levels D_i across the profiles.



Notes: See Figure 3.4.

Figure 3.11: Boxplots of the impairments of psychological and sensory functions across the profiles.

Bladt, M., M. Fuino, A. Shemendyuk, and J. Wagner, 2023, Modelling the Burden of Long-Term Care for Institutionalised Elderly Based on Care Duration and Intensity, *Annals of Actuarial Science*, 17(1):83–117.

Börsch-Supan, A., M. Brandt, C. Hunkler, T. Kneip, J. Korbmacher, F. Malter, B. Schaan, S. Stuck, and S. Zuber, 2013, Data Resource Profile: The Survey of Health, Ageing and Retirement in Europe (SHARE), *International Journal of Epidemiology*, 42(4):992–1001.

Brito, M. R., E. L. Chávez, A. J. Quiroz, and J. E. Yukich, 1997, Connectivity of the Mutual k-Nearest-Neighbor Graph in Clustering and Outlier Detection, *Statistics & Probability Letters*, 35(1):33–42.

Brown, J. R. and A. Finkelstein, 2009, The Private Market for Long-Term Care Insurance in the United States: A Review of the Evidence, *Journal of Risk and Insurance*, 76(1):5–29.

Carrino, L., C. E. Orso, and G. Pasini, 2018, Demand of Long-Term Care and Benefit Eligibility Across European Countries, *Health Economics*, 27(8):1175–1188.

Chung, F. R., 1997, *Spectral Graph Theory.* 92. American Mathematical Society, Providence, Rhode Island.

Colombo, F., A. Llena-Nozal, J. Mercier, and F. Tjadens, 2011, *Help Wanted? Providing and Paying for Long-Term Care.* OECD Health Policy Studies. OECD Publishing, Paris.

Correia, C., K. J. Lopez, K. E. Wroblewski, M. Huisingh-Scheetz, D. W. Kern, R. C. Chen, L. P. Schumm, W. Dale, M. K. McClintock, and J. M. Pinto, 2016, Global Sensory Impairment in Older Adults in the United States, *Journal of the American Geriatrics Society*, 64(2):306–313.

Cosandey, J., 2016, *De Nouvelles Mesures pour les Soins aux Personnes Âgées.* Avenir Suisse, Zurich, Switzerland.

Crimmins, E. M., H. Shim, Y. S. Zhang, and J. K. Kim, 2019, Differences between Men and Women in Mortality and the Health Dimensions of the Morbidity Process, *Clinical Chemistry*, 65(1):135–145.

Davidson, I. A., M. E. Dewey, and J. R. M. Copeland, 1988, The Relationship Between Mortality and Mental Disorder: Evidence From the Liverpool Longitudinal Study, *International Journal of Geriatric Psychiatry*, 3(2):95–98.

Deeg, D. J. H., F. Portrait, and M. Lindeboom, 2002, Health Profiles and Profile-Specific Health Expectancies of Older Women and Men: The Netherlands, *Journal of Women & Aging*, 14(1-2):27–46.

Dorr, D. A., S. D. Horn, and R. J. Smout, 2005, Cost Analysis of Nursing Home Registered Nurse Staffing Times, *Journal of the American Geriatrics Society*, 53(5):840–845.

Fattori, A., I. M. Oliveira, R. M. d. A. Alves, and M. E. Guariento, 2014, Cluster Analysis to Identify Elderly People's Profiles: A Healthcare Strategy Based on Frailty Characteristics, *Sao Paulo Medical Journal*, 132(4):224–230.

Fisher, G. G. and L. H. Ryan, 2017, Overview of the Health and Retirement Study and Introduction to the Special Issue, *Work, Aging and Retirement*, 4(1):1–9.

Fong, J. H., 2019, Disability Incidence and Functional Decline among Older Adults with Major Chronic Diseases, *BMC Geriatrics*, 19(1):323.

Fong, J. H., M. Sherris, and J. Yap, 2017, Forecasting Disability: Application of a Frailty Model, *Scandinavian Actuarial Journal*, 2017(2):125–147.

Fu, Y., M. Sherris, and M. Xu, 2022, Functional Disability with Systematic Trends and Uncertainty: A Comparison between China and the US, *Annals of Actuarial Science*, 16(2):289–318.

Fuino, M., A. Ugarte Montero, and J. Wagner, 2022, On the Drivers of Potential Customers' Interest in Long-Term Care Insurance: Evidence from Switzerland, *Risk Management and Insurance Review*, 25(3):271–302.

Fuino, M. and J. Wagner, 2018a, Long-Term Care Models and Dependence Probability Tables by Acuity Level: New Empirical Evidence from Switzerland, *Insurance: Mathematics and Economics*, 81:51–70.

Fuino, M. and J. Wagner, 2018b, Old-Age Care Prevalence in Switzerland: Drivers and Future Development, *European Actuarial Journal*, 8(2):321–362.

Fuino, M. and J. Wagner, 2020, Duration of Long-Term Care: Socio-economic Factors, Type of Care Interactions, and Evolution, *Insurance: Mathematics and Economics*, 90:151–168.

Germain, C. M., E. Vasquez, J. A. Batsis, and D. R. McQuoid, 2016, Sex, Race, and Age Differences in Muscle Strength and Limitations in Community Dwelling Older Adults: Data from the Health and Retirement Survey (HRS), *Archives of Gerontology and Geriatrics*, 65:98–103.

Gottlieb, D. and O. S. Mitchell, 2020, Narrow Framing and Long-Term Care Insurance, *Journal of Risk and Insurance*, 87(4):861–893.

Guccione, A. A., D. T. Felson, J. J. Anderson, J. M. Anthony, Y. Zhang, P. W. Wilson, M. Kelly-Hayes, P. A. Wolf, B. E. Kreger, and W. B. Kannel, 1994, The Effects of Specific Medical Conditions on the Functional Limitations of Elders in the Framingham Study, *American Journal of Public Health*, 84(3):351–358.

Hedinger, D., O. Hämmig, and M. Bopp, 2015, Social Determinants of Duration of Last Nursing Home Stay at the End of Life in Switzerland: A Retrospective Cohort Study Health Services Research, *BMC Geriatrics*, 15(1):1–8.

HRS Codebook, 2020, HRS 2020 Final Release, Online. Section C: Physical Health, Question 36 (RC036 Heart Condition).

Institute of Medicine, 2008, *Retooling for an Aging America: Building the Health Care Workforce*. Nummer 2 in Health Status and Health Care Service Utilization. The National Academies Press, Washington, DC.

Jennings, L. A., S. Hollands, E. Keeler, N. S. Wenger, and D. B. Reuben, 2020, The Effects of Dementia Care Co-Management on Acute Care, Hospice, and Long-Term Care Utilization, *Journal of the American Geriatrics Society*, 68(11):2500–2507.

Johnson, R. W., 2019, What Is the Lifetime Risk of Needing and Receiving Long-Term Services and Supports?, Technischer Bericht, Urban Institute, Washington, D.C.

Juster, F. T. and R. Suzman, 1995, An Overview of the Health and Retirement Study, *The Journal of Human Resources*, 30:S7–S56.

Kaplan, E. L. and P. Meier, 1958, Nonparametric Estimation from Incomplete Observations, *Journal of the American Statistical Association*, 53(282):457–481.

Katz, P. R., 2011, An International Perspective on Long Term Care: Focus on Nursing Homes, *Journal of the American Medical Directors Association*, 12(7):487–492.e1.

Kempen, G., A. M. Myers, and L. E. Powell, 1995, Hierarchical Structure in ADL and IADL: Analytical Assumptions and Applications for Clinicians and Researchers, *Journal of Clinical Epidemiology*, 48(11):1299–1305.

Khan, N., C. V. Chalitsios, Y. Nartey, G. Simpson, F. Zaccardi, M. Santer, P. J. Roderick, B. Stuart, A. J. Farmer, and H. Dambha-Miller, 2023, Clustering by Multiple Long-Term Conditions and Social Care Needs: A Cross-Sectional Study Among 10 026 Older Adults in England, *Journal of Epidemiology & Community Health*.

Khil, L., J. Wellmann, and K. Berger, 2015, Impact of Combined Sensory Impairments on Health-Related Quality of Life, *Quality of Life Research*, 24(9):2099–2103.

Kitchener, M., T. Ng, N. Miller, and C. Harrington, 2006, Institutional and Community—Based Long-Term Care, *Journal of Health & Social Policy*, 22(2):31–50.

Koroukian, S. M., N. Schiltz, D. F. Warner, J. Sun, P. M. Bakaki, K. A. Smyth, K. C. Stange, and C. W. Given, 2016, Combinations of Chronic Conditions, Functional Limitations, and Geriatric Syndromes that Predict Health Outcomes, *Journal of General Internal Medicine*, 31(6):630–637.

López-Ortiz, S., S. Lista, S. Peñín-Grandes, J. Pinto-Fraga, P. L. Valenzuela, R. Nisticò, E. Emanuele, A. Lucia, and A. Santos-Lozano, 2022, Defining and Assessing Intrinsic Capacity in Older People: A Systematic Review and a Proposed Scoring System, *Ageing Research Reviews*, 79:101640.

Makam, A. N., T. Tran, M. E. Miller, L. Xuan, O. K. Nguyen, and E. A. Halm, 2019, The Clinical Course after Long-Term Acute Care Hospital Admission among Older Medicare Beneficiaries, *Journal of the American Geriatrics Society*, 67(11):2282–2288.

Marengoni, A., S. Angleman, R. Melis, F. Mangialasche, A. Karp, A. Garmen, B. Meinow, and L. Fratiglioni, 2011, Aging with Multimorbidity: A Systematic Review of the Literature, *Ageing Research Reviews*, 10(4):430–439.

Mathers, C., 1996, Trends in Health Expectancies in Australia 1981–1993, *Journal of the Australian Population Association*, 13(1):1–15.

Moore, D. C., T. J. Keegan, L. Dunleavy, and K. Froggatt, 2019, Factors Associated With Length of Stay in Care Homes: A Systematic Review of International Literature, *Systematic Reviews*, 8(1):56.

Ng, A. Y., M. I. Jordan, and Y. Weiss, 2001, On Spectral Clustering: Analysis and an Algorithm, In *NIPS'01: Proceedings of the 14th International Conference on Neural Information Processing Systems: Natural and Synthetic*, Seiten 849–856.

Nichols, B. L., C. R. Davis, and D. R. Richardson, 2010, An Integrative Review of Global Nursing Workforce Issues., *Annual Review of Nursing Research*, 28:113–132.

OECD, 2017, *Health at a Glance 2017: OECD Indicators*. OECD Publishing, Paris.

Pack, S., 2009, Poor Physical Health and Mortality in Patients with Schizophrenia., *Nursing Standard (Royal College of Nursing Great Britain, 1987)*, 23(21):41–45.

Roussel, B. and C. Tilquin, 1993, *Bio-Psycho-Social Profile of Clients in Long Term Care and Planning of Nursing Care Required*. Équipe de Recherche Opérationnelle en Santé, Montreal. Reference manual.

Schwarz, G., 1978, Estimating the Dimension of a Model, *The Annals of Statistics*, 6(2):461–464.

Sherris, M. and P. Wei, 2021, A Multi-state Model of Functional Disability and Health Status in the Presence of Systematic Trend and Uncertainty, *North American Actuarial Journal*, 25(1):17–39.

Si, Y., K. Hanewald, S. Chen, B. Li, H. Bateman, and J. R. Beard, 2023, Life-Course Inequalities in Intrinsic Capacity and Healthy Ageing, China., *Bulletin of the World Health Organization*, 101(5):307–316C.

Sonnega, A., J. D. Faul, M. B. Ofstedal, K. M. Langa, J. W. R. Phillips, and D. R. Weir, 2014, Cohort Profile: the Health and Retirement Study (HRS), *International Journal of Epidemiology*, 43(2):576–585.

Spasova, S., R. Baeten, S. Coster, D. Ghailani, R. Peña-Casas, and B. Vanhercke, 2018, *Challenges in Long-Term Care in Europe. A Study of National Policies*. European Social Policy Network (ESPN), Brussels. European Commission.

Spetz, J., L. Trupin, T. Bates, and J. M. Coffman, 2015, Future Demand For Long-Term Care Workers Will Be Influenced By Demographic And Utilization Changes, *Health Affairs*, 34(6):936–945.

Stark, A. J., R. L. Kane, R. A. Kane, and M. Finch, 1995, Effect on Physical Functioning of Care in Adult Foster Homes and Nursing Homes, *The Gerontologist*, 35(5):648–655.

Swiss Federal Statistical Office, 2021, Structure of the Permanent Resident Population by Canton, 2010-2021, Data file. Published on: 25.08.2022.

The MathWorks Inc., 2022, *Partition Data Using Spectral Clustering*. Natick, Massachusetts, United States.

Tobis, S., K. Jaracz, S. Kropińska, D. Talarska, J. Hoe, K. Wieczorowska-Tobis, and A. Suwalska, 2021, Needs of Older Persons Living in Long-term Care Institutions: On the Usefulness of Cluster Approach, *BMC Geriatrics*, 21(1):316.

Ugarte Montero, A. and J. Wagner, 2023, On Potential Information Asymmetries in Long-Term Care Insurance: A Simulation Study Using Data from Switzerland, *Insurance: Mathematics and Economics*, 111:230–241.

van den Akker, M., F. Buntinx, J. F. M. Metsemakers, S. Roos, and J. Knottnerus, 1998, Multimorbidity in General Practice: Prevalence, Incidence, and Determinants of Co-Occurring Chronic and Recurrent Diseases, *Journal of Clinical Epidemiology*, 51(5):367–375.

Vanella, P., M. Heß, and C. B. Wilke, 2020, A Probabilistic Projection of Beneficiaries of Long-Term Care Insurance in Germany by Severity of Disability, *Quality & Quantity*, 54(3):943–974.

Venables, W. N. and B. D. Ripley, 2002, *Modern Applied Statistics with S*. Springer, New York, fourth Auflage. ISBN 0-387-95457-0.

von Luxburg, U., 2007, A Tutorial on Spectral Clustering, *Statistics and Computing*, 17(4):395–416.

Wang, Q., Y. Zhou, X. Ding, and X. Ying, 2018, Demand for Long-Term Care Insurance in China, *International Journal of Environmental Research and Public Health*, 15(1).

Wong, Y. C. and J. Leung, 2012, Long-term Care in China: Issues and Prospects, *Journal of Gerontological Social Work*, 55(7):570–586.

World Health Organization, 1980, International classification of impairments, disabilities, and handicaps: a manual of classification relating to the consequences of disease, published in accordance with resolution WHA29.35 of the Twenty-ninth World Health Assembly, May 1976.

World Health Organization, 2015, *World report on ageing and health*. World Health Organization, Geneva.

World Health Organization, 2016, *International Statistical Classification of Diseases and Related Health Problems - 10th revision*. Geneva, Switzerland, Fifth Auflage.

Wu, C., A. B. Newman, B.-R. Dong, and M. C. Odden, 2018, Index of Healthy Aging in Chinese Older Adults: China Health and Retirement Longitudinal Study, *Journal of the American Geriatrics Society*, 66(7):1303–1310.

Xu, M., M. Sherris, and R. Meyricke, 2019, Systematic Mortality Improvement Trends and Mortality Heterogeneity: Insights from Individual-Level HRS Data, *North American Actuarial Journal*, 23(2):197–219.

Zhao, Y., Y. Hu, J. P. Smith, J. Strauss, and G. Yang, 2012, Cohort Profile: The China Health and Retirement Longitudinal Study (CHARLS), *International Journal of Epidemiology*, 43(1):61–68.

Zhou, Y. and L. Ma, 2022, Intrinsic Capacity in Older Adults: Recent Advances, *Aging and Disease*, 13(2):353–359.

Chapter 4

Evolution of Institutional Long-Term Care Costs Based on Health Factors

As many developed countries face the challenges of an aging population, the need to efficiently plan and finance long-term care (LTC) becomes increasingly important. Understanding the dynamics of care requirements and their associated costs is essential for sustainable healthcare systems. In this study, we employ a multi-state Markov model to analyze the transitions between care states of elderly individuals within institutional LTC in the canton of Geneva, Switzerland. Utilizing a comprehensive dataset of 21 494 elderly residents, we grouped care levels into four broader categories reflecting the range from quasi-autonomy to severe dependency. Our model considers fixed covariates at admission, such as demographic details, medical diagnoses, and levels of dependence, to forecast transitions and associated costs. The main results illustrate significant variations in care trajectories and LTC costs across different health profiles, notably influenced by gender and initial care state. Females generally require longer periods with less intensive care, while conditions like severe and nervous diseases show quicker progression to more intensive care and higher initial costs. These transitions and expected length of stay in each state directly impact LTC costs, highlighting the necessity of advanced strategies to manage the financial burden. Our findings offer insights that can be utilized to optimize LTC services in response to the specific needs of institutionalized elderly people. These findings can be applied to enhance healthcare planning, the preparedness of infrastructure, and the design of insurance products.

This is a joint work with J. Wagner.

4.1 Introduction

The demographic shift toward an aging population poses significant challenges to long-term care (LTC) systems worldwide. As life expectancy increases, so does the prevalence of age-related health problems, necessitating expanded services and resources to support the elderly, particularly in their activities of daily living (ADL). Studies like those by OECD (2017) and Kempen et al. (1995) have highlighted the growing demand for healthcare services as more individuals live into their later years, often accompanied by complex health conditions such as multiple diseases (van den Akker et al., 1998) which amplify the need for continuous care (Stark et al., 1995).

In this context, institutional LTC emerges as a critical component of elder care, designed to support those who require substantial assistance. Unlike home or family-based care, institutional settings provide organized, comprehensive care that integrates medical, personal, and social services in a single facility. However, this system also involves significant challenges in terms of financing (Brown and Finkelstein, 2009), availability of care facilities (Katz, 2011), and the recruitment and training of professional caregivers (Nichols et al., 2010). The integration of effective management strategies and sustainable financing solutions is essential to prepare for the coming increase in demand, underscoring the importance of detailed analysis and strategic planning in LTC provision (Colombo et al., 2011; Cosandey, 2016).

Research on LTC costs highlights the significance of modeling in understanding and predicting the financial implications associated with varying durations of care and intensities of service provision. The economic burden on LTC facilities is primarily determined by the length of stay of residents, which varies based on demographic factors, medical conditions, and the severity of physical and psychological impairments (Mathers, 1996; Deeg et al., 2002; Germain et al., 2016). Works by Bladt et al. (2023) and Shemendyuk and Wagner (2024) have shown how age, gender, and specific health profiles influence the demand for care and, consequently, the costs incurred. Particularly, individuals with complex health conditions such as musculoskeletal and osteoarticular disorders often have extended stays due to lower mortality rates (Makam et al., 2019). Moreover, the intensity of care, measured by the daily time nurses spend with patients, directly impacts the cost structure within LTC settings (Dorr et al., 2005). Studies such as Guccione et al. (1994) and Fong (2019) have shown how the level of dependency due to multiple morbidities increases the need for more intensive and frequent care interventions, thereby escalating the overall costs. This correlation is further complicated by impairments in psychological and sensory functions, which necessitate higher levels of assistance and lead to greater dependency (Marengoni et al., 2011; Barnett et al., 2012).

In LTC cost analysis, multi-state modeling plays a critical role in mapping the complex relationships between health conditions and care trajectories. The development of semi-Markov models, as explored by Fuino and Wagner (2018), enhances understanding of the care paths essential for elderly care management and the design of tailored insurance products. These models effectively track the transitions between different states of health, which are directly influenced by the severity of conditions and determine the duration of stay and intensity of care required (Fong et al., 2015; Sherris and Wei, 2021). The actuarial assessment of LTC products often relies on such models, as they allow for the estimation of transition probabilities that are not only dependent on the current health state but also on the duration within that state, providing a more nuanced view of care dynamics (Pritchard, 2006; Christiansen, 2012; Haberman and

Pitacco, 2018). Historically, these models have been used to determine insurance premiums and manage risk by considering both the progression of the health status and its implications on care needs (Govorun et al., 2015; Ai et al., 2017). Studies like those by Czado and Rudolph (2002) and Helms et al. (2005) have extended traditional Markov models to incorporate time-dependent variables, which significantly impact the calculation of costs in LTC settings. This semi-Markov approach, recognized for its ability to integrate time-dependent transitions, offers a sophisticated framework for predicting LTC costs by accounting for the complexity of health trajectories and the direct impact of functional disabilities on life expectancy and subsequent care requirements (Janssen and Manca, 2001; Foucher et al., 2010).

Using a multi-state model, our study aims to analyze the evolution of individual health and its implications on institutional LTC needs and their financing in the context of Switzerland. By leveraging the Swiss social health insurance system's categorization of LTC needs into twelve levels, our model captures transitions between different states of care, including the absorbing state of death. We utilize a comprehensive panel dataset from the LTC institutions of the Canton of Geneva covering the years from 1996 to 2018, which includes detailed records of 21 494 individuals collected using the Canadian "PLAISIR" method (Roussel and Tilquin, 1993). We estimate transition probabilities and associated costs linking them to the individual characteristics known at admission in the institution. This methodology aids nursing staff by predicting care requirements from initial health assessments, supports infrastructure planning by forecasting occupancy, and informs both public and private insurers about expected costs. The latter is essential not only for designing social health insurance policies but also for developing novel private insurance products.

By analyzing various health profiles, our study suggests that the baseline health profile, most commonly observed among institutionalized elderly people, incurs higher LTC costs due to extended care needs stemming from prolonged survival times. Conversely, profiles characterized by severe conditions and nervous diseases demonstrate swift progression to higher dependency states, accumulating significant costs early on, especially among females. Another notable finding is that individuals with cerebrovascular conditions experience a slower progression to severe states yet eventually accumulate substantial costs. Moreover, the tumor disease profile uniquely displays rapid transitions to death, yielding the lowest overall costs due to the shortened duration of care.

The remainder of this paper is structured as follows. Section 4.2 develops a multi-state model for panel data to assess the changes in the health status of institutionalized elderly and the impact on LTC costs within the Swiss social health insurance framework. Section 4.3 presents our dataset and statistical analysis, emphasizing the advantages of using medical evaluations over traditional survey-based data. Section 4.4 applies the developed multi-state model, discussing the transformation of variables, model fitting, and examining transition probabilities and associated costs across various health profiles. Finally, Section 4.5 provides conclusions, summarizing the insights obtained from our analysis and suggesting directions for future research.

4.2 Modeling insured LTC costs: framework and methodology

In this section, we develop a model to assess the changes in the health status of institutionalized elderly and the effect on LTC costs within the Swiss social health insurance framework. We start with an overview of the care classification and the reimbursement levels in Switzerland. Next, we introduce the individual's evolution of care and formulate a time-homogeneous multi-state Markov model that describes the underlying process. Then, we detail the likelihood function and the role of initial covariates in determining transition intensities. Finally, we describe the calculation of key metrics, such as transition probabilities and expected length of stay in the care states, that are essential for estimating the costs of care.

Swiss social health insurance reimbursement scheme. The cost of institutional LTC is significant and, in Switzerland, directly related to the daily care needs of the elderly. While housing costs are borne out-of-pocket by the individuals, Swiss social health insurance reimburses care costs along a twelve-level classification, each level of care needs correlating to specific reimbursement amounts as described by the Federal Department of Home Affairs (2016, Section 3, Art. 7 and 7a). This approach ensures that the financial compensation for LTC is systematically organized, making it directly proportional to the intensity of care required.

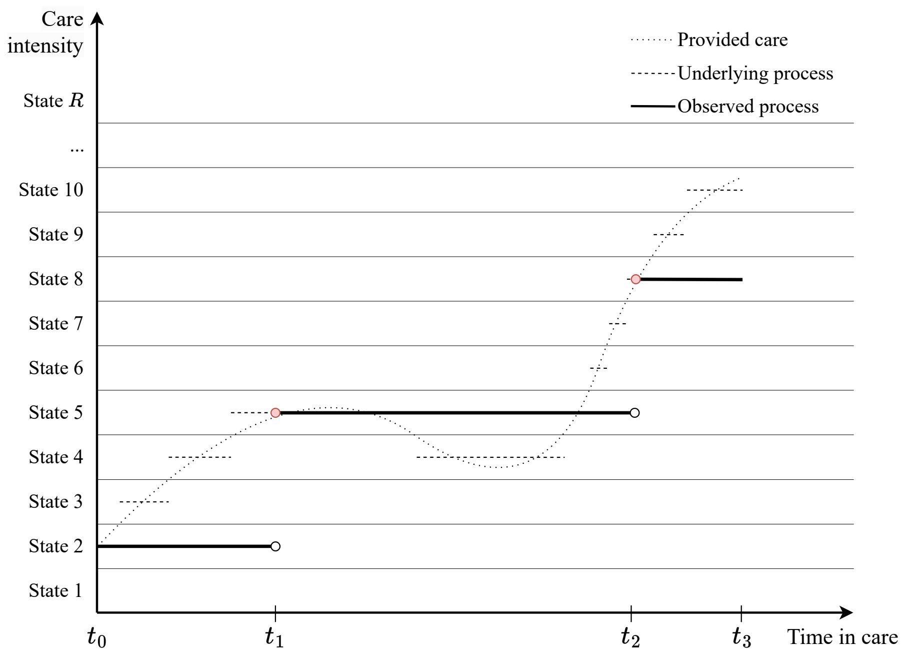
In Switzerland, reimbursement for LTC is determined by twelve ordered levels based on daily care requirements. Under this system, social health insurance pays out daily amounts based on the required level of care:

$$\text{Payout}(r) = 9.60 \times r, \quad \text{(in CHF)}, \tag{20}$$

where $r = 1, 2, \ldots, 12$ denotes one of the twelve categories derived from the minutes of required care per day. These categories start with up to 20 minutes per day, represented by the index $r = 1$ and coming with costs of CHF 9.60. The categories increase by 20 minutes per day for the next states $r = 2, \ldots, 11$. For example, an elderly person requiring 21 to 40 minutes of care per day is represented by category $r = 2$ and the costs yield CHF 19.20. This pattern continues until the final category, $r = 12$, which represents 220 or more minutes of care per day and yields costs of CHF 115.20.

Comparable cash-for-care schemes exist in other European countries, where LTC insurance benefits are structured in several tiers, similar to the Swiss model's categorization of dependency levels. Countries such as Austria, France, and Germany have developed systems that reflect different levels of dependency, similar to the Swiss categorization of care needs. Da Roit and Le Bihan (2010, see Table 1) provide a comprehensive analysis of the European landscape, highlighting the differences in schemes and the funding systems in countries such as Sweden, Netherlands, France, Germany, Austria, and Italy, and their respective financial implications. Furthermore, Yang et al. (2016) examined China's approach to LTC financing, revealing diverse strategies such as Shanghai's social health insurance, Qingdao's LTC insurance, and Nanjing's means testing. Despite differences in healthcare integration and government funding reliance, these models share a core objective with their European counterparts, namely, to provide an adequate reimbursement scheme for the institutional LTC.

Multi-state model framework. In the following, we consider an insurance reimbursement scheme that pays for provided care based on R categories. Assuming continuous evolution of the provided care, the payout levels are evolving as a discrete-space continuous-time jump process. In Figure 4.1, we illustrate a sample path of care intensity over time, i.e., the evolution of a person's care needs since admission to the institution. The *provided care* is denoted by the dotted curve and represents the continuous evolution of care provided to the elderly. The *under-*



Note: The dotted curve in graph (a) represents the continuous evolution of care provided at the institution, while the dashed and solid lines represent the underlying and observed processes corresponding to discrete states of care reimbursements.

Figure 4.1: Illustration of the care intensity path over time.

lying and *observed processes* represented by the dashed and solid lines, respectively, correspond to the R reimbursement levels that follow the multi-state process. The underlying process is directly related to the provided care so that the corresponding multi-state process evolves from one neighboring state to another. Also, it is possible to transition to the absorbing state denoted as "Death" at any point. Figure 4.2 shows the diagram with the possible transitions between the model's states. Unlike the underlying process, the observed process represents the administrative data collection procedure that starts at the date of admission $t_0 = 0$ and, in general, is carried out periodically at undetermined times t_1, t_2, and so on. The last observation in time t_3 illustrated in Figure 4.1 can indicate the person's moment of death or correspond to the current length of stay in the institution (e.g., related to the end of the observation period due to data extraction). In the latter case, the duration until the next state transition (time-to-event) remains undetermined, and the health state at the date of data extraction is therefore unknown (see the mismatch between the underlying and observed processes in time t_3).

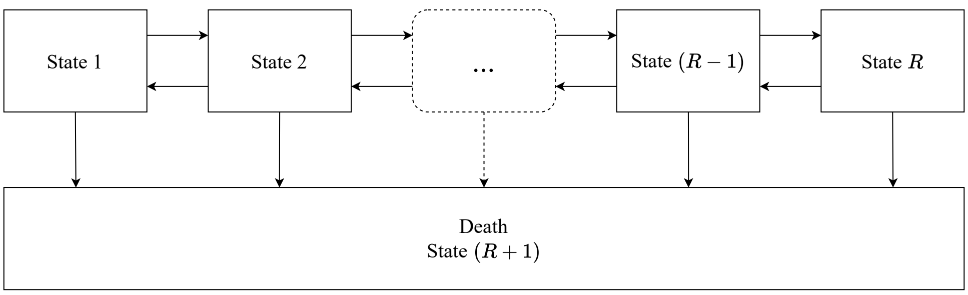


Figure 4.2: Transitions of the underlying process in the LTC multi-state model.

In our analysis, we aim to apply a multi-state Markov model on panel data. For doing so, we consider a framework consisting of $(R+1)$ states, where each state $r = 1, 2, \ldots, R$ indicates different care needs, and the state $(R+1)$ denotes the terminal state of death. The transition intensities $q_{rs}(\mathbf{z})$ measure the instantaneous probability of transitioning from state r to state s, for $r, s = 1, \ldots, R+1$, $r \neq s$, and are independent of the process history under the Markov assumption (Cox and Miller, 1965). These transition intensities are contained in a matrix Q of dimension $(R+1) \times (R+1)$ with the rows summing up to zero, i.e., the diagonal elements are defined as $q_{rr}(\mathbf{z}) = -\sum_{s \neq r} q_{rs}(\mathbf{z})$. The model allows only for transitions between neighboring states and to the absorbing state so that the matrix Q has the following form:

$$Q = \begin{pmatrix} -q_{12} - q_{1,R+1} & q_{12} & 0 & \cdots & 0 & q_{1,R+1} \\ q_{21} & -q_{21} - q_{23} - q_{2,R+1} & q_{23} & \cdots & 0 & q_{2,R+1} \\ 0 & q_{32} & -q_{32} - q_{34} - q_{3,R+1} & \cdots & 0 & q_{3,R+1} \\ \vdots & \vdots & \vdots & \ddots & \vdots & \vdots \\ 0 & 0 & 0 & \cdots & -q_{R,R-1} - q_{R,R+1} & q_{R,R+1} \\ 0 & 0 & 0 & \cdots & 0 & 0 \end{pmatrix} \tag{21}$$

In a transition probability matrix $P(t)$, the element $p_{rs}(t)$ represents the probability of an individual transitioning from state r to state s over time t, assuming a time-homogeneous Markov process. The matrix $P(t)$ is defined by the matrix exponential of Q scaled by the time interval t, i.e.,

$$P(t) = \mathrm{Exp}(tQ). \tag{22}$$

This matrix is crucial for our analysis of care trajectories as it helps to assess the expected length of stay in each care state and thus facilitates the cost evaluations.

Likelihood for panel data. To calculate the maximum likelihood estimate of the transition intensity matrix Q, Kalbfleisch and Lawless (1985) and Kay (1986) established a method for a general multi-state model in continuous time with an arbitrary transition matrix $P(t)$. In this context, $i = 1, \ldots, M$ indexes unique trajectories of M individuals through various care states over time. The indices i and j of the function $\mathcal{L}$ represent the likelihood contribution from the j-th transition of the i-th individual in terms of the transition probability matrix. Here, j represents a specific transition event for that individual, moving from one observed state to another over a discrete interval. For intermittently observed processes, the likelihood contribution for individual i from a pair of successive observed states $S(t_j)$ and $S(t_{j+1})$ is given by:

$$\mathcal{L}_{i,j} = p_{S(t_j)S(t_{j+1})}(t_{j+1} - t_j),$$

where $p_{rs}(t)$ denotes the probability of transitioning from state r to state s over time t, derived from the transition probability matrix $P(t)$.

In cases where the times of death are exactly known, the contribution to the likelihood accounts for the uncertainty in the state just before death by summing over all potential states s preceding the terminal state of death:

$$\mathcal{L}_{i,j} = \sum_{s=1}^{R} p_{S(t_j),s}(t_{j+1} - t_j) \cdot q_{s,(R+1)}.$$

In panel data that is limited in time, some individuals are observed to reach the absorbing state, while others are still alive at the end of the observation period, with their most recent health state recorded. The subsequent transition for the surviving individuals, whether to another care state or death, is not observed, leading to right-censoring. For the likelihood calculation, this scenario requires accounting for both the certainty of the last known state and the potential for any future state transitions. In this context, n_i denotes the index of the last observation for individual i. The likelihood for transitions from this last observed state includes all possible subsequent states excluding death and is represented as:

$$\mathcal{L}_{i,n_i} = \sum_{s=1}^{R} p_{S(t_{n_i}),s}(t_{n_i+1} - t_{n_i}).$$

The total likelihood $\mathcal{L}(Q)$ of the multi-state model is constructed by multiplying all individual likelihood contributions $\mathcal{L}_{i,j}$ across every transition and for each individual in the study:

$$\mathcal{L}(Q) = \prod_{i,j} \mathcal{L}_{i,j}. \tag{23}$$

Effect of covariates. In our analysis, we aim to consider the effect of covariates $\mathbf{z}$ that are valued at the time of entry into institutional LTC and do not evolve over time. Incorporating fixed covariates simplifies the estimation of future care costs, even under uncertainty about future health outcomes. This is also consistent with practical needs for predicting care trajectories at the time of entry for new patients. According to Marshall and Jones (1995), the transition intensities q_{rs} can be modeled as functions of these covariates using a proportional hazards method:

$$q_{rs}(\mathbf{z}) = q_{rs}^{(0)} \exp(\boldsymbol{\beta}_{rs}^T \mathbf{z}), \tag{24}$$

where $\mathbf{z}$ represents the vector of covariates fixed at entry, $\boldsymbol{\beta}_{rs}$ is the vector of coefficients associated with the covariates $\mathbf{z}$ for the transition from state r to state s, and $q_{rs}^{(0)}$ is the baseline transition intensity as defined in the matrix Q above. Consequently, incorporating these covariates into the transition intensities influences the total likelihood function. The process of finding optimal values involves maximizing the likelihood function $\mathcal{L}(Q)$ in Equation (23) with respect to $q_{rs}^{(0)}$ and $\boldsymbol{\beta}_{rs}$.

Model output. Once the model parameters are estimated from the data, we compute the key metrics of interest. Specifically, we want to evaluate the probability of transitioning to a state by a given time t, denoted in Equation (22), and the average time an individual starting in state r is expected to spend in each state $s = 1, 2, \dots, R, R+1$, including death, up to time t:

$$E_{rs}(t, \mathbf{z}) = \int_0^t p_{rs}(u, \mathbf{z})\, \mathrm{d}u. \tag{25}$$

The latter allows for estimating the average care costs over a specified period. Given the payout amounts from Equation (20), the average cost of an institutionalized individual starting in state r with initial covariates $\mathbf{z}$ over time t can be described as:

$$C_r(t, \mathbf{z}) = \sum_{s=1}^{R} E_{rs}(t, \mathbf{z}) \cdot \text{Payout}(s). \tag{26}$$

Here, we consider the average costs as the average number of days spent in a particular state by the time t multiplied by the daily cost of the states. In the $(R+1)$-th state, representing death, no cost arises. However, in the case of modeling a mixed insurance product, a lump-sum term representing a one-time death benefit could be added.

4.3 Dataset and descriptive statistics

In this section, we present the main characteristics of our dataset and statistical analysis. Section 4.3.1 provides an overview of our dataset, which offers several advantages over typical survey-based datasets commonly used in LTC research.[1] These advantages are based on the medical evaluations of an individual's health compared to self-reported data, and consistent follow-up during the study. This enables a more precise examination of the health transitions and care requirements within the institutionalized elderly population, overcoming the common limitations of uncertain times of transitions between states and imprecise health reports. Next, in Section 4.3.2, we analyze the health evaluations recorded in our dataset and the observed transitions among different care states. After consolidating the twelve available care levels into four broader categories, we utilize the Aalen-Johansen estimator to calculate state occupancy over time, enhancing our understanding of care dynamics. Additionally, we stratify these estimates by key covariates such as gender, medical diagnoses, and levels of dependence and provide an analysis of the associated LTC costs.

4.3.1 Description of the data

This study is based on the private dataset from nursing homes in the Canton of Geneva, Switzerland, which was previously studied by Bladt et al. (2023) and later by Shemendyuk and Wagner (2024). The dataset includes $M = 21\,494$ individuals aged 65 or older,[2] consisting of 17 832 complete observations of individuals who died during the study period and 3 662 right-censored observations of those still alive at the time of data extraction.[3] This study covers the period from 1996 to 2018 and is collected using the EROS assessment tool, a methodology developed by Roussel and Tilquin (1993). In our dataset, all institutionalized individuals have no

[1] See for example, the Health and Retirement Study in the United States (HRS), originally reviewed by Juster and Suzman (1995) and later by Sonnega et al. (2014) and Fisher and Ryan (2017), available at `https://hrs.isr.umich.edu/`; the Survey of Health, Ageing and Retirement in Europe (SHARE), see `https://share-eric.eu/` and its introduction by Börsch-Supan et al. (2013); and the China Health, Aging, and Retirement Longitudinal Study (CHARLS) from `https://charls.pku.edu.cn/en/` explained by Zhao et al. (2012).

[2] The reduction in the number of observations from Shemendyuk and Wagner (2024) is due to additional quality checks that were implemented when incorporating subsequent health evaluations for each individual. Specifically, we excluded 8 individuals due to discrepancies between the recorded number of health evaluations and the value registered in the personal summary data field. Additionally, 27 and 20 individuals were excluded due to incorrect or inconsistent entry or exit dates, respectively.

[3] Right-censored observations refer to those individuals whose health state is recorded from their entry into the institution until the last observed health evaluation but where the recording is interrupted by the end of the observation period. Thus, the duration until the next transition (time-to-event) remains undetermined, and similarly, the health state at the time of data extraction is not recorded.

instances of leaving and reentering the institution, thus, providing consistent tracking of their LTC pathways.

Our data captures several categories of variables: demographic information, medical diagnoses, levels of dependence, impairments of psychological and sensory functions, and the intensity of care. The latter quantifies the care provided to an individual over a one-week health evaluation period and is measured in minutes of care per week. Based on this variable and within the Swiss reimbursement scheme, we derive one of the twelve cost levels according to the daily care requirement, see Federal Department of Home Affairs (2016) and Section 4.2. Table 4.1 highlights the variables related to the pathway of elderly people receiving institutional LTC. Further, we borrow parts of the explanation of the other available variables from Bladt et al. (2023, Section 3.1) and Shemendyuk and Wagner (2024, Section 2.1) and provide specific details where needed. Since we account for multiple health evaluations per individual, we provide more details on the intensity of care variable and its related reimbursement level. Furthermore, we introduce the observed time spent in a state.

Pathway variables. For each individual $i = 1, 2, \ldots, M$, our data records their stay in institutional LTC from admission until death, if applicable, or the date of the data extraction, August 21st, 2018. Upon entry into the facility, every individual undergoes a detailed initial health screening lasting for one week, initializing the start of their care path. This initial screening, indexed as $j = 0$ and time $t = 0$, forms a baseline of health information, including medical diagnoses, levels of dependence, and impairments of psychological and sensory functions, alongside the intensity of care.

The subsequent health evaluations $j = 1, 2, \ldots, n_i$ of an individual i are periodically conducted at random intervals, typically ranging from one to two years. These evaluations update each individual's health information, reflecting changes in their care needs. Each health evaluation is indexed by j, denoting the evaluation sequence for an individual, and the specific time t_{ij} when the evaluation was conducted, recorded in days from the initial entry into the institution. The intensity of care $T_{t_{ij}}$, observed during these evaluations, is measured in minutes of care provided per week at each time point t_{ij}. Dividing $T_{t_{ij}}$ by seven gives the daily intensity of care and indicates the level of care $r_{t_{ij}}$, corresponding to one of the 12 ordered levels of the Swiss reimbursement scheme. These categories reflect the range of care needs from minimal assistance to extensive care requirements, with higher numbers indicating a greater need for daily care. By the end of the study, each individual's care path is characterized by the number of health evaluations n_i, including the initial screening at entry.

We update the intensity of care and the corresponding level of care throughout subsequent health evaluations while keeping the values from the initial assessment for the other covariates (see below). This approach limits the model's complexity and enables a straightforward prediction of LTC costs based on the initial values of the covariates.

Demographic variables. The demographic characteristics of the individuals in our study are primarily defined by the age at entry into the institution (AG) and the gender (GE). The age at entry is computed based on the date of birth and the date of admission, reflecting the full years that have passed until the entry into institutional LTC. Our dataset consists of a broad age range at entry, from 65 years, ensuring that all individuals are of retirement age or older,

Variable	Description	Values
Basic information on the pathways		
M	Number of individuals in the dataset	21 494
i	Index of an individual	$1, 2, 3, \ldots, M$
n_i	Number of health evaluations for individual i during the study period	$1, 2, 3, \ldots$
j	Index of the health evaluation for individual i	$0, 1, 2, \ldots, n_i$
t_{ij}	Time of the health evaluation j for individual i	$1, 2, 3, \ldots$ (in days after admission)
$T_{t_{ij}}$	Intensity of care provided per week observed at time t_{ij} for individual i at their health evaluation j	number of minutes (between 0 and 10 080)
$r_{t_{ij}}$	Care level derived from daily care observed at time t_{ij} for individual i at their health evaluation j	$1, 2, 3, \ldots, 12$ (categorical)
Demographic variables		
AG	Age at entry in the institution	$65, 66, 67, \ldots$ (in years)
GE	Gender	female, male (binary)
Medical diagnoses		
ND	Number of diagnoses	$1, 2, 3, \ldots, 9$
$D1$	Diagnosis of first importance	mental, cerebrovascular, respiratory, blood, nervous, osteoarticular, endocrine, heart, tumors, other (categorical)
Di	Diagnosis of k-th importance, $k = 2, 3, \ldots, 9$	see $D1$, plus “none”
Levels of dependence		
DP	Dependence in ADL	$1, 2, 3, \ldots, 9$ (categorical)
PM	Physical mobility limitations	”
OR	Orientation problems	”
OC	Occupational limitations	”
SI	Social integration limitations	”
Impairments of psychological and sensory functions		
VS	Vision	adequate, mild, moderate, severe
HR	Hearing	”

Note: *Only two of the 16 available impairments of psychological and sensory functions appear in our model after the variable selection procedure (see Section 4.4.1).

Table 4.1: Description of the variables.

to the oldest recorded entry at 106 years. Gender is identified as a binary factor, distinguishing between “male” and “female” categories.

Medical diagnoses. Our dataset includes up to nine medical diagnoses ($D1, D2, \ldots, D9$) for each individual, with $D1$ representing the primary condition and the others ranked by decreasing importance. If an individual has fewer than nine diagnoses, subsequent values are assigned as “none.” Diagnoses are encoded following the International Classification of Diseases (ICD) standards detailed by the World Health Organization (2016), and aggregated further into general groups: mental, cerebrovascular, respiratory, blood, nervous, osteoarticular, endocrine, heart, tumors, and an "other" category for remaining conditions.[4]

Levels of dependence. Dependence levels are evaluated based on five dimensions to measure individuals' varying degrees of physical and social limitations. These dimensions include limitations in ADL (denoted as DP), physical mobility (PM), orientation (OR), occupational activities (OC), and social integration (SI). Following the guidelines established by the World Health Organization (1980), these variables are recorded on a nine-point scale as ordered factors that categorize the severity of limitations from minimal to severe with levels 1 to 9, respectively (also see Bladt et al., 2023, Sect. 3.1 and Table 2). Specifically, DP evaluates the individuals' independence in performing both basic ADL, such as personal hygiene, eating, and dressing, and instrumental ADL, like housekeeping and cooking. PM assesses the ability to move effectively within the environment, considering the use of mechanical aids but excluding assistance from others. OR measures cognitive functions related to understanding and interacting with the environment. OC assesses the capacity to engage in customary activities reflecting the individual's age and gender within the institutional setting. Lastly, SI looks at the individuals' ability to participate in social activities and maintain social relationships, which are essential for life in an institutional context.

Impairments of psychological and sensory functions. Health records from this group are detailed across 16 variables, each measured on an ordered four-point scale ranging from adequate to severe. These scales assess the severity of psychological and sensory function impairments, incorporating any compensatory mechanisms the individual may use, such as glasses or medication for psychological impairments, and comparing performance against the normative standards of a healthy person of the same age and gender. The impairments evaluated include recent memory (RM), long-term memory (LM), thinking (TH), perception and attention (PA), consciousness and wakefulness (CW), orientation related to time, person, and space (TP), decision-making (DM), impulses (IM), will and motivation (WM), emotions including feelings and mood (EM), behavior (BH), language (LG), sight (VS), hearing (HR), making oneself understood (SU), and understanding others (OU). A comprehensive overview of the original definitions in Roussel and Tilquin (1993), the descriptions of the levels associated with these variables and their impact on an individual's health profile, is available in (Bladt et al., 2023, Sect. 3.1).

Heath profiles. This dataset was explored in Shemendyuk and Wagner (2024), revealing that institutionalized elderly can be categorized into eight distinct health profiles. In Sections 4.4.3 and 4.4.4, we utilize them to examine the impact of covariates on LTC costs. The following qualitative summary presents the dominant characteristics of each profile ordered from the largest to the smallest group:

1. *Baseline health profile*: This is the largest group, mainly comprising older women, characterized by minimal care needs and the longest median length of stay, suggesting relatively better health compared to other groups.
2. *General severe conditions*: Includes individuals with significant mental health challenges and high levels of dependence, requiring considerably more care and exhibiting shorter stays than the baseline profile.

[4]For details on the definition of the disease groups and adaptations from ICD-9 to ICD-10, see Bladt et al. (2023, Footnotes 7 and 8) and Shemendyuk and Wagner (2024, Footnote 2).

3. *Moderate-severe conditions with nervous diseases*: Features the youngest average age at entry and is distinguished by predominant nervous system pathologies, requiring care levels similar to the previous profile.
4. *Moderate conditions with endocrine diseases*: Unique for its high prevalence of endocrine disorders, this group displays moderate levels of dependence and healthcare needs, positioned between the baseline and more severe profiles.
5. *Moderate conditions with cerebrovascular diseases*: Characterized by notable cerebrovascular issues, this profile exhibits slightly higher dependence and healthcare needs than the endocrine profile.
6. *Moderate conditions with respiratory diseases*: Marked by significant respiratory issues, individuals in this group have moderate care needs and one of the shorter median stays.
7. *Moderate conditions with blood diseases*: This profile includes a notable presence of blood disorders associated with moderate care needs and a relatively short median length of stay.
8. *Moderate conditions with tumor diseases*: This is the smallest group characterized by a high prevalence of tumor-related diseases and the shortest median length of stay.

4.3.2 Descriptive statistics

In the following, we present descriptive statistics that detail the health pathways of individuals receiving institutional LTC. We identify the transitions between care states and note significant observations, such as the absence of individuals in the lowest care state and the prevalence of high levels of care before death. To manage the model's complexity and allow for robust estimates, we consolidate the various care states into broader categories. These categories range from care levels that indicate autonomy to those that indicate severe dependency. This classification allows us to apply the Aalen-Johansen estimator to evaluate occupancy probabilities and associated costs over time. We stratify further by gender, medical diagnoses, and levels of dependence, and explore the implications of these factors on care progression and costs.

While the dataset contains the observations of 21 494 individual care paths (3 662, 17.0%, of which are right-censored), it counts 54 386 health evaluations, including the initial health evaluation at entry. The complete observations contribute to 45 180 evaluations (83.1%), whereas the right-censored paths contribute to 9 206 evaluations (16.9%). Using successive health assessments, we establish transitions considering two consecutive known states $S(t_j)$ and $S(t_{j+1})$ for all individuals and their paths. For individuals still alive at the end of the study, the last observed state does not lead to another within the study period, so the last transition is marked as "RC," indicating right-censored time-to-event. Table 4.2 reports the number of observed transitions between the care levels.

From Table 4.2, we observe that none of the individuals were in the lowest care state ($r = 1$), receiving less than 20 minutes of care per day. This suggests that individuals requiring minimal care either do not enter institutional LTC or their needs are evaluated beyond the lowest care level. Furthermore, state $r = 12$ is the most prevalent final state before death, indicating significant care needs for individuals in the final stages of life.

Furthermore, the statistics in Table 4.2 reveal a trend in which individuals primarily transition to higher levels of care. For instance, from state $r = 3$, part of the individuals remain on the same care level (891 transitions), and a significant number progress to care states $r = 4$ (722

From …	… to 1	2	3	4	5	6	7	8	9	10	11	12	Death	RC
1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2	0	175	226	104	35	19	23	19	7	13	5	5	69	6
3	0	40	891	722	363	193	163	139	119	108	69	99	355	169
4	0	10	244	838	682	436	284	282	252	233	142	185	601	250
5	0	0	43	258	486	444	345	337	349	274	183	249	632	273
6	0	0	14	76	203	357	390	352	379	291	202	284	648	270
7	0	0	7	33	82	160	333	448	465	363	256	354	755	307
8	0	0	6	29	44	53	159	429	731	500	368	574	1 138	315
9	0	1	5	29	29	48	72	215	732	823	613	1 096	1 816	429
10	0	0	3	13	22	30	35	88	321	937	817	1 389	2 360	451
11	0	0	4	6	14	19	17	46	129	395	838	1 550	2 389	389
12	0	0	1	5	11	12	19	27	75	174	501	3 696	7 069	803

Note: The categories from 1 to 12 correspond to the care levels. The abbreviation "RC" stands for right-censored observations corresponding to individuals whose last observed state does not lead to another transition.

Table 4.2: Number of observed transitions between care levels and right-censoring counts.

transitions) and $r = 5$ (363 transitions). When focusing on state $r = 7$, a significant number of people transition to states $r = 8$ (448 transitions) and $r = 9$ (465 transitions), while only 282 individuals move to lower levels of care ($r = 3, 4, 5$ or 6). This observation is consistent with findings from the extant literature, such as those by Liddle (1992), which suggest that the health conditions of individuals in LTC settings tend to deteriorate due to factors like inadequate resources and underestimation of disabilities. Therefore, it is generally observed that the care needs of elderly individuals in institutional LTC increase over time, with few improvements resulting in mostly only a one-level decrease in care needs. However, worsening conditions can lead to a significant increase in care needs, up to two or three levels higher from one evaluation to another.

Absolute counts of right-censoring become more important in higher care levels, notably for transitions from states $r = 9, 10, 11$ and 12, reaching 803 right-censored transitions for $r = 12$. This observation underscores the critical need for careful planning of LTC services, as a significant number of individuals continue to require intensive care (see, e.g., Burt et al., 2014). This also underlines the relevance of accounting for right-censoring in our model.

To simplify the analysis, avoid computational challenges, and obtain robust results when constructing a multi-state model with many states and limited data, we group the care levels. This is particularly important in scenarios where the dataset may not support a highly detailed model without risking overfitting, especially when assessing the impact of covariates. Accordingly, we aggregate the care categories into four broader groups as depicted in Figure 4.3: state A includes levels $r = 1, 2, 3$, state B encompasses $r = 4, 5, 6$, state C comprises $r = 7, 8, 9$, and state D spans levels $r = 10, 11, 12$. This approach aligns and is comparable with the categorization used in prior studies that assess dependency based on limitations in activities of daily living; see, e.g., Rickayzen and Walsh (2002); Biessy (2015); Fuino and Wagner (2018); Esquível et al. (2021). Here, state A is indicative of quasi-autonomy with less than one hour of care per day, B reflects mild dependency or 1-2 hours per day, and C and D mirror moderate and severe dependency levels, corresponding to 2-3 and 3+ hours per day, respectively. The number of observed tran-

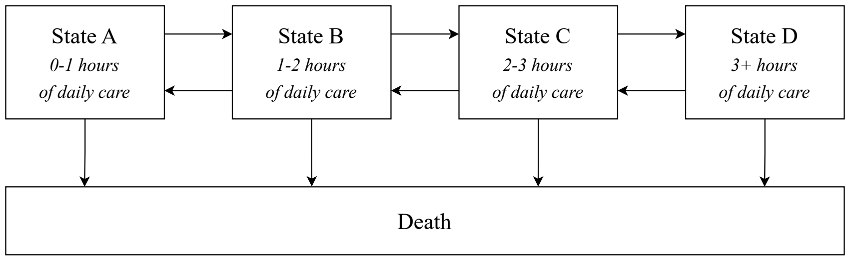


Figure 4.3: Transitions of the underlying process in the model with aggregated care levels.

sitions for the aggregated groups and their respective proportions are presented in Table 4.3. Using the care costs defined in Equation (20), we consider the following average care costs in the four groups: CHF 19.20 for state A, CHF 48 for state B, CHF 76.80 for state C, and CHF 105.60 for state D.

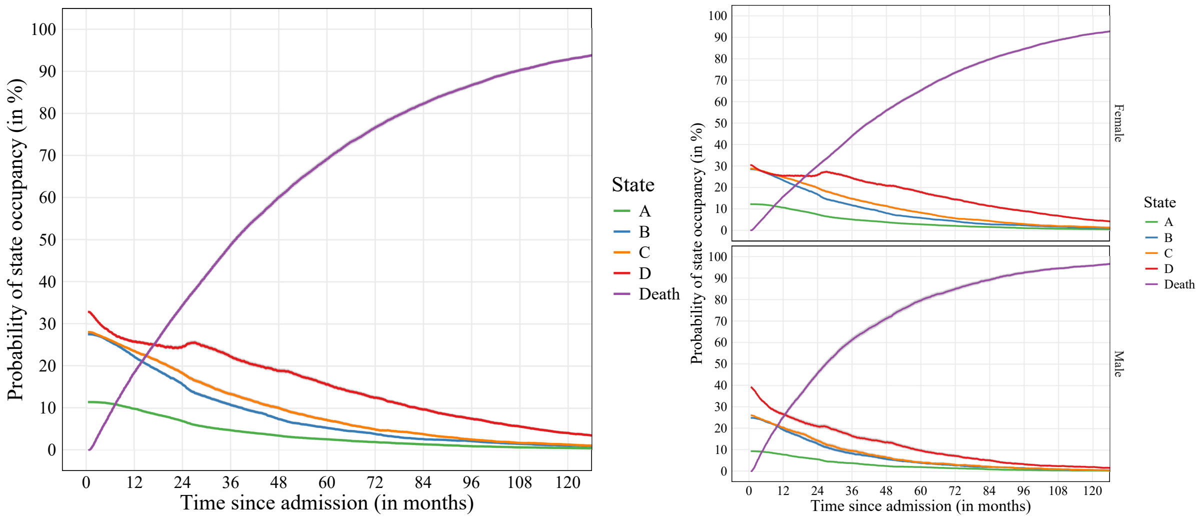
	. . . to											
From . . .	A	(%)	B	(%)	C	(%)	D	(%)	Death	(%)	RC	(%)
A	1 332	(32.2)	1 436	(34.7)	470	(11.4)	299	(7.2)	424	(10.3)	175	(4.2)
B	311	(2.6)	3 780	(32.1)	2 970	(25.2)	2 043	(17.3)	1 881	(16.0)	793	(6.7)
C	19	(0.1)	507	(3.7)	3 584	(25.9)	4 947	(35.8)	3 709	(26.8)	1 051	(7.6)
D	8	(0.0)	132	(0.5)	757	(3.1)	10 297	(41.8)	11 818	(47.9)	1 643	(6.7)

Note: States A, B, C, and D represent less than 1, 1-2, 2-3 and 3+ hours of daily care, respectively. The abbreviation "RC" stands for right-censoring. The shares sum up to 100% in each row.

Table 4.3: Number of transitions between the aggregated care levels and right-censoring counts.

To analyze transitions between aggregated care levels, we use the Aalen-Johansen estimator from the `survival` package in R, see Therneau (2024). It allows us to assess the probability of occupying each care state over time and calculate the corresponding care costs, also accounting for covariates. For an initial overview of the dataset, Figure 4.4a presents Aalen-Johansen estimates across the four aggregated states. The occupancy probabilities demonstrate a tendency for individuals to transition from lower states to more intensive care levels over time. The initial state distribution indicates that approximately 11.5% of the individuals entered institutional LTC in state A, while 32.9% began in state D. The rise in occupancy for state D at times around 26-28 months is probably due to the combined effect of people starting in lower states and developing higher dependency levels over time, and of those starting in state D tending to have a higher death rate, indicating a pivotal moment for care provision in institutional LTC. Further, we present Aalen-Johansen estimates stratified by gender, first medical diagnosis, and levels of dependence. Table 4.5 in the Appendix presents the details in numbers as well as the results stratified by age at entry.

Gender. As shown by the Aalen-Johansen estimates stratified by gender in Figure 4.4b, the probability of males in all care states generally decreases over time. For females, while the overall declining trend in state occupancy is similar, we observe a more pronounced bump in the probability of being in state D at durations of 26 to 28 months since admission. Upon admission, 39.3% of men are in the highest care state D compared to 26.2% in state C, denoting a 13.1% difference between these two states. In contrast, the distribution among females shows a more balanced initial allocation, with states B, C, and D each accounting for around 28-30%, indicating a relatively uniform spread in care requirements at the time of admission.

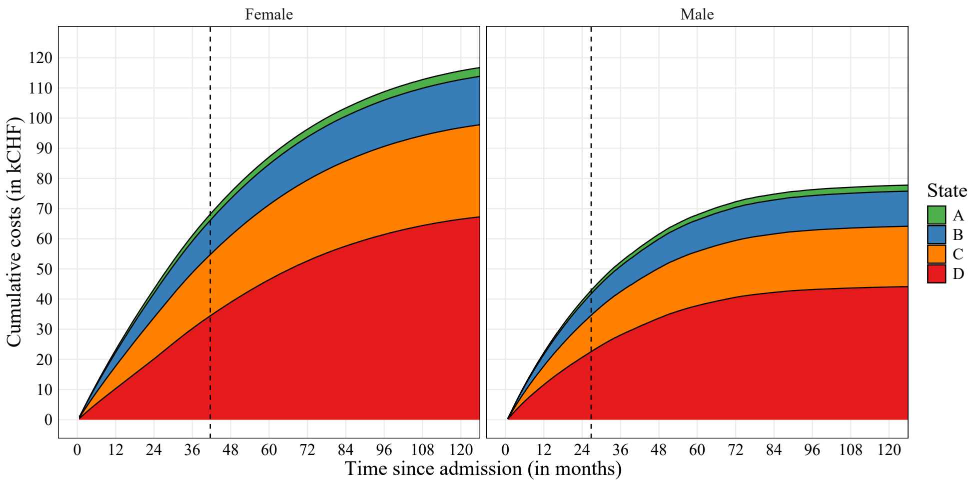


(a) Full dataset. (b) Results by gender.

Figure 4.4: Aalen-Johansen estimates with 95% confidence intervals of state occupancy probabilities.

Figure 4.5 presents the cumulative LTC costs for institutionalized elderly by gender. These costs are derived from the Aalen-Johansen estimates of state occupancy, applied in conjunction with Equation (26) to evaluate the average cost. Here, for a female starting in states A, B, C, and D, with initial probabilities of 12.2%, 28.5%, 28.8%, and 30.5%, respectively (see also Figure 4.4b), the mean duration in each state is inferred from the Aalen-Johansen estimates. These durations are then multiplied by each state's average daily costs. The cumulative costs for males are calculated in the same way, taking into account their initial state probabilities of 9.5%, 25.0%, 26.2%, and 39.3% in the states from A to D, respectively. After one year, the cumulative costs are comparable for both genders, with CHF 22 841 for women and CHF 21 960 for men. However, as time progresses, we observe a steeper increase in costs for females than males; by the fifth year, a woman reaches cumulative costs of CHF 86 367 on average compared to CHF 67 635 for a man, and by the tenth year, the costs for females average at CHF 115 350 while males cost CHF 77 543. The majority of these expenses are accumulated from state D, which is the most resource-intensive state. This finding is consistent with the trends observed in the Aalen-Johansen estimates from Figure 4.4b, which indicated a quicker progression to higher dependency states and higher mortality among males. Indeed, the higher mortality in men significantly limits the costs when compared to women.

Medical diagnoses. Figure 4.11 in the Appendix presents the Aalen-Johansen estimates and the corresponding cumulative costs for individuals with a particular primary diagnosis $D1$ at admission. Individuals with cerebrovascular and nervous conditions predominantly begin in higher care states, with approximately 45% and 50% being allocated at admission in states C and D, respectively, reflecting the substantial care needs associated with these diagnoses. In contrast, patients with a mental diagnosis exhibit a more uniform distribution, with around 30% entering states B, C, and D, respectively, which indicates varied care needs at the admission. Patients with osteoarticular, heart, and other conditions show a tendency to start predominantly in state B, suggesting that these conditions are initially present with a relatively mild level of



Note: The vertical dashed line indicates the median survival time.

Figure 4.5: Cumulative 10-year LTC costs by gender based on Aalen-Johansen estimates.

dependency. Notably, those with osteoarticular conditions display lower mortality rates, and the probability of being in state D remains relatively constant at about 20% for up to 56 months after admission. In contrast, individuals diagnosed with tumors have the highest mortality rate, with the median survival time being approximately 8 months.

In terms of cumulative costs, the highest average costs stem from patients with mental and nervous diagnoses, which correlates with their higher needs for care and longer occupation times in state D. Costs for heart disease are more evenly spread across states B, C, and D, suggesting a more balanced progression through the care levels. A similar pattern is observed in patients with osteoarticular diagnoses, who tend to reside in less demanding care states despite longer average lifespans, resulting in lower cumulative costs.

Levels of dependence. Figures 4.12-4.16 in the Appendix present the stratified Aalen-Johansen estimates and cumulative costs across different levels of dependence: dependence from others (DP), physical mobility (PM), orientation (OR), occupation (OC), and social integration (SI). Lower levels in these dependence measures upon admission are related to lower levels of initial care. However, as time progresses, a shift occurs with individuals increasingly transitioning to higher care states C and D. Conversely, those entering LTC with high levels of dependence in any of the five variables predominantly occupy state D, displaying a generally consistent decline in survival curves, with notable exceptions. For instance, individuals with a physical mobility (PM) score of 7 and 8 exhibit a significant increase in the probability of being in state D at approximately 26 months after admission. This pattern is also observable in the levels 6 and 7 of the orientation (OR) and social integration (SI) variables. Financially, significant contributions to cumulative costs from state A are primarily seen in those with lower initial levels of dependency. In contrast, for individuals with higher dependency levels, the costs are mainly concentrated in state D, with a lower but still notable portion stemming from state C.

4.4 Model application and results

When applying the multi-state model described in Section 4.2, we use the aggregated care levels denoted as states A, B, C, D, and Death as introduced in Section 4.3.2. For model fitting, we use the `msm` package in R. It is specifically designed for handling panel data (Jackson, 2011). This package supports both numerical and categorical covariates; however, the inclusion of categorical variables significantly increases computational demands due to a sharp rise in the number of parameters that need optimization as seen in Equation (24). Our dataset encompasses a large number of individuals, each with a comprehensive set of health evaluations and numerous variables previously identified as significant in determining care needs and duration of stay in institutional LTC (Bladt et al., 2023; Shemendyuk and Wagner, 2024).[5] To simplify the model fitting, we transform categorical covariates into numerical formats where feasible. We then refine the model by selecting the most relevant variables in our multi-state context. Following these adjustments, the model is analyzed to examine the transition probability matrices for both genders across different ages at entry. This allows us to estimate the average length of stay in each state and calculate the associated costs.

4.4.1 Data transformation and variable selection

Data transformation. In this paper, we use the methodology detailed in the study by Shemendyuk and Wagner (2024) for calculating pathology scores based on medical diagnoses. It was shown that these scores are critical for assessing the health profiles of the elderly within institutional LTC, which are indicative of the amount of care received and the length of stay. Similarly, the model uses age at entry, levels of dependence, and impairments of psychological and sensory functions as numerics. The exception is the gender variable, which remains binary.

In order to apply the multi-state model to the available data, it is necessary to transform the categorical medical diagnoses, ordered according to importance, into a numerical format. In order to account for the full pathology profile and to maintain the importance ranking of each diagnosis, a score must be calculated for the set of aggregated disease groups: mental, cerebrovascular, nervous, osteoarticular, heart, tumors, and other. The scoring system is adapted as follows:

$$\text{Score}(d) = \sum_{i=1}^{9} (10 - i) \cdot \mathbb{I}(Di = d).$$

Here, d is one of the disease groups, Di is the medical diagnosis at i-th importance rank, and $\mathbb{I}(\cdot)$ is the indicator function. This score is weighted by the rank of the diagnosis, with the first-ranked diagnosis contributing most significantly to the score, and the contribution decreases as the rank lowers.

Variable selection. In order to identify the most influential covariates for our multi-state model, we begin with a null model constructed from the full panel data, which consists of ob-

[5] Demographic factors such as age and gender are known to affect the length of stay (Mathers, 1996; Deeg et al., 2002; Germain et al., 2016; Fong et al., 2017; Fuino and Wagner, 2020), while the pathologies, including conditions like musculoskeletal and osteoarticular disorders, influence both stay duration and care intensity (Davidson et al., 1988; Pack, 2009; Makam et al., 2019). Additionally, levels of dependence and impairments in psychological and sensory functions are critical in determining care needs, with multimorbidity leading to increased care burdens (Guccione et al., 1994; Arrighi et al., 2010; Marengoni et al., 2011; Barnett et al., 2012; Koroukian et al., 2016; Albarrán et al., 2019; Fong, 2019; Jennings et al., 2020).

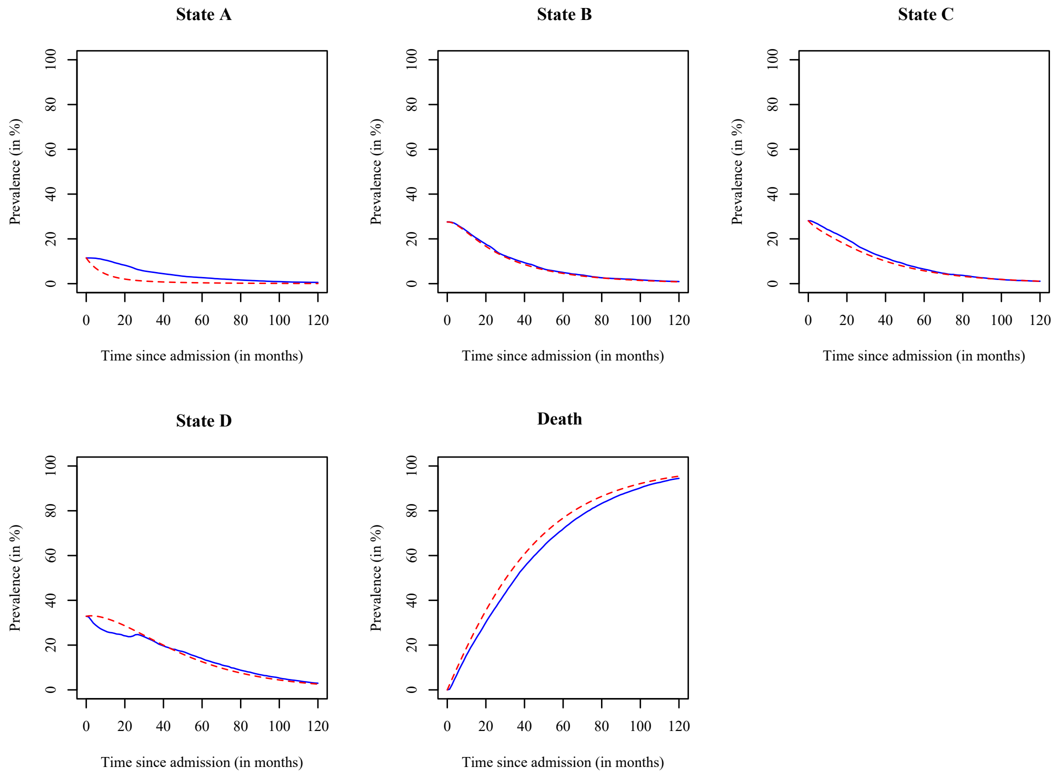
served transitions among the states without including any covariates. We then apply a stepwise forward procedure based on the Akaike Information Criterion (AIC, see Akaike 1974). In this iterative procedure, one covariate is introduced at a time to the existing model, with the AIC score calculated for each addition. The covariate that yields the greatest reduction in the AIC score is integrated into the model and built upon in the next iteration. This procedure is repeated until the inclusion of new covariates does not result in an improvement in the AIC score. The final model incorporates selected covariates, including age at entry AG, gender GE, number of diagnoses ND, pathology scores for cerebrovascular, nervous, osteoarticular, heart, and tumor diseases, as well as dependency in ADL DP, physical mobility PM, orientation OR, and visual VS and hearing impairments HR.

4.4.2 Goodness of fit

In this section, we analyze the quality of the multi-state model fit, determining whether the model under- or overestimates the probability transitions. This ensures that our interpretations of the results are accurate. We introduce a *reference profile* representing the person with the most common values of the covariates in the dataset. That is, regarding the variables selected for the modeling, the reference profile is characterized by an 87-year-old woman with nine medical diagnoses, the most important of which is in the mental category ($D1$ = mental), followed by eight pathologies $D2, \dots, D9$ from the "other" group. She is in quasi-permanent need of assistance ($DP = 7$), with mobility limited to the institution ($PM = 6$), and has moderate disorientation ($OR = 5$). Her visual and hearing impairments are classified as "mild". As a result, her score of mental diagnoses is 9, the "other" group leads to a score of 36, while the scores of the remaining pathology groups are zero.

A first indication of the goodness of fit of a multi-state model can be obtained by estimating the observed numbers of individuals occupying a state over a series of times and plotting these against forecasts from the fitted model for each state. Figure 4.6 shows the observed share of individuals and the forecasted prevalence rates across all states for an individual corresponding to the reference health profile. The initial probability of being at each state is determined from the data (see Section 4.3.2).

Across all states, the prevalence estimated with the model generally follows the trends of the observed data, indicating a reasonably good model fit. The discrepancies between observed and expected prevalences appear minimal in states B and C for all times, suggesting a good performance in predicting medium-level care states. However, there are deviations in states A, D, and Death, which could indicate that the effects of certain variables are not fully captured by the model for these states. In particular, the model tends to strongly underestimate the prevalence of individuals in state A in the first five years after admission. This suggests that the model prematurely transitions individuals with the reference health profile to higher dependency states, whereas observations in the data tell that they continue to receive minimal care for much longer periods. This persistent underestimation implies an external factor not captured by the model, influencing the low demand for care. Conversely, in state D, the fit improves significantly after approximately 26 months. However, in the first 26 months after admission, the model overestimates the number of people in this highly care-intensive state. This overestimation seems correlated with a slight underestimation in state C during the same period, suggesting a



Note: The solid and dashed lines correspond to the observed prevalence from the data and the expected prevalence from the model, respectively.

Figure 4.6: Goodness of fit of the multi-state model for the reference profile.

misclassification of individuals into a higher care state. Additionally, the underestimation in state A could contribute to this early discrepancy in state D. Finally, the model slightly overestimates the probability of death, hinting at additional factors prolonging survival not accounted for in the current model.

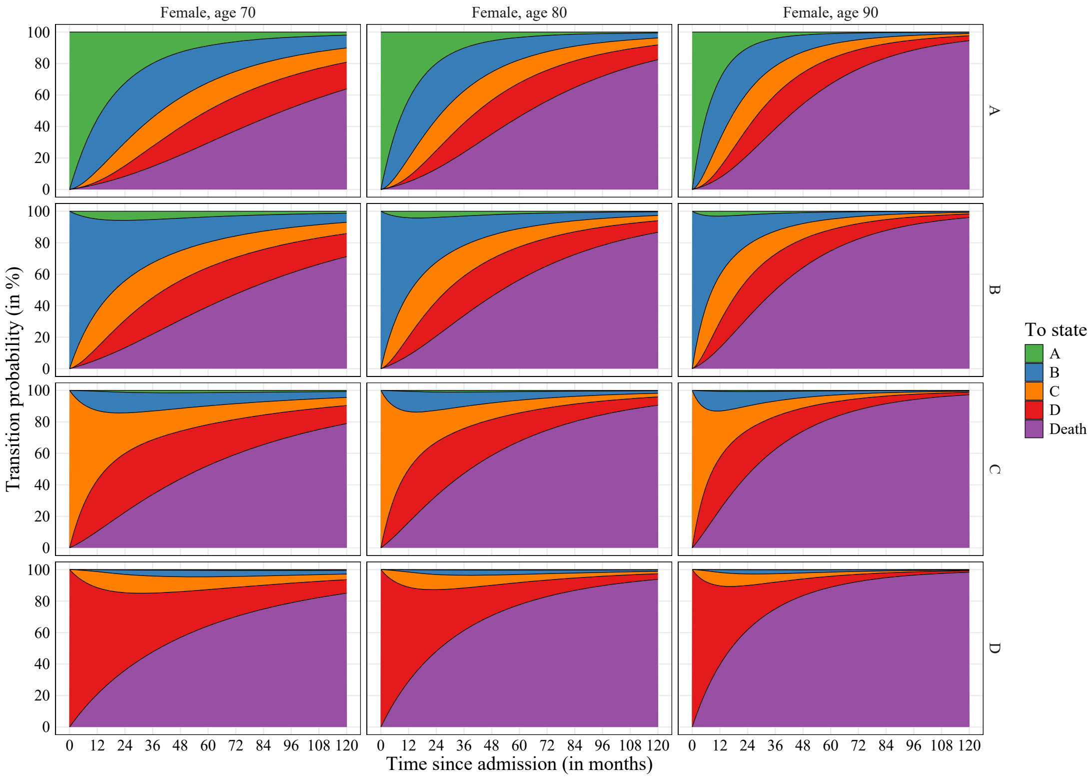
4.4.3 Results for the baseline health profile

To better understand the impact of covariates on care trajectories within institutional LTC settings, we analyze the transition probability matrices derived from Equation (22). These matrices reveal how the probabilities of transitioning from one care state to another evolve over time. For categorical covariates, such as gender GE, it is straightforward to visualize differences by comparing side-by-side plots of transition probabilities for females and males. However, this direct comparison approach becomes more complex with numerical covariates, as it would require generating and comparing numerous plots across a spectrum of values for each variable. To avoid this complication and still capture the effects of covariates on care trajectories, we consider the health profiles of elderly individuals in institutional LTC described in Section 4.3.1. These profiles allow us to illustrate and analyze the expected progression through care states over time, offering insights into how specific covariates influence these transitions.

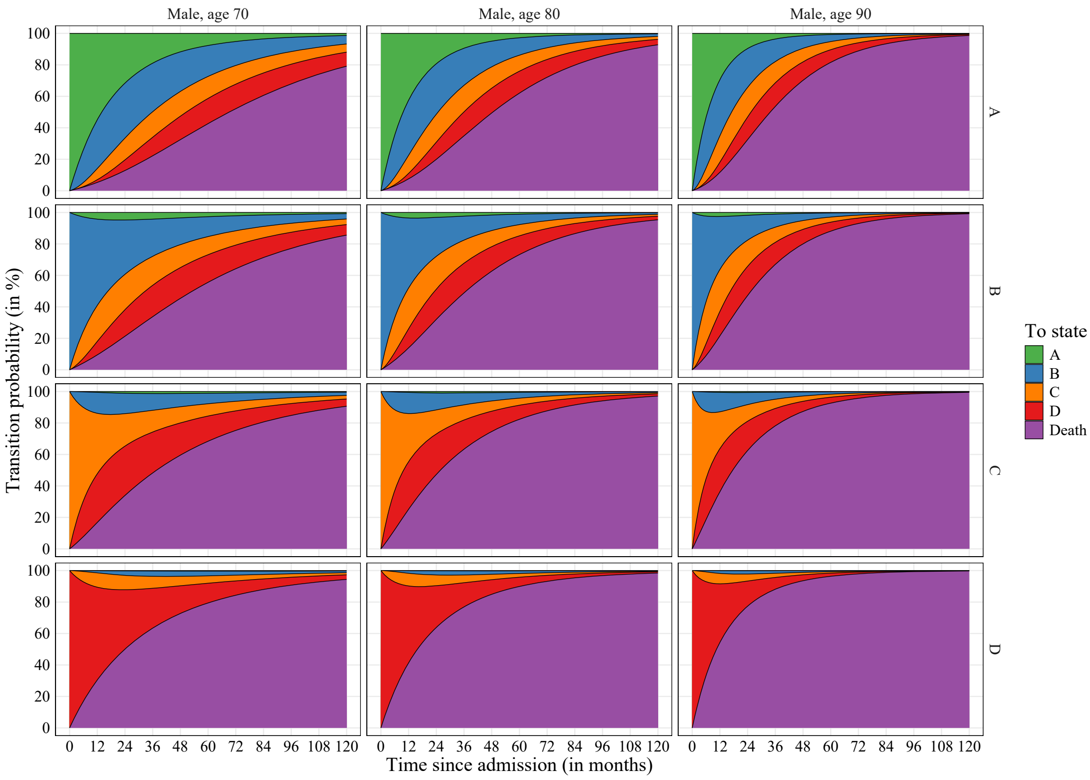
Baseline health profile. Individuals in this group represent the most common health profile among institutionalized elderly, typically requiring minimal daily care and exhibiting the longest survival times (see the introduction of the health profiles in Section 4.3.1 and Shemendyuk and Wagner, 2024, Table 3). This group predominantly consists of females (77.5%). It is characterized by a median age at entry of 87 years, with six medical diagnoses in the median, and resulting median diagnosis scores of 5, 7, and 14 for osteoarticular, heart, and other groups, respectively, while scores for other diseases are zero. The median levels of dependence are $DP = 7$, $PM = 6$, and $OR = 5$, with median visual and hearing impairments classified as "mild".

Figure 4.7a illustrates the fitted transition probabilities $P_{rs}(t, \mathbf{z})$ over time t for females with covariates $\mathbf{z}$ of the baseline health profile across the entry ages of 70, 80, and 90 years, stratified by the starting state r (see the label on the right axis indicating the starting state A, B, C, or D in each row of graphs). Females entering the institution at age 70 are more likely to remain in a state with lower care longer than their older counterparts. Notably, at age 90, females demonstrate a higher probability of transitioning directly from state A to state D, indicating a potentially rapid escalation in care needs. Generally, females exhibit more pronounced stability in the lower states and a less steep increase in transitions to state D and death at younger entry ages, reflecting resilience in maintaining lower care states. In contrast, Figure 4.7b illustrates the transition probabilities for males. As age at entry increases, males show a noticeable decrease in remaining in or transitioning to state A, while the likelihood of moving to state D or death increases, particularly for those entering at higher ages. Across all ages, transitions from states B and C to D are more likely than remaining stable, indicating a general trend towards increasing care needs over time. Additionally, the transition to death from states B and C is most pronounced for the oldest male group, highlighting the influence of age on care trajectories and mortality within institutional LTC settings.

Figure 4.8a displays the average cumulative costs $C_r(t, \mathbf{z})$ by time t for females with covariates $\mathbf{z}$, stratified by age at entry for the four starting states r. In this case, the baseline health profile defines the covariates. Across all age groups, women demonstrate higher cumulative costs than their male counterparts (cf. Figure 4.8b). The vertical dashed lines on the graphs represent the median survival times, denoted by δ, that depend on the individual's starting state r and covariates $\mathbf{z}$. This time marks the duration until the death probability for an individual reaches 50%. In these graphs, the lines are consistently positioned further to the right for females than for males, suggesting that women remain in the LTC system longer. This extended duration contributes to the overall higher costs, as women are more likely to be alive and hence accumulate higher expenses over time. The length of stay is consistently longer for younger individuals and for those admitted to an institution in a state with lower care needs. The prolonged period in state D for females significantly increases the cumulative costs, highlighting the impact of longevity on LTC costs. Similarly, Figure 4.8b displays the costs for males. The costs exhibit the greatest increase in the initial period following admission, with a pronounced increase for those entering at age 70, indicating that younger males accumulate higher costs at a more rapid pace. The median survival times show that younger entrants reach the transition to death later, corresponding to their higher cumulative costs. Over time, costs associated with state D become more significant for all age groups, emphasizing the financial impact of higher dependency care. However, the costs for state A remain negligible, reflecting its minimal contribution to overall LTC costs for this profile.

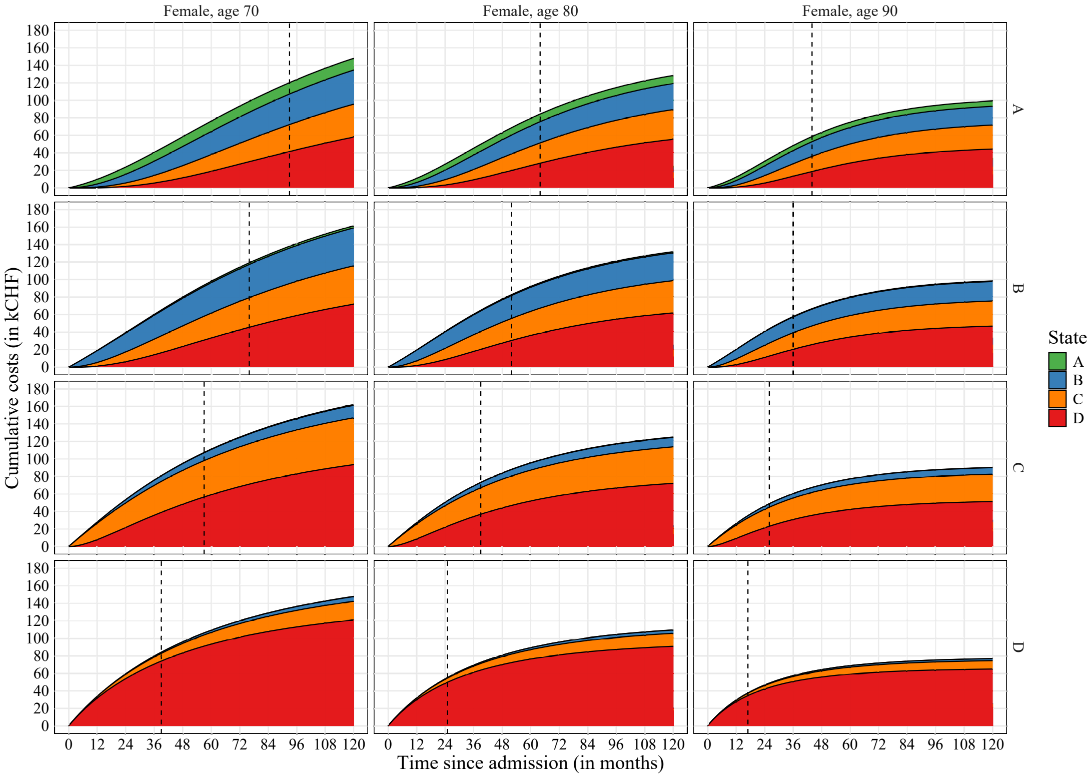


(a) Females.

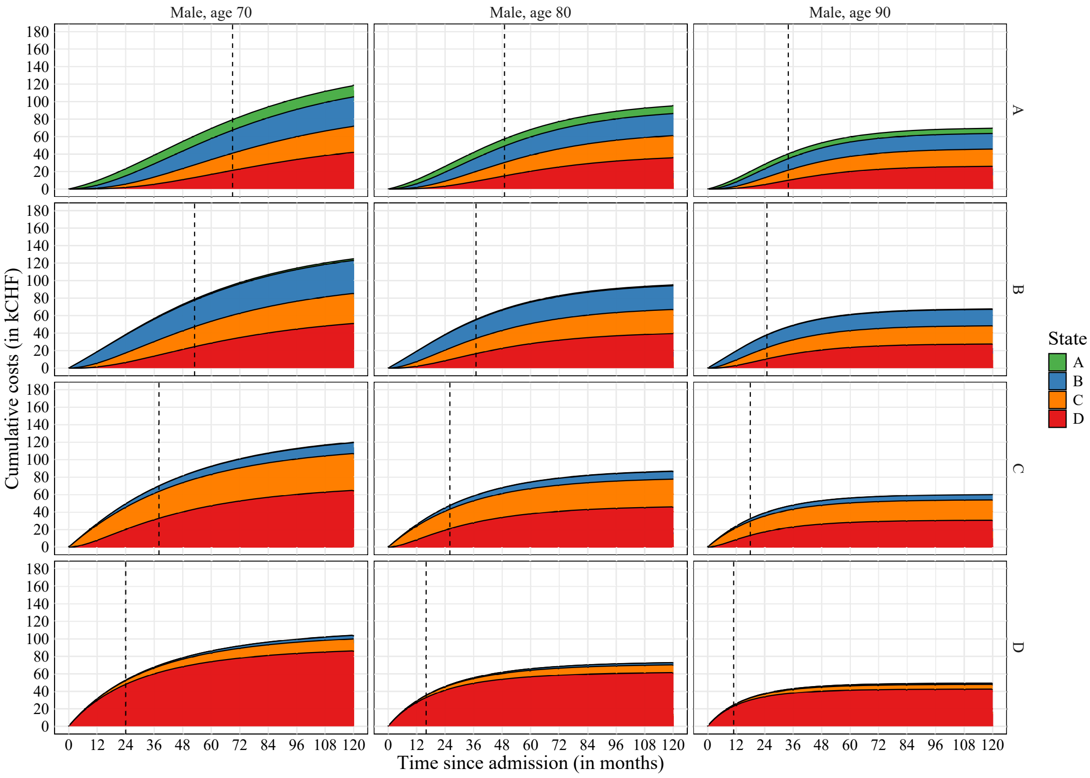


(b) Males.

Figure 4.7: Transition probabilities for females and males in the baseline health profile.



(a) Females.



(b) Males.

Note: Vertical dashed lines indicate the median survival times.

Figure 4.8: Average cumulative costs for females and males in the baseline health profile.

4.4.4 Results for other health profiles

To study the effects of levels of dependence and medical diagnoses, we select four other health profiles (see Section 4.3.1) that offer the most significant insights or present unique characteristics. In the presentation of the results, we focus on the transition probabilities and associated costs for an 80-year-old individual, as shown in Figures 4.9 and 4.10. Specifically, we analyze the second and third most common profiles: general severe conditions (short: severe) and moderate-severe conditions with nervous diseases (short: nervous); the fifth most common profile: moderate conditions with cerebrovascular diseases (short: cerebrovascular); and the eighth profile, noted for the shortest duration of stay: moderate conditions with tumor diseases (short: tumor). We omit the remaining three profiles, characterized by moderate conditions with endocrine, respiratory, and blood diseases from the detailed discussion. Indeed, these pathology groups are not explicitly included in our multi-state model, which limits the extent to which their specific impacts can be assessed.

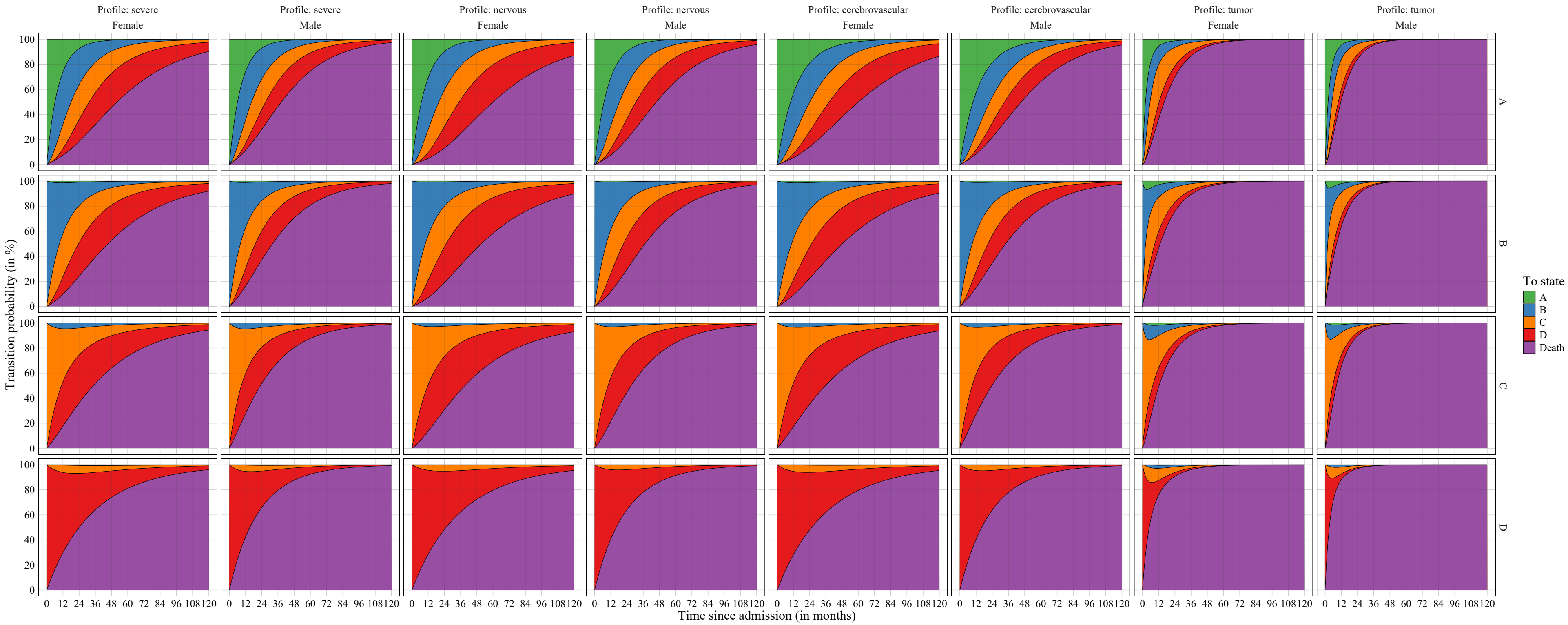
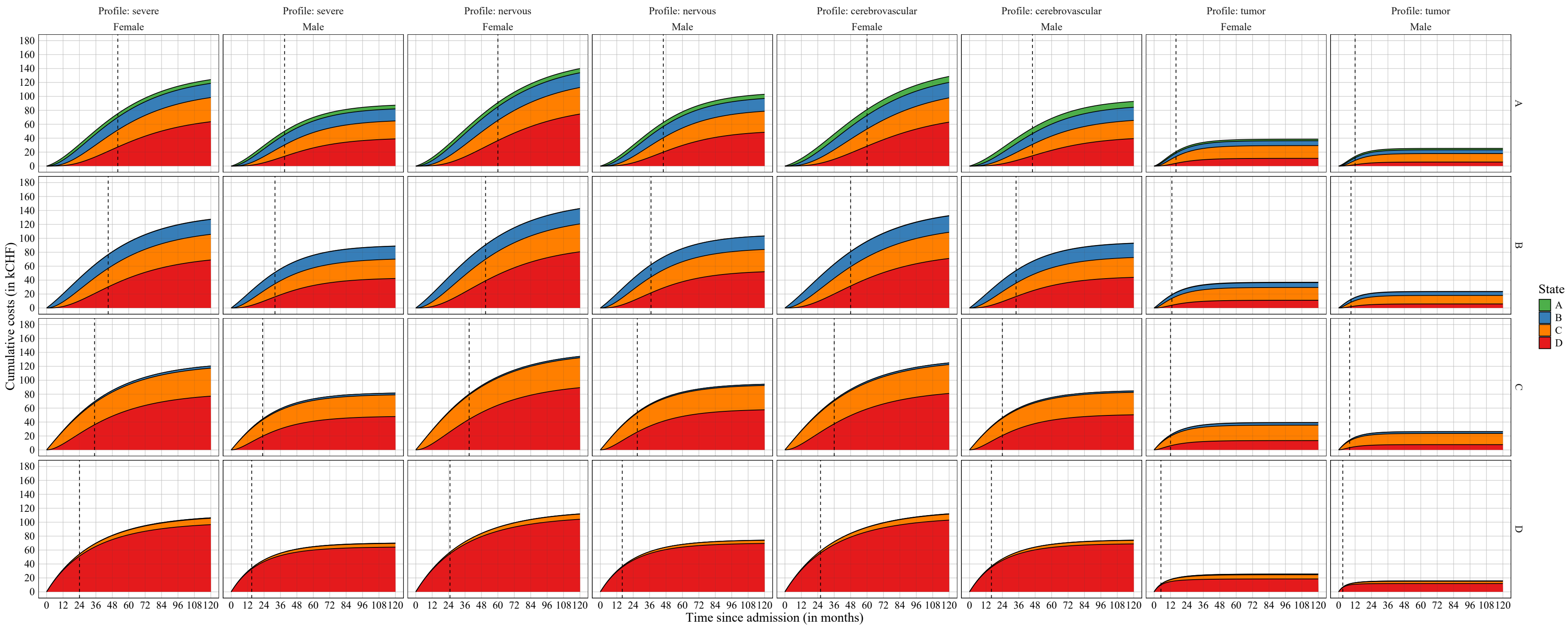


Figure 4.9: Transition probabilities for an 80-year-old elderly person in selected health profiles.



Note: See Figure 4.8.

Figure 4.10: Average costs for an 80-year-old elderly person in selected health profiles.

General severe conditions. This profile is characterized by having six diagnoses ($ND = 6$), with median values of 9, 6, and 13 for the mental, heart, and other pathology scores, respectively. The levels of dependence are the highest among all eight groups with $DP = 8$, $PM = 8$, and $OR = 6$. Finally, the visual and hearing impairments are classified as "mild".

The transition probabilities for the severe profile in Figure 4.9 (see the short-hand notation "severe") present distinct patterns compared to the baseline health profile (see Figure 4.7). Individuals transition to state D more rapidly and maintain a higher probability of staying in state D throughout the observed period. Both male and female individuals in the severe profile exhibit a higher and earlier transition to death, reflecting the greater health burden and higher levels of dependence. Moreover, the transition from states A and B to higher states occurs quicker in the severe profile than in the baseline. This reflects the significant impact of more severe medical conditions and higher dependence levels compared to the generally healthier baseline group. From Figure 4.10, we observe that females' costs rise more steeply initially, especially from states C and D, reflecting higher early dependency, while males' costs increase more gradually. This pattern indicates that in severe conditions, while females rapidly transition to high-dependency states, implying higher costs, males progress into these states at a slower rate. However, both genders eventually accumulate comparable costs by the end of the observed period compared to the baseline profile, highlighting the significant financial impact of high-dependency care over time. These findings indicate the necessity for early intervention and efficient resource allocation in managing severe health profiles in institutional LTC.

Moderate-severe conditions with nervous diseases. This health profile is the third most prevalent and similar to the severe profile, yet it is distinguished by a notable prevalence of medical diagnoses from the nervous group. In particular, the median number of diagnoses is smaller by one ($ND = 5$), followed by a redistribution among the pathology scores (mental 8, heart 4, and other = 10), complemented by the median score of 9 in "nervous" pathologies. The levels of dependence and visual and hearing impairments are identical to those observed in the severe profile, with the exception of physical mobility, which is reduced by one unit ($PM = 7$).

The nervous profile (short "nervous" in Figures 4.9 and 4.10) exhibits longer median survival times across all states in comparison to the severe profile. Upon initial admission in state D, transition probabilities to the lower state C are notably less frequent in the nervous profile, which contributes to prolonged stays in state D. This indicates a sustained higher level of dependency and increased care costs. Furthermore, the similar levels of dependence and impairment to those observed in the severe profile highlight the nuanced differences in care needs driven by nervous pathologies. The cumulative cost curves for the nervous and severe profiles demonstrate comparable behaviors during the initial months, indicating comparable initial care costs across the profiles. However, as time progresses, the nervous profile incurs higher cumulative costs, especially in state D, where prolonged high-level care leads to increased expenditure. This sustained higher cost in state D aligns with the longer stay observed in the transition probability analysis, emphasizing the financial implications of managing chronic nervous conditions in LTC settings. In summary, while the initial cost impact is similar between the profiles, the long-term financial burden is greater for the nervous profile due to extended periods of high-dependency care.

Moderate conditions with cerebrovascular diseases. Ranking as the fifth most prevalent, this profile typically encompasses individuals diagnosed with six medical conditions ($ND = 6$).

The median pathology scores for these patients are 7, 6, and 9 for the mental, heart, and other scores, respectively, and notably 8 for the cerebrovascular score. The levels of dependence and visual and hearing impairments are one unit higher than those observed in the baseline group and mirror those observed in the nervous profile. In comparison, the cerebrovascular profile has a lower median score for other pathologies at 9 against 13 in the severe profile, similar levels of mental and heart conditions, and a one-unit lower score in physical mobility.

The transition probability graphs for the cerebrovascular profile (short: cerebrovascular) in Figure 4.9 show a longer survival time compared to the severe profile, with individuals tending to remain longer in their initial state, particularly in states A and B. For both females and males in the cerebrovascular profile, transitions to higher dependency states and death take place later in time (broader curves), suggesting a slower progression of care needs. For females diagnosed with cerebrovascular conditions, the cost trajectories consistently accumulate higher costs over time compared to those with severe profiles. Notably, when starting from states B, C, or D, the costs align more closely with those observed in the nervous profile, indicating a substantial financial burden. Conversely, for males diagnosed with cerebrovascular conditions, the cost trajectories for those starting in states A and B reach slightly higher levels after 10 years compared to those with severe profiles, suggesting a slight increase in LTC costs. However, males starting in states C and D exhibit almost identical cost trajectories across both profiles, indicating that severe conditions and cerebrovascular diseases impose a comparable financial burden in these states. Overall, while cerebrovascular diseases tend to increase the cumulative costs of LTC, particularly for females, the impact on males is less pronounced and varies significantly based on the initial state of care.

Moderate conditions with tumor diseases. This group, identified as the least prevalent, is distinguished by a higher number of medical diagnoses ($ND = 8$). Individuals in this category show median pathology scores of 4, 9, and 17 for heart, other, and tumor, respectively. Relative to the baseline profile, this group shares similar levels of dependence and sensory impairments but has slightly increased physical mobility by one level.

The tumor profile (short: tumor) demonstrates a remarkably higher mortality rate compared to other profiles. Particularly for those starting in state C, there is a prolonged period of stability before an eventual shift to the death state, indicating sustained intensive care needs. An unusual pattern emerges in states A and B, where individuals are more likely to remain in state A or revert to it within the first year of admission, unlike other profiles, which typically show a progression to higher states. This evolution is specific to individuals with tumor diseases. The cost graphs for the tumor profile show relatively smaller costs, as median survival times do not surpass twelve months, particularly in states C and D. Compared to other health profiles, the tumor profile distinctly features rapid transitions to death and a higher likelihood of remaining in or returning to the lowest care states. These observations underscore the tumor profile's distinct impact on LTC costs, where high initial care needs are offset by significantly reduced life expectancy.

4.4.5 Summary and discussion of the results

Overview of results. Our study of institutionalized elderly across various health profiles has yielded detailed insights into the transitions and associated LTC costs. Notably, the model demonstrated a robust fit for the majority of conditions. However, it also indicated a potential poor estimation in states A, D, and death, which could affect the accuracy of transition and survival predictions.

Key findings emerged from analyzing different profiles: the baseline health profile, most prevalent among the elderly, indicated that females generally incur higher LTC costs due to their prolonged care needs. The two profiles with general severe conditions and moderate-severe conditions with nervous diseases highlighted rapid progression to high-dependency states with considerable initial costs, particularly prominent among females who transitioned quicker to these states. Females with cerebrovascular conditions often experience slower progression to higher dependency states but eventually accumulate higher costs, suggesting that strategies specific to medical conditions might be necessary to manage care effectively. The profile characterized by tumor diseases profile was particularly notable for its rapid transitions to death, resulting in lower overall costs due to shorter survival times, presenting a unique economic dynamic compared to other conditions.

These insights highlight the critical need for precise model fitting and the development of care strategies that account for age, gender, and specific health conditions. This understanding is crucial for policymakers and healthcare providers to optimize resource allocation and improve care outcomes for the aging population. It also underscores the necessity of strategic interventions in managing severe conditions to alleviate their financial impacts.

Table 4.4 provides a breakdown of the average time $E_{rs}(\delta, \mathbf{z})$ (see Equation 25) an individual starting in state r is expected to spend in the care state s, stratified by health profile determined by $\mathbf{z}$ including gender and age, up to their median survival time δ, excluding any duration spent in the state of death. Specifically, we present results showing the average time spent in each care state E_{rA}, E_{rB}, E_{rC} and E_{rD} and the total expected costs C_r (see Equation 26) up to the point where 50% of individuals are expected to have passed away. Aligning with previous analysis, we detail the results for individuals admitted at the age of 80. Summary data for 70 and 90-year-old admitted individuals are included as complementary age groups to offer insights into how care needs and associated costs vary with age. The "Prevalence" column reflects the distribution of individuals within each profile and gender in the overall dataset, providing information on the typicality of each scenario. This table is pivotal for understanding the care needs and financial implications associated with different health profiles in institutional LTC, aiding in strategic planning and resource allocation to efficiently meet the needs.

Nursing resources. The columns $E_{rs}(\delta)$ with $s = \mathrm{A, B, C, D}$ in Table 4.4 provide relevant metrics that directly impact nursing requirements in LTC settings. The numbers provide the average duration elderly individuals spend in the four care states before transitioning to death. Analyzing the length of stay for various health profiles reveals distinct patterns in managing care needs across both genders and the initial care states. For instance, in the baseline health profile, females admitted to the institution in state A experience longer durations across all states compared to males (e.g., 14.9 months for females and 14 for males in state A), which indicates a prolonged need for lighter care levels. In contrast, in the severe and nervous profiles, both genders exhibit shorter stays in lower states like A and B but consistently spend more time in the highest dependency state when starting in state D. For example, females in the nervous profile, on average, spend $E_{\mathrm{DD}}(\delta) = 17$ months in state D, while males spend 11 months. In

			$AG = 80$						$AG = 70$		$AG = 90$	
Gender	Initial state r	Preva-lence	$E_{r\mathrm{A}}(\delta)$	$E_{r\mathrm{B}}(\delta)$	$E_{r\mathrm{C}}(\delta)$	$E_{r\mathrm{D}}(\delta)$	δ	$C_r(\delta)$	δ	$C_r(\delta)$	δ_r	$C_r(\delta)$
Baseline health profile (26.3% of the data)												
Female	A	(29.7)	14.9	16.6	9.9	8.8	64	84.3	93	120.3	44	58.7
	B	(46.0)	1.7	17.9	10.8	9.5	52	82.9	76	119.2	36	57.8
	C	(18.0)	0.3	4.1	12.9	11.5	39	73.2	57	107.4	26	48.9
	D	(6.4)	0.0	0.4	2.0	15.5	25	55.1	39	84.1	17	37.6
Male	A	(25.9)	14.0	12.9	6.6	4.7	49	57.3	69	79.3	34	40.3
	B	(47.6)	1.1	14.5	7.4	5.1	37	55.7	53	78.8	25	38.1
	C	(18.5)	0.1	2.9	9.6	6.6	26	47.7	38	70.2	18	32.6
	D	(8.1)	0.0	0.2	1.0	10.2	16	35.5	24	52.8	11	24.3
Profile: severe (19.0% of the data)												
Female	A	(0.5)	9.1	12.5	10.4	8.5	52	75.3	75	107.6	36	52.3
	B	(13.7)	0.4	13.4	11.4	9.4	45	76.8	66	112.1	31	52.8
	C	(37.3)	0.0	1.3	13.4	11.2	35	69.3	50	100.8	24	46.9
	D	(48.5)	0.0	0.1	1.2	16.0	24	54.2	36	80.8	16	36.4
Male	A	(0.2)	8.8	10.0	7.0	4.4	39	50.0	55	69.8	27	34.9
	B	(10.4)	0.3	11.2	8.0	5.0	32	51.2	46	73.5	22	35.2
	C	(34.5)	0.0	0.9	10.0	6.1	23	44.5	34	66.5	16	30.2
	D	(54.9)	0.0	0.0	0.6	10.2	15	34.2	23	51.8	10	23.0
Profile: nervous (18.2% of the data)												
Female	A	(3.2)	10.3	13.4	12.4	11.4	60	91.2	86	129.6	42	64.1
	B	(18.9)	0.3	14.1	13.2	12.1	51	90.8	74	131.2	36	63.8
	C	(37.1)	0.0	0.9	14.9	13.7	39	80.2	56	116.3	27	54.9
	D	(40.8)	0.0	0.0	0.9	17.0	25	57.0	38	85.8	17	38.7
Male	A	(1.8)	10.1	11.1	8.8	6.2	46	62.7	65	87.6	32	43.9
	B	(14.8)	0.2	12.1	9.7	6.8	37	62.2	53	88.8	26	43.7
	C	(29.8)	0.0	0.7	11.7	8.0	27	54.1	39	78.9	19	37.4
	D	(53.6)	0.0	0.0	0.4	11.0	16	36.6	24	54.5	11	25.0
Profile: cerebrovascular (12.8% of the data)												
Female	A	(6.8)	14.3	13.4	10.5	8.9	60	81.2	86	115.4	42	57.0
	B	(20.8)	0.5	14.8	11.8	9.8	48	81.1	70	117.9	33	55.6
	C	(27.5)	0.0	1.0	14.0	11.6	36	71.7	52	105.3	24	47.4
	D	(44.9)	0.0	0.1	1.2	17.4	26	58.6	38	85.7	17	38.8
Male	A	(5.3)	13.7	10.6	7.0	4.6	46	54.5	65	76.2	32	38.1
	B	(17.1)	0.3	12.3	8.2	5.1	34	53.8	49	77.4	23	36.5
	C	(23.9)	0.0	0.7	10.6	6.4	24	46.4	35	68.8	16	30.5
	D	(53.7)	0.0	0.0	0.5	11.0	16	36.6	24	54.5	11	25.1
Profile: tumor (1.1% of the data)												
Female	A	(8.2)	3.6	3.5	4.1	1.2	16	20.7	23	28.8	11	14.7
	B	(30.3)	0.6	3.5	4.2	1.2	13	19.2	18	25.9	9	13.7
	C	(26.2)	0.2	1.2	5.9	1.9	12	21.5	17	30.5	9	15.8
	D	(35.2)	0.0	0.0	0.4	3.1	5	11.0	8	17.0	3	6.9
Male	A	(3.6)	3.3	2.6	2.6	0.6	12	13.8	16	17.9	8	9.5
	B	(30.4)	0.4	2.7	2.7	0.6	9	12.4	12	16.2	6	8.6
	C	(27.7)	0.1	0.8	4.2	1.0	8	14.3	12	21.0	6	10.5
	D	(38.4)	0.0	0.0	0.2	2.0	3	6.8	5	10.8	2	4.5

Notes: The column "Prevalence" indicates the distribution in % per profile and per gender. The median survival time δ indicates the time in months where the probability of death reaches 50%. The average times of stay E_{rs} and the total costs C_r are calculated with regard to the time δ and expressed in months and kCHF, respectively.

Table 4.4: Time spent in care and care costs up to the median survival time by health profile, gender, and age.

comparison, females and males in the healthy profile spend 15.5 and 10.2 months, respectively, in state D. Notably, individuals with cerebrovascular conditions exhibit a similar pattern to the baseline health profile. In particular, they have slightly lower lengths of stay in the lower care states and slightly longer durations in the higher-intensity states. Finally, the tumor-afflicted individuals, regardless of gender, exhibit significantly reduced E_{rs} across all states due to accelerated deterioration of health, with a distinctive tendency to spend the majority of their time in the state they entered the institutional LTC.

This complex nature of LTC demands a nuanced approach to nursing, especially in managing prolonged care in higher dependency states. The data highlights the extended periods in states C and D for conditions like cerebrovascular and nervous diseases, where patients often require intense and sustained care. This situation is particularly critical for females who demonstrate a need for prolonged high-level care, underscoring the importance of gender-specific care strategies and resource allocation. To effectively address these diverse and complex care requirements, a well-trained nursing workforce is essential. Continuous education and specialized training are crucial to equip caregivers with the skills necessary for managing these complex health profiles. Furthermore, the Swiss healthcare system is constrained by a deficit of qualified local caregivers (Zúñiga et al., 2010; Haller et al., 2015), which reflects the necessity for supportive immigration policies that facilitate the influx of competent care providers (Nichols et al., 2010). These strategies are essential for maintaining high standards of care, improving patient outcomes, and adequately responding to the evolving needs of an aging population in institutional LTC settings. By investing in educational advancement and incorporating a strategy that includes gender and profile-specific care planning, LTC facilities can optimize staffing and resource use, ensuring that the aging population's dynamic demands are met effectively.

Infrastructure. The median survival times offer a good perspective on infrastructure needs in LTC settings, revealing how long individuals are expected to utilize care facilities. This data is essential for planning future care infrastructure and resource allocation within these institutions. Across all health profiles and genders, the median survival times decrease significantly with increasing age at entry. For example, females in the baseline health profile starting in state A exhibit a median survival time of 93 months at age 70, which drops to 44 months at age 90. This illustrates a marked decline in longevity as age increases, reflecting greater immediacy in care needs and infrastructure planning for older entrants. Focusing on $AG = 80$, females typically demonstrate longer survival times across all profiles and starting states, which is particularly pronounced in the baseline health, nervous, and cerebrovascular profiles. For instance, baseline health females starting in state A have a median survival time of $\delta = 64$ months, compared to 49 months for their male counterparts. Similarly, females in the cerebrovascular profile starting in state A have a median survival time of 60 months versus 46 months for males, indicating a substantial gender disparity in care duration that could impact resource planning. This trend persists in the severe profile, showing smaller δ, while maintaining the gender disparity. For example, females in the severe health profile starting in state D have a median survival time of 24 months, compared to 15 months for males. Tumor profiles present the most drastic differences, with extremely short durations, highlighting a distinct infrastructure challenge. Tumor-affected females starting in state D have a survival time of only 5 months at age 80, significantly lower than other profiles. This disparity underscores the necessity for LTC facilities to adapt their infrastructure to accommodate not only the varying lengths of stay associated with different medical conditions, coming with a distinct prevalence but also the specific needs that arise from gender differences in survival rates.

The observed variations in median survival times have direct implications for LTC infrastructure planning. Facilities must ensure they have sufficient beds and appropriately configured rooms to accommodate the different types and durations of stay that can be anticipated for each health profile. For instance, the significantly shorter median survival times for older entrants across all profiles, such as tumor patients at age 90 having median times as low as 2 months, suggest a need for flexible room allocations that can adapt to high turnover rates. Conversely, profiles with longer survival times, such as baseline health females entering at age 70 with survival times up to 93 months, require stable, long-term accommodations. Additionally, the data indicates a potential shift in care strategy, where individuals with longer predicted survival times and less intensive care needs, such as those in the baseline health profile, could benefit from expanded home-care services. This shift could alleviate pressure on LTC institutions by reducing the demand for in-facility resources, allowing these institutions to focus on patients with more severe conditions who require intensive, specialized care. These strategic infrastructure adjustments are crucial for optimizing care delivery, infrastructure, and resource allocation in response to the aging population's diverse needs.

Basic health insurance. The analysis of expected costs at the median survival times provides insights into the financial implications of different health profiles on nursing costs covered by basic health insurance in Switzerland. Notably, females incur higher costs compared to males, reflecting longer survival times and potentially more intensive care needs. For instance, nervous conditions in females aged 80 show an average cost of $C_{\mathrm{A}}(\delta) = 91.2$ thousand Swiss francs, significantly higher than their male counterparts at 62.7 thousand. This trend persists across profiles and ages, with younger individuals ($AG = 70$) incurring higher costs due to longer survival periods. Comparatively, tumor profiles exhibit much lower costs across all ages due to significantly shorter survival times, emphasizing the rapid progression to death. For example, tumor-affected females aged 80 have costs of $C_{\mathrm{A}}(\delta) = 20.7$ thousand, which is considerably lower than those with cerebrovascular conditions at 81.2 thousand. Across various health profiles, a clear pattern emerges where the costs associated with initial higher care states (such as states C and D) tend to be lower compared to those starting from lower states like A and B, particularly for those entering at older ages ($AG = 90$). This trend is largely attributed to increased mortality rates in higher initial states, shortening the duration of care and thus reducing cumulative costs. However, for individuals entering at a younger age ($AG = 70$), this pattern shifts notably for severe, nervous, and cerebrovascular profiles, where the highest costs are often recorded for those starting in state B, suggesting prolonged care durations before reaching higher mortality states. In contrast, the tumor profile uniquely shows the highest costs from state C, indicating specific care dynamics associated with this condition.

Our results provide insights for basic health insurers and policymakers in efficiently planning and allocating resources to meet the diverse needs of the aging population. By understanding the expected costs linked to various health profiles and entry states, policies and pricing models can be refined to reflect the true financial risk associated with different levels of care. Additionally, this data allows policymakers to better forecast LTC funding requirements and develop strategies to ensure that essential care services are sustainable and accessible. Such detailed cost analysis aids in the financial planning of public health services, ensuring that funds are utilized effectively. Furthermore, it can support the optimization of private insurance packages.

Private insurance. Private insurance plays a pivotal role in supplementing the shortcomings of basic health insurance, particularly in the coverage of out-of-pocket expenses, including lodging, meals, and specialized medications that are not reimbursed under social insurance policies. The median survival times, δ, derived from our model, provide crucial insights for private insurers, as they can use these durations to estimate costs associated with per diems, lodging, and meals over the expected period an individual will require LTC. This approach allows insurers to assess the premiums required upfront to cover these ongoing costs effectively. Additionally, the average lengths of stay in each care state, E_{rs}, facilitate the development of personalized insurance products tailored to the intensity of care an individual is likely to require. This personalized approach not only ensures that individuals receive the appropriate level of support and care but also helps insurers manage risks and resources more effectively. In the case of LTC insurance products with a savings component proposed to individuals before they require any care, the prevalence of different health profiles by gender highlighted in Table 4.4 provides insurers basic insight for weighting different levels of care demand. In addition, our results enable, for example, the pricing of insurance products that can be made available to elderly individuals at the moment they are admitted to an institution. Using the age, gender, and health care profile of a person at entry, the insurer could offer to cover the expected out-of-pocket expenses until death against a lump-sum payment. We believe that our approach enhances the base of knowledge for private insurers to provide robust financial solutions that support individuals throughout their time in LTC, ensuring that all necessary expenses are covered comprehensively.

4.5 Conclusion

In this study, we conducted a comprehensive analysis of a private dataset from nursing homes in the Canton of Geneva, Switzerland, encompassing 21 494 elderly individuals aged 65 or older. Our research utilized a multi-state Markov model to assess transitions between grouped care states – ranging from quasi-autonomy to severe dependency – within the Swiss social health insurance framework. By systematically grouping the care levels and focusing on significant variables at admission, such as demographic information, medical diagnoses, and levels of dependence, we have identified key patterns and trends in the evolution of care needs over time. This approach not only facilitated a clearer understanding of the longitudinal care dynamics, but also allowed us to model the long-term costs associated with different levels of care required by the elderly in institutional LTC settings.

We aggregated the twelve care levels of the Swiss system into four broader categories, ranging from minimal assistance to severe dependency. This classification enables comparison with other studies and provides a clear framework for assessing the impact of various health conditions on LTC trajectories. Utilizing common health profiles among institutionalized elderly allowed us to analyze the influence of demographic and medical covariates on transition probabilities and associated costs. The baseline health profile, which is the most prevalent, incurs higher LTC costs due to extended care durations. In contrast, profiles characterized by severe conditions and nervous diseases show a rapid progression to higher dependency states, resulting in considerable initial costs. Particularly, females in these profiles transition more quickly to high-dependency states, highlighting the need for targeted care strategies that consider both medical and demographic factors. Individuals with cerebrovascular conditions tend to have a slower progression to higher care states but eventually accumulate higher costs, suggesting that prolonged care interventions are necessary. Conversely, the tumor profile is marked by rapid transitions to death, resulting in lower overall costs due to shorter survival times. These distinct patterns emphasize the importance of adapting care and financial planning to the specific health profiles of elderly individuals in institutional LTC settings.

The integration of demographic information, medical diagnoses, and levels of dependence at the point of admission enables the model to provide insights for the planning of care and infrastructure, as well as the design of insurance products, addressing both public and private sectors. Analysis of health profiles revealed a nuanced variation in care needs, depending on the initial state of both genders at different ages. This variation in care duration underscores the necessity for advanced nursing strategies and gender-specific care planning. Additionally, the data on median survival times is crucial for predicting infrastructure needs, indicating a requirement for facilities to adapt to varying lengths of stay and high turnover rates, particularly for older entrants and patients with rapidly progressing conditions like tumors. The analysis relevant to basic health insurance demonstrates that costs are influenced by the patient's health profile and age at entry, with women generally incurring higher costs due to longer survival times. Conversely, those in more intensive initial care states accumulate lower costs due to decreased care durations. Private insurers can utilize the insights into projected median survival times and expected care state durations to develop insurance products that accurately reflect the costs and care needs of LTC patients. This enables the provision of comprehensive solutions that meet all necessary expenses not covered by the basic insurance scheme.

While our study offers valuable insights through the use of a multi-state Markov model, it lacks a comparison between the estimated costs derived from the model and the actual costs documented in real data. Such a comparison could enhance the validity of our findings by aligning the obtained predictions with practical outcomes. Additionally, our analysis is constrained by the nature of our panel data, which captures the health states only at discrete intervals. This limitation prevents us from precisely determining the exact times of transitions between care states, leading to potential discrepancies in the fit of our model. Moreover, the study's reliance on fixed covariates at the point of admission restricts our ability to account for changes in an individual's condition over time, potentially skewing the assessment of transition probabilities and cost implications. Assuming the transitions occur at the time of observations, a semi-Markov approach that allows the transition probabilities to depend not only on the current state but also on the duration of stay in that state and changing covariates could potentially address this issue.

Future research could significantly benefit from incorporating time-varying covariates into the models used to predict transitions and costs in institutional LTC. Allowing variables such as health status, level of dependence, and medical conditions to change over time, would offer more accurate predictions. Additionally, exploring joint modeling approaches where the evolution of care intensity directly influences survival probabilities could provide a more dynamic understanding of the development of LTC needs. Such models could uncover the interdependencies between care requirements and survival, leading to more effective care planning and potentially improving patient outcomes by allowing for more personalized and timely interventions in care strategies.

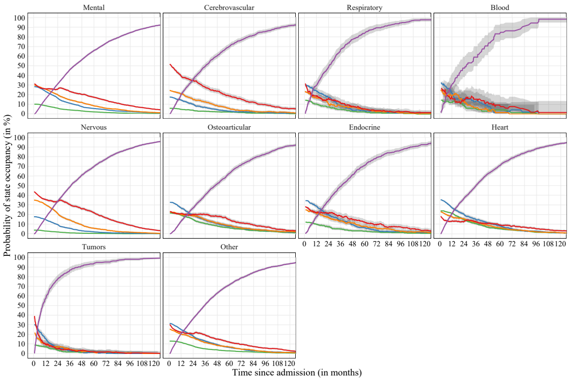
4.6 Appendix

		Entry			After 1 year			After 5 years			After 10 years		
Variable	State	M	(%)	$\hat{p}$	M	(%)	$\hat{p}$	M	(%)	$\hat{p}$	M	(%)	$\hat{p}$
Age at entry AG													
65-69	A	80	(0.4)	12.7	73	(0.3)	11.6	32	(0.1)	6.0	15	(0.1)	3.5
	B	203	(0.9)	32.3	174	(0.8)	28.6	70	(0.3)	13.9	30	(0.1)	8.3
	C	144	(0.7)	22.9	139	(0.6)	22.9	63	(0.3)	13.7	23	(0.1)	5.9
	D	201	(0.9)	32.0	152	(0.7)	25.1	105	(0.5)	21.2	38	(0.2)	11.0
70-79	A	457	(2.1)	11.9	394	(1.8)	10.6	143	(0.7)	4.2	42	(0.2)	1.3
	B	989	(4.6)	25.8	793	(3.7)	21.6	228	(1.1)	7.2	59	(0.3)	2.1
	C	1022	(4.8)	26.7	865	(4.0)	23.6	280	(1.3)	9.3	77	(0.4)	3.0
	D	1358	(6.3)	35.5	1115	(5.2)	30.2	667	(3.1)	22.0	206	(1.0)	8.7
80-89	A	1399	(6.5)	12.5	1196	(5.6)	10.9	287	(1.3)	2.9	39	(0.2)	0.4
	B	3112	(14.5)	27.8	2438	(11.3)	22.6	497	(2.3)	5.5	70	(0.3)	0.9
	C	3184	(14.8)	28.4	2604	(12.1)	24.5	675	(3.1)	7.6	88	(0.4)	1.2
	D	3505	(16.3)	31.3	2668	(12.4)	25.0	1416	(6.6)	16.3	266	(1.2)	3.8
90-99	A	527	(2.5)	9.3	413	(1.9)	7.5	38	(0.2)	0.8	2	(0.0)	0.0
	B	1602	(7.5)	28.2	1162	(5.4)	21.6	127	(0.6)	2.9	9	(0.0)	0.2
	C	1640	(7.6)	28.9	1179	(5.5)	22.1	188	(0.9)	4.4	6	(0.0)	0.2
	D	1915	(8.9)	33.7	1310	(6.1)	24.4	402	(1.9)	9.5	25	(0.1)	0.8
100+	A	3	(0.0)	1.9	2	(0.0)	1.9	0	(0.0)	0.0	0	(0.0)	0.0
	B	17	(0.1)	10.9	14	(0.1)	9.0	1	(0.0)	0.7	0	(0.0)	0.0
	C	46	(0.2)	29.5	23	(0.1)	15.7	0	(0.0)	0.0	0	(0.0)	0.0
	D	90	(0.4)	57.7	50	(0.2)	33.3	4	(0.0)	3.1	0	(0.0)	0.0
Gender GE													
Female	A	1905	(8.9)	12.2	1623	(7.6)	10.6	394	(1.8)	2.8	76	(0.4)	0.6
	B	4446	(20.7)	28.5	3478	(16.2)	23.3	737	(3.4)	5.8	140	(0.7)	1.3
	C	4490	(20.9)	28.8	3676	(17.1)	24.8	1014	(4.7)	8.3	167	(0.8)	1.6
	D	4747	(22.1)	30.5	3798	(17.7)	25.4	2163	(10.1)	17.8	465	(2.2)	4.9
Male	A	561	(2.6)	9.5	455	(2.1)	7.9	106	(0.5)	2.1	22	(0.1)	0.5
	B	1477	(6.9)	25.0	1103	(5.1)	19.5	186	(0.9)	4.0	28	(0.1)	0.8
	C	1546	(7.2)	26.2	1134	(5.3)	20.5	192	(0.9)	4.4	27	(0.1)	0.8
	D	2322	(10.8)	39.3	1497	(7.0)	26.8	431	(2.0)	9.9	70	(0.3)	2.2
Primary diagnosis $D1$													
Mental	A	763	(3.5)	10.3	632	(2.9)	8.7	149	(0.7)	2.3	29	(0.1)	0.5
	B	2104	(9.8)	28.4	1669	(7.8)	23.6	341	(1.6)	5.8	71	(0.3)	1.4
	C	2212	(10.3)	29.9	1822	(8.5)	25.9	483	(2.2)	8.6	77	(0.4)	1.8
	D	2324	(10.8)	31.4	1843	(8.6)	26.1	968	(4.5)	17.4	220	(1.0)	5.2
Cerebro-vascular	A	75	(0.3)	6.0	61	(0.3)	5.0	24	(0.1)	2.2	2	(0.0)	0.2
	B	221	(1.0)	17.8	171	(0.8)	14.6	26	(0.1)	3.0	8	(0.0)	0.9
	C	305	(1.4)	24.5	246	(1.1)	20.5	58	(0.3)	5.8	14	(0.1)	1.6
	D	644	(3.0)	51.7	470	(2.2)	39.6	184	(0.9)	18.9	42	(0.2)	5.6
Respi-ratory	A	49	(0.2)	14.4	35	(0.2)	10.6	7	(0.0)	2.3	0	(0.0)	0.0
	B	103	(0.5)	30.2	77	(0.4)	23.8	11	(0.1)	3.7	1	(0.0)	0.4
	C	81	(0.4)	23.8	54	(0.3)	16.6	13	(0.1)	4.9	1	(0.0)	0.4
	D	108	(0.5)	31.7	63	(0.3)	19.0	15	(0.1)	5.4	4	(0.0)	1.6
Blood	A	12	(0.1)	14.5	10	(0.0)	12.0	3	(0.0)	4.4	0	(0.0)	0.0
	B	27	(0.1)	32.5	18	(0.1)	21.7	0	(0.0)	1.6	0	(0.0)	0.0
	C	21	(0.1)	25.3	15	(0.1)	18.9	1	(0.0)	1.6	0	(0.0)	0.0
	D	23	(0.1)	27.7	14	(0.1)	17.0	6	(0.0)	9.4	1	(0.0)	1.7
Nervous	A	152	(0.7)	3.9	112	(0.5)	2.9	20	(0.1)	0.5	8	(0.0)	0.3
	B	694	(3.2)	17.7	550	(2.6)	14.7	67	(0.3)	2.1	8	(0.0)	0.4
	C	1370	(6.4)	34.9	1100	(5.1)	30.2	174	(0.8)	5.8	19	(0.1)	0.7
	D	1706	(7.9)	43.5	1320	(6.1)	35.6	652	(3.0)	21.9	97	(0.5)	4.1
Osteo-articular	A	333	(1.5)	21.5	297	(1.4)	19.4	88	(0.4)	6.2	16	(0.1)	1.2
	B	506	(2.4)	32.7	398	(1.9)	26.9	101	(0.5)	7.7	21	(0.1)	1.7
	C	349	(1.6)	22.5	299	(1.4)	19.8	112	(0.5)	8.7	28	(0.1)	2.4
	D	360	(1.7)	23.3	312	(1.5)	20.7	189	(0.9)	14.7	39	(0.2)	3.5
Endo-crine	A	78	(0.4)	12.1	62	(0.3)	9.9	15	(0.1)	2.8	3	(0.0)	0.6
	B	221	(1.0)	34.4	178	(0.8)	28.8	35	(0.2)	6.3	6	(0.0)	1.4
	C	160	(0.7)	24.9	134	(0.6)	21.4	41	(0.2)	7.7	7	(0.0)	1.8
	D	184	(0.9)	28.6	137	(0.6)	22.1	66	(0.3)	12.0	15	(0.1)	3.8
Heart	A	438	(2.0)	23.8	377	(1.8)	21.1	85	(0.4)	5.2	17	(0.1)	1.1
	B	647	(3.0)	35.2	478	(2.2)	27.1	126	(0.6)	8.3	14	(0.1)	1.0
	C	418	(1.9)	22.8	318	(1.5)	17.8	99	(0.5)	6.5	15	(0.1)	1.1
	D	334	(1.6)	18.2	231	(1.1)	13.1	134	(0.6)	9.0	42	(0.2)	3.3
Tumors	A	34	(0.2)	8.9	26	(0.1)	7.0	4	(0.0)	1.3	0	(0.0)	0.3
	B	116	(0.5)	30.3	55	(0.3)	16.0	3	(0.0)	1.5	0	(0.0)	0.0
	C	82	(0.4)	21.4	38	(0.2)	10.4	5	(0.0)	1.7	0	(0.0)	0.0
	D	151	(0.7)	39.4	35	(0.2)	9.5	6	(0.0)	1.9	2	(0.0)	0.7
Other	A	532	(2.5)	13.0	466	(2.2)	11.7	105	(0.5)	2.9	23	(0.1)	0.7
	B	1284	(6.0)	31.4	987	(4.6)	25.1	213	(1.0)	6.5	39	(0.2)	1.4
	C	1038	(4.8)	25.4	784	(3.6)	20.3	220	(1.0)	6.9	33	(0.2)	1.2
	D	1235	(5.7)	30.2	870	(4.0)	22.2	374	(1.7)	12.0	73	(0.3)	3.1

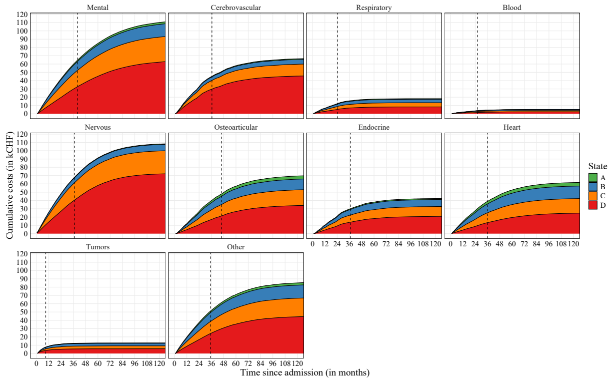
		Entry			After 1 year			After 5 years			After 10 years		
Variable	State	M	(%)	$\hat{p}$	M	(%)	$\hat{p}$	M	(%)	$\hat{p}$	M	(%)	$\hat{p}$
Dependence in ADL DP													
1-6	A	1873	(8.7)	52.1	1570	(7.3)	44.9	356	(1.7)	11.6	70	(0.3)	2.6
	B	1661	(7.7)	46.2	1341	(6.2)	39.6	410	(1.9)	15.2	93	(0.4)	4.0
	C	56	(0.3)	1.6	165	(0.8)	4.9	245	(1.1)	9.3	63	(0.3)	2.9
	D	2	(0.0)	0.1	97	(0.5)	2.8	270	(1.3)	10.3	106	(0.5)	5.3
7	A	593	(2.8)	6.8	507	(2.4)	5.8	144	(0.7)	1.7	28	(0.1)	0.4
	B	4165	(19.4)	47.7	3146	(14.6)	37.3	488	(2.3)	6.5	74	(0.3)	1.1
	C	3319	(15.4)	38.0	2684	(12.5)	32.4	730	(3.4)	10.4	101	(0.5)	1.7
	D	661	(3.1)	7.6	877	(4.1)	10.5	1020	(4.7)	15.0	218	(1.0)	3.9
8	A	0	(0.0)	0.0	1	(0.0)	0.0	0	(0.0)	0.0	0	(0.0)	0.0
	B	97	(0.5)	1.3	93	(0.4)	1.3	25	(0.1)	0.4	1	(0.0)	0.0
	C	2651	(12.3)	35.1	1953	(9.1)	27.2	228	(1.1)	3.9	29	(0.1)	0.6
	D	4814	(22.4)	63.7	3398	(15.8)	47.2	1025	(4.8)	17.8	155	(0.7)	3.7
9	A	0	(0.0)	0.0	0	(0.0)	0.0	0	(0.0)	0.0	0	(0.0)	0.0
	B	0	(0.0)	0.0	1	(0.0)	0.1	0	(0.0)	0.1	0	(0.0)	0.1
	C	10	(0.0)	0.6	8	(0.0)	0.5	3	(0.0)	0.2	1	(0.0)	0.1
	D	1592	(7.4)	99.4	923	(4.3)	59.7	279	(1.3)	20.1	56	(0.3)	4.3
Physical mobility limitations PM													
1-5	A	1266	(5.9)	57.0	1107	(5.2)	50.6	309	(1.4)	15.3	62	(0.3)	3.4
	B	852	(4.0)	38.4	744	(3.5)	34.6	326	(1.5)	17.2	87	(0.4)	5.4
	C	87	(0.4)	3.9	133	(0.6)	6.2	175	(0.8)	9.4	55	(0.3)	3.6
	D	15	(0.1)	0.7	56	(0.3)	2.6	187	(0.9)	10.0	95	(0.4)	5.9
6	A	1110	(5.2)	17.7	894	(4.2)	14.8	171	(0.8)	3.2	32	(0.1)	0.7
	B	3119	(14.5)	49.8	2393	(11.1)	39.7	442	(2.1)	8.6	64	(0.3)	1.4
	C	1591	(7.4)	25.4	1395	(6.5)	23.6	495	(2.3)	10.0	69	(0.3)	1.7
	D	442	(2.1)	7.1	587	(2.7)	10.0	731	(3.4)	15.1	146	(0.7)	4.3
7	A	79	(0.4)	1.4	67	(0.3)	1.2	16	(0.1)	0.3	0	(0.0)	0.0
	B	1572	(7.3)	28.8	1190	(5.5)	22.9	122	(0.6)	3.0	16	(0.1)	0.5
	C	2586	(12.0)	47.4	2017	(9.4)	38.7	330	(1.5)	8.0	39	(0.2)	1.2
	D	1217	(5.7)	22.3	1066	(5.0)	20.5	660	(3.1)	16.5	104	(0.5)	3.4
8	A	11	(0.1)	0.5	9	(0.0)	0.4	4	(0.0)	0.2	3	(0.0)	0.2
	B	377	(1.8)	17.3	243	(1.1)	12.3	27	(0.1)	1.8	1	(0.0)	0.1
	C	1121	(5.2)	51.5	770	(3.6)	38.2	99	(0.5)	6.8	10	(0.0)	0.8
	D	667	(3.1)	30.7	519	(2.4)	25.3	196	(0.9)	13.4	28	(0.1)	2.5
9	A	0	(0.0)	0.0	1	(0.0)	0.0	0	(0.0)	0.0	1	(0.0)	0.0
	B	3	(0.0)	0.1	11	(0.1)	0.2	6	(0.0)	0.1	0	(0.0)	0.0
	C	651	(3.0)	12.1	495	(2.3)	9.6	107	(0.5)	2.4	21	(0.1)	0.5
	D	4728	(22.0)	87.8	3067	(14.3)	59.4	820	(3.8)	18.7	162	(0.8)	4.3
Orientation problems OR													
1-4	A	1574	(7.3)	45.1	1379	(6.4)	40.4	378	(1.8)	11.9	79	(0.4)	2.7
	B	1338	(6.2)	38.4	1080	(5.0)	32.1	407	(1.9)	13.5	98	(0.5)	3.6
	C	377	(1.8)	10.8	394	(1.8)	11.8	266	(1.2)	8.9	78	(0.4)	2.9
	D	199	(0.9)	5.7	225	(1.0)	6.7	306	(1.4)	10.4	119	(0.6)	4.6
5	A	876	(4.1)	11.7	684	(3.2)	9.4	117	(0.5)	1.9	18	(0.1)	0.3
	B	3417	(15.9)	45.8	2588	(12.0)	36.4	428	(2.0)	7.4	57	(0.3)	1.2
	C	1818	(8.5)	24.4	1483	(6.9)	20.8	509	(2.4)	9.1	74	(0.3)	1.8
	D	1345	(6.3)	18.0	1147	(5.3)	16.1	767	(3.6)	13.6	154	(0.7)	3.8
6	A	16	(0.1)	0.3	15	(0.1)	0.3	5	(0.0)	0.1	1	(0.0)	0.0
	B	1059	(4.9)	18.3	818	(3.8)	14.8	72	(0.3)	1.6	12	(0.1)	0.4
	C	2508	(11.7)	43.3	1894	(8.8)	34.9	280	(1.3)	6.6	21	(0.1)	0.6
	D	2212	(10.3)	38.2	1605	(7.5)	29.4	671	(3.1)	16.3	115	(0.5)	4.0
7	A	0	(0.0)	0.0	0	(0.0)	0.0	0	(0.0)	0.0	0	(0.0)	0.0
	B	103	(0.5)	4.3	88	(0.4)	3.7	16	(0.1)	0.7	1	(0.0)	0.0
	C	912	(4.2)	38.4	712	(3.3)	31.1	118	(0.5)	5.9	14	(0.1)	0.8
	D	1359	(6.3)	57.2	977	(4.5)	42.5	376	(1.7)	19.4	68	(0.3)	4.2
8-9	A	0	(0.0)	0.0	0	(0.0)	0.0	0	(0.0)	0.0	0	(0.0)	0.0
	B	6	(0.0)	0.3	7	(0.0)	0.3	0	(0.0)	0.0	0	(0.0)	0.0
	C	421	(2.0)	17.7	327	(1.5)	14.4	33	(0.2)	1.7	7	(0.0)	0.4
	D	1954	(9.1)	82.1	1341	(6.2)	58.6	474	(2.2)	24.6	79	(0.4)	4.7
Occupational limitations OC													
1-5	A	1139	(5.3)	56.6	1004	(4.7)	50.6	286	(1.3)	15.3	65	(0.3)	3.7
	B	743	(3.5)	36.9	648	(3.0)	33.0	272	(1.3)	15.2	79	(0.4)	4.8
	C	100	(0.5)	5.0	139	(0.6)	7.1	171	(0.8)	9.6	55	(0.3)	3.3
	D	31	(0.1)	1.5	60	(0.3)	3.0	191	(0.9)	10.8	84	(0.4)	5.4
6	A	1042	(4.8)	17.7	833	(3.9)	14.6	157	(0.7)	3.2	22	(0.1)	0.6
	B	2883	(13.4)	49.0	2225	(10.4)	39.6	408	(1.9)	8.9	57	(0.3)	1.5
	C	1334	(6.2)	22.7	1167	(5.4)	20.7	423	(2.0)	9.4	63	(0.3)	1.9
	D	630	(2.9)	10.7	683	(3.2)	12.1	602	(2.8)	13.4	127	(0.6)	4.0
7	A	255	(1.2)	2.5	215	(1.0)	2.2	47	(0.2)	0.5	10	(0.0)	0.1
	B	2137	(9.9)	21.1	1570	(7.3)	16.3	207	(1.0)	2.7	29	(0.1)	0.5
	C	3853	(17.9)	38.1	2912	(13.5)	30.7	481	(2.2)	6.5	52	(0.2)	0.9
	D	3875	(18.0)	38.3	2854	(13.3)	30.0	1158	(5.4)	16.0	190	(0.9)	3.7
8-9	A	30	(0.1)	0.9	26	(0.1)	0.7	10	(0.0)	0.3	1	(0.0)	0.0
	B	160	(0.7)	4.6	138	(0.6)	4.0	36	(0.2)	1.1	3	(0.0)	0.1
	C	749	(3.5)	21.6	592	(2.8)	17.5	131	(0.6)	4.1	24	(0.1)	0.8
	D	2533	(11.8)	73.0	1698	(7.9)	50.2	643	(3.0)	20.9	134	(0.6)	4.7
Social integration limitations SI													
1-4	A	921	(4.3)	48.8	818	(3.8)	44.2	220	(1.0)	12.8	45	(0.2)	2.9
	B	667	(3.1)	35.4	566	(2.6)	30.7	215	(1.0)	13.1	55	(0.3)	3.7
	C	197	(0.9)	10.4	202	(0.9)	11.0	164	(0.8)	10.1	42	(0.2)	2.9
	D	101	(0.5)	5.4	109	(0.5)	6.0	158	(0.7)	9.9	69	(0.3)	5.1
5	A	1172	(5.5)	22.7	948	(4.4)	18.9	202	(0.9)	4.5	42	(0.2)	1.0
	B	2379	(11.1)	46.1	1842	(8.6)	37.3	412	(1.9)	9.8	70	(0.3)	2.0
	C	964	(4.5)	18.7	887	(4.1)	18.1	353	(1.6)	8.6	70	(0.3)	2.2
	D	642	(3.0)	12.4	620	(2.9)	12.4	539	(2.5)	13.0	121	(0.6)	3.8
6	A	361	(1.7)	4.8	301	(1.4)	4.0	75	(0.3)	1.2	10	(0.0)	0.2
	B	2423	(11.3)	31.9	1828	(8.5)	25.3	247	(1.1)	4.3	35	(0.2)	0.7
	C	2675	(12.4)	35.2	2066	(9.6)	28.6	438	(2.0)	7.8	52	(0.2)	1.1
	D	2140	(10.0)	28.2	1617	(7.5)	22.4	827	(3.8)	14.8	155	(0.7)	3.8
7	A	12	(0.1)	0.2	11	(0.1)	0.2	3	(0.0)	0.1	1	(0.0)	0.0
	B	452	(2.1)	8.5	343	(1.6)	6.7	49	(0.2)	1.2	8	(0.0)	0.3
	C	2025	(9.4)	38.0	1517	(7.1)	30.4	232	(1.1)	5.8	24	(0.1)	0.7
	D	2838	(13.2)	53.3	2028	(9.4)	40.3	718	(3.3)	18.4	117	(0.5)	4.0
8-9	A	0	(0.0)	0.0	0	(0.0)	0.0	0	(0.0)	0.0	0	(0.0)	0.0
	B	2	(0.0)	0.1	2	(0.0)	0.1	0	(0.0)	0.1	0	(0.0)	0.1
	C	175	(0.8)	11.5	138	(0.6)	9.2	19	(0.1)	1.3	6	(0.0)	0.4
	D	1348	(6.3)	88.4	921	(4.3)	62.0	352	(1.6)	26.2	73	(0.3)	5.9

Note: Column "M" represents the number of individuals at risk, and "%" indicates the share calculated on the original 21 494 individuals. The Aalen-Johansen estimate of the occupation probability is presented in "$\hat{p}$".

Table 4.5: Prevalence of states at different times across selected covariates derived from Aalen-Johansen estimator.



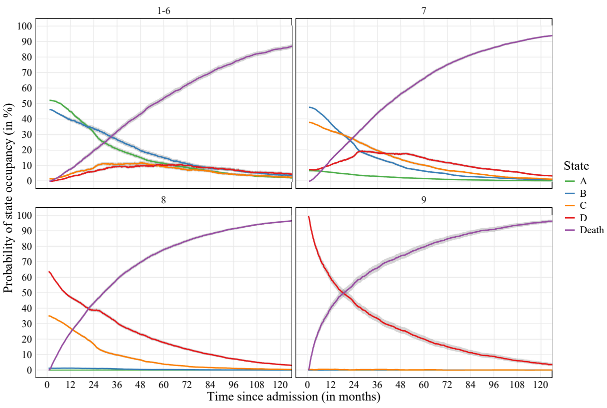
(a) Aalen-Johansen estimates.



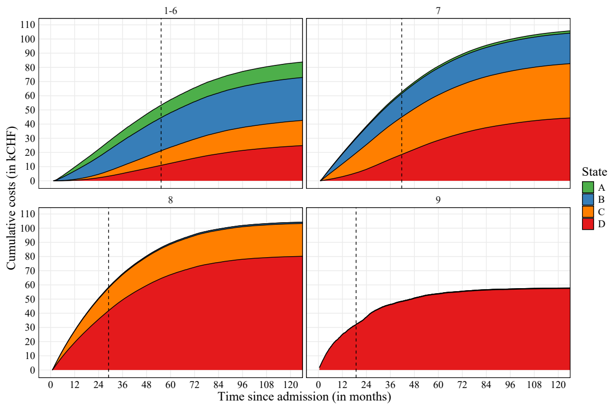
(b) Cumulative costs.

Note: See Figure 4.5.

Figure 4.11: Aalen-Johansen estimates with 95% confidence intervals of state occupancy probabilities and cumulative 10-year LTC costs stratified by the primary medical diagnosis ($D1$).



(a) Aalen-Johansen estimates.



(b) Cumulative costs.

Note: See Figure 4.5.

Figure 4.12: Aalen-Johansen estimates with 95% confidence interval of state occupancy probabilities and cumulative 10-year LTC costs stratified by the dependency from others (DP).

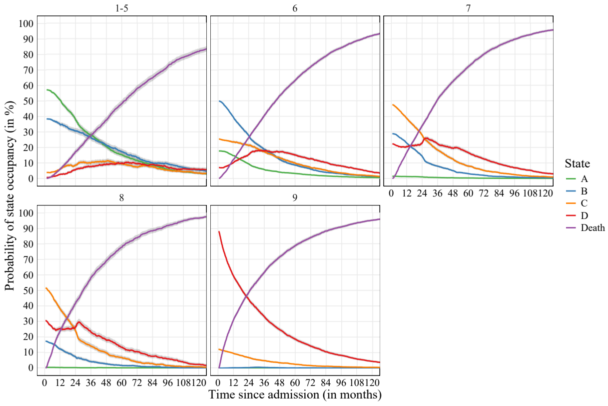
Bibliography

Ai, J., P. L. Brockett, L. L. Golden, and W. Zhu, 2017, Health State Transitions and Longevity Effects on Retirees' Optimal Annuitization, *Journal of Risk and Insurance*, 84(S1):319–343.

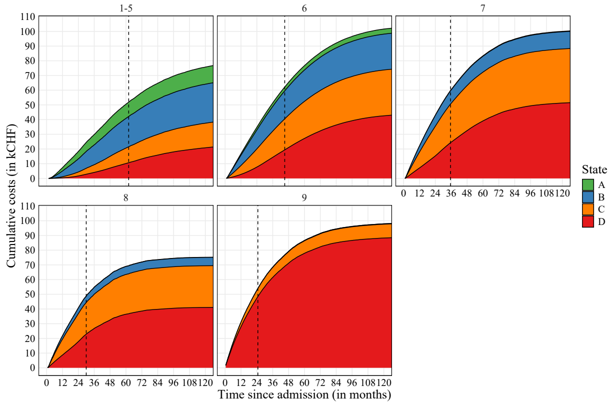
Akaike, H., 1974, A New Look at the Statistical Model Identification, *IEEE Transactions on Automatic Control*, 19(6):716–723.

Albarrán, I., P. J. Alonso-González, A. Arribas-Gil, and A. Grané, 2019, How Functional Data Can Enhance the Estimation of Health Expectancy: The Case of Disabled Spanish Population, *ASTIN Bulletin*, 49(1):57–84.

Arrighi, H. M., T. McLaughlin, and C. Leibman, 2010, Prevalence and Impact of Dementia-



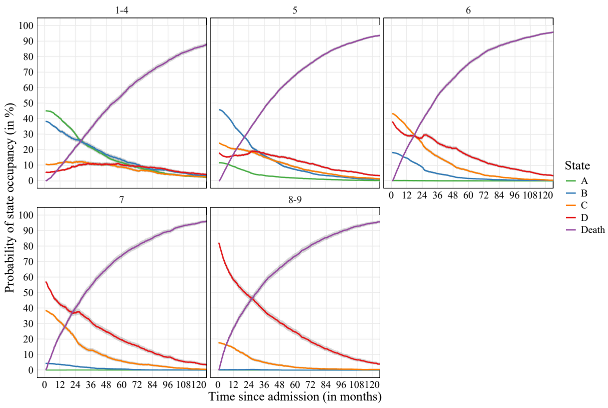
(a) Aalen-Johansen estimates.



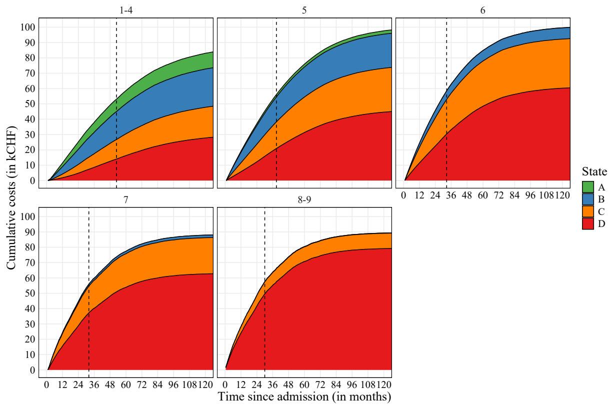
(b) Cumulative costs.

Note: See Figure 4.5.

Figure 4.13: Aalen-Johansen estimates with 95% confidence interval of state occupancy probabilities and cumulative 10-year LTC costs stratified by the physical mobility (PM).



(a) Aalen-Johansen estimates.



(b) Cumulative costs.

Note: See Figure 4.5.

Figure 4.14: Aalen-Johansen estimates with 95% confidence interval of state occupancy probabilities and cumulative 10-year LTC costs stratified by the orientation in space (OR).

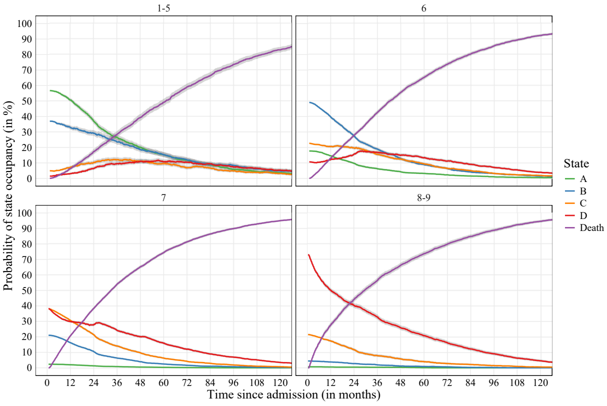
related Functional Limitations in the United States, 2001 to 2005, *Alzheimer Disease & Associated Disorders*, 24(1).

Barnett, K., S. W. Mercer, M. Norbury, G. Watt, S. Wyke, and B. Guthrie, 2012, Epidemiology of Multimorbidity and Implications for Health Care, Research, and Medical Education: A Cross-Sectional Study, *The Lancet*, 380(9836):37–43.

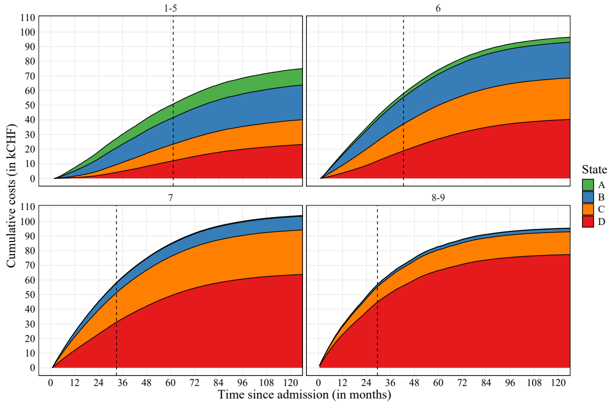
Biessy, G., 2015, Long-term care insurance: a multi-state semi-markov model to describe the dependency process for elderly people, *Bull. Français d'Actuariat*, 15(29):41–74.

Bladt, M., M. Fuino, A. Shemendyuk, and J. Wagner, 2023, Modelling the burden of long-term care for institutionalised elderly based on care duration and intensity, *Annals of Actuarial Science*, 17(1):83–117.

Börsch-Supan, A., M. Brandt, C. Hunkler, T. Kneip, J. Korbmacher, F. Malter, B. Schaan,



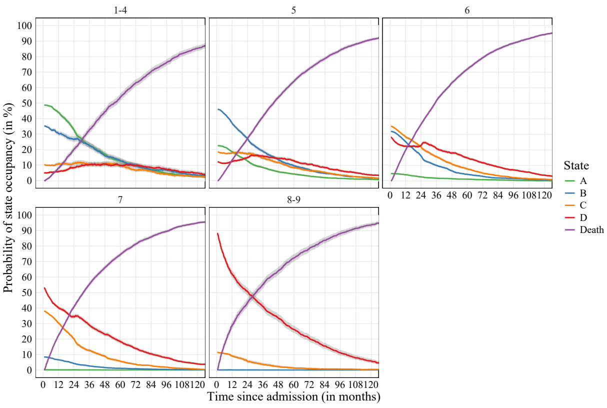
(a) Aalen-Johansen estimates.



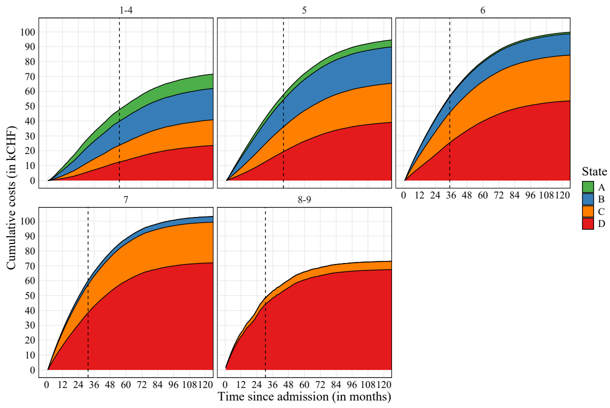
(b) Cumulative costs.

Note: See Figure 4.5.

Figure 4.15: Aalen-Johansen estimates with 95% confidence interval of state occupancy probabilities and cumulative 10-year LTC costs stratified by the occupation (OC).



(a) Aalen-Johansen estimates.



(b) Cumulative costs.

Note: See Figure 4.5.

Figure 4.16: Aalen-Johansen estimates with 95% confidence interval of state occupancy probabilities and cumulative 10-year LTC costs stratified by the social integration (SI).

S. Stuck, and S. Zuber, 2013, Data Resource Profile: The Survey of Health, Ageing and Retirement in Europe (SHARE), *International Journal of Epidemiology*, 42(4):992–1001.

Brown, J. R. and A. Finkelstein, 2009, The Private Market for Long-Term Care Insurance in the United States: A Review of the Evidence, *Journal of Risk and Insurance*, 76(1):5–29.

Burt, J., J. Rick, T. Blakeman, J. Protheroe, M. Roland, and P. Bower, 2014, Care plans and care planning in long-term conditions: a conceptual model, *Primary Health Care Research & Development*, 15(4):342–354.

Christiansen, M. C., 2012, Multistate models in health insurance, *AStA Advances in Statistical Analysis*, 96(2):155–186.

Colombo, F., A. Llena-Nozal, J. Mercier, and F. Tjadens, 2011, *Help Wanted? Providing and Paying for Long-Term Care.* OECD Health Policy Studies. OECD Publishing, Paris.

Cosandey, J., 2016, *De Nouvelles Mesures pour les Soins aux Personnes Âgées.* Avenir Suisse, Zurich, Switzerland.

Cox, D. R. and H. D. Miller, 1965, *The Theory of Stochastic Processes.* Chapman and Hall, London.

Czado, C. and F. Rudolph, 2002, Application of survival analysis methods to long-term care insurance, *Insurance: Mathematics and Economics*, 31(3):395–413.

Da Roit, B. and B. Le Bihan, 2010, Similar and Yet So Different: Cash-for-Care in Six European Countries' Long-Term Care Policies, *The Milbank Quarterly*, 88(3):286–309.

Davidson, I. A., M. E. Dewey, and J. R. M. Copeland, 1988, The Relationship Between Mortality and Mental Disorder: Evidence From the Liverpool Longitudinal Study, *International Journal of Geriatric Psychiatry*, 3(2):95–98.

Deeg, D. J. H., F. Portrait, and M. Lindeboom, 2002, Health Profiles and Profile-Specific Health Expectancies of Older Women and Men: The Netherlands, *Journal of Women & Aging*, 14(1-2):27–46.

Dorr, D. A., S. D. Horn, and R. J. Smout, 2005, Cost Analysis of Nursing Home Registered Nurse Staffing Times, *Journal of the American Geriatrics Society*, 53(5):840–845.

Esquível, M. L., G. R. Guerreiro, M. C. Oliveira, and P. Corte Real, 2021, Calibration of Transition Intensities for a Multistate Model: Application to Long-Term Care, *Risks*, 9(2):37.

Federal Department of Home Affairs, 2016, Ordonnance du DFI du 29 septembre 1995 sur les prestations dans l'assurance obligatoire des soins en cas de maladie. In French. Accessed: 20 February, 2024.

Fisher, G. G. and L. H. Ryan, 2017, Overview of the Health and Retirement Study and Introduction to the Special Issue, *Work, Aging and Retirement*, 4(1):1–9.

Fong, J. H., 2019, Disability Incidence and Functional Decline among Older Adults with Major Chronic Diseases, *BMC Geriatrics*, 19(1):323.

Fong, J. H., A. W. Shao, and M. Sherris, 2015, Multistate Actuarial Models of Functional Disability, *North American Actuarial Journal*, 19(1):41–59.

Fong, J. H., M. Sherris, and J. Yap, 2017, Forecasting Disability: Application of a Frailty Model, *Scandinavian Actuarial Journal*, 2017(2):125–147.

Foucher, Y., M. Giral, J. Soulillou, and J. Daures, 2010, A flexible semi-Markov model for interval-censored data and goodness-of-fit testing, *Statistical Methods in Medical Research*, 19(2):127–145. Publisher: SAGE Publications Ltd STM.

Fuino, M. and J. Wagner, 2018, Long-term care models and dependence probability tables by acuity level: New empirical evidence from Switzerland, *Insurance: Mathematics and Economics*, 81:51–70.

Fuino, M. and J. Wagner, 2020, Duration of Long-Term Care: Socio-economic Factors, Type of Care Interactions, and Evolution, *Insurance: Mathematics and Economics*, 90:151–168.

Germain, C. M., E. Vasquez, J. A. Batsis, and D. R. McQuoid, 2016, Sex, Race, and Age Differences in Muscle Strength and Limitations in Community Dwelling Older Adults: Data from the Health and Retirement Survey (HRS), *Archives of Gerontology and Geriatrics*, 65:98–103.

Govorun, M., G. Latouche, and S. Loisel, 2015, Phase-type aging modeling for health dependent costs, *Insurance: Mathematics and Economics*, 62:173–183.

Guccione, A. A., D. T. Felson, J. J. Anderson, J. M. Anthony, Y. Zhang, P. W. Wilson, M. Kelly-Hayes, P. A. Wolf, B. E. Kreger, and W. B. Kannel, 1994, The Effects of Specific Medical Conditions on the Functional Limitations of Elders in the Framingham Study, *American Journal of Public Health*, 84(3):351–358.

Haberman, S. and E. Pitacco, 2018, *Actuarial Models for Disability Insurance*. Routledge, New York.

Haller, G., C. Combescure, C. Mamie, D. Zoccatelli, and F. Clergue, 2015, Impact of policies regulating foreign physician migration to Switzerland: a modelling case study in anaesthesia, *BMC Health Services Research*, 15(1):204.

Helms, F., C. Czado, and S. Gschlößl, 2005, Calculation of LTC Premiums Based on Direct Estimates of Transition Probabilities, *ASTIN Bulletin: The Journal of the IAA*, 35(2):455–469.

Jackson, C., 2011, Multi-State Models for Panel Data: The msm Package for R, *Journal of Statistical Software*, 38:1–28.

Janssen, J. and R. Manca, 2001, Numerical Solution of non-Homogeneous Semi-Markov Processes in Transient Case*, *Methodology And Computing In Applied Probability*, 3(3):271–293.

Jennings, L. A., S. Hollands, E. Keeler, N. S. Wenger, and D. B. Reuben, 2020, The Effects of Dementia Care Co-Management on Acute Care, Hospice, and Long-Term Care Utilization, *Journal of the American Geriatrics Society*, 68(11):2500–2507.

Juster, F. T. and R. Suzman, 1995, An Overview of the Health and Retirement Study, *The Journal of Human Resources*, 30:S7–S56.

Kalbfleisch, J. D. and J. F. Lawless, 1985, The analysis of panel data under a markov assumption, *Journal of the American Statistical Association*, 80(392):863–871.

Katz, P. R., 2011, An International Perspective on Long Term Care: Focus on Nursing Homes, *Journal of the American Medical Directors Association*, 12(7):487–492.e1.

Kay, R., 1986, A Markov Model for Analysing Cancer Markers and Disease States in Survival Studies, *Biometrics*, 42(4):855–865.

Kempen, G., A. M. Myers, and L. E. Powell, 1995, Hierarchical Structure in ADL and IADL: Analytical Assumptions and Applications for Clinicians and Researchers, *Journal of Clinical Epidemiology*, 48(11):1299–1305.

Koroukian, S. M., N. Schiltz, D. F. Warner, J. Sun, P. M. Bakaki, K. A. Smyth, K. C. Stange, and C. W. Given, 2016, Combinations of Chronic Conditions, Functional Limitations, and Geriatric Syndromes that Predict Health Outcomes, *Journal of General Internal Medicine*, 31(6):630–637.

Liddle, P. F., 1992, Severe persistent mental illness, *Psychiatric Bulletin*, 16(12):743–745.

Makam, A. N., T. Tran, M. E. Miller, L. Xuan, O. K. Nguyen, and E. A. Halm, 2019, The Clinical Course after Long-Term Acute Care Hospital Admission among Older Medicare Beneficiaries, *Journal of the American Geriatrics Society*, 67(11):2282–2288.

Marengoni, A., S. Angleman, R. Melis, F. Mangialasche, A. Karp, A. Garmen, B. Meinow, and L. Fratiglioni, 2011, Aging with Multimorbidity: A Systematic Review of the Literature, *Ageing Research Reviews*, 10(4):430–439.

Marshall, G. and R. H. Jones, 1995, Multi-state models and diabetic retinopathy, *Statistics in Medicine*, 14(18):1975–1983.

Mathers, C., 1996, Trends in Health Expectancies in Australia 1981–1993, *Journal of the Australian Population Association*, 13(1):1–15.

Nichols, B. L., C. R. Davis, and D. R. Richardson, 2010, An Integrative Review of Global Nursing Workforce Issues., *Annual Review of Nursing Research*, 28:113–132.

OECD, 2017, *Health at a Glance 2017: OECD Indicators*. OECD Publishing, Paris.

Pack, S., 2009, Poor Physical Health and Mortality in Patients with Schizophrenia., *Nursing Standard (Royal College of Nursing Great Britain, 1987)*, 23(21):41–45.

Pritchard, D. J., 2006, Modeling Disability in Long-Term Care Insurance, *North American Actuarial Journal*, 10(4):48–75.

Rickayzen, B. D. and D. E. P. Walsh, 2002, A Multi-State Model of Disability for the United Kingdom: Implications for Future Need for Long-Term Care for the Elderly, *British Actuarial Journal*, 8(2):341–393.

Roussel, B. and C. Tilquin, 1993, *Bio-Psycho-Social Profile of Clients in Long Term Care and Planning of Nursing Care Required*. Équipe de Recherche Opérationnelle en Santé, Montreal. Reference manual.

Shemendyuk, A. and J. Wagner, 2024, On the factors determining the health profiles and care needs of institutionalized elders, *Insurance: Mathematics and Economics*, 114:223–241.

Sherris, M. and P. Wei, 2021, A Multi-state Model of Functional Disability and Health Status in the Presence of Systematic Trend and Uncertainty, *North American Actuarial Journal*, 25(1):17–39.

Sonnega, A., J. D. Faul, M. B. Ofstedal, K. M. Langa, J. W. R. Phillips, and D. R. Weir, 2014, Cohort Profile: the Health and Retirement Study (HRS), *International Journal of Epidemiology*, 43(2):576–585.

Stark, A. J., R. L. Kane, R. A. Kane, and M. Finch, 1995, Effect on Physical Functioning of Care in Adult Foster Homes and Nursing Homes, *The Gerontologist*, 35(5):648–655.

Therneau, T. M., 2024, *A Package for Survival Analysis in R*. R package version 3.5-8.

van den Akker, M., F. Buntinx, J. F. M. Metsemakers, S. Roos, and J. Knottnerus, 1998, Multimorbidity in General Practice: Prevalence, Incidence, and Determinants of Co-Occurring Chronic and Recurrent Diseases, *Journal of Clinical Epidemiology*, 51(5):367–375.

World Health Organization, 1980, International classification of impairments, disabilities, and handicaps: a manual of classification relating to the consequences of disease, published in accordance with resolution WHA29.35 of the Twenty-ninth World Health Assembly, May 1976.

World Health Organization, 2016, *International Statistical Classification of Diseases and Related Health Problems - 10th revision.* Geneva, Switzerland, Fifth Auflage.

Yang, W., A. Jingwei He, L. Fang, and E. Mossialos, 2016, Financing institutional long-term care for the elderly in China: a policy evaluation of new models, *Health Policy and Planning*, 31(10):1391–1401.

Zhao, Y., Y. Hu, J. P. Smith, J. Strauss, and G. Yang, 2012, Cohort Profile: The China Health and Retirement Longitudinal Study (CHARLS), *International Journal of Epidemiology*, 43(1):61–68.

Zúñiga, F., G. Jenni, U. Wiesli, and R. Schwendimann, 2010, Entwicklung der Rolle der Advanced Practice Nurse in der stationären Langzeitpflege älterer Menschen in der Schweiz, *Pflege*, 23(6):375–383. Publisher: Hogrefe AG.