

DOCTORAL THESIS IN ECONOMICS

Essays on Intra-Family Moral Hazard

Cristina Maria Oliveira Barbosa

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2025



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Doctoral Thesis in Economics

Supervised by
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September 2025

*To the lovers of my life, Ricardo and Marias, Margarida and Beatriz. I genuinely thank you
for all your motivation, support, and love. This thesis is not mine, but ours!*

Biographical note

Cristina Maria Oliveira Barbosa is a woman. She was born in 1985 in Sanfins, a small parish of Santa Maria da Feira, Portugal. She is married and mother of two girls.

She was one of the first graduates of Gerontology in Portugal. She got it from the Health School of the University of Aveiro in 2007. She enrolled at the ISCET-University Institute of Lisbon in 2011 for the Master of Economics and Public Policies. She defended her Master's dissertation in 2013, entitled "Governance Strategies to an Ageing Society - Local Role in Multi-Level Processes". In 2017, she was awarded a Ph.D scholarship from the Portuguese Foundation for Science and Technology, and she enrolled in the Doctoral program in Economics at FEP-University of Porto.

After some personal and professional challenges and experiences, she has the great pleasure of studying economics and aging and presenting her Ph.D thesis.

Acknowledgments

I gratefully acknowledge the financial support from the Portuguese Foundation for Science and Technology through the Ph.D scholarship SFRH/BD/117377/2016.

I would like to thank my supervisor, Professor Nuno Sousa Pereira, for his guidance and overall insights.

I thank Professor José Jorge for his shared knowledge and supervision of the theoretical approach.

Furthermore, I have to distinctly thank Professor Paula Brito for providing me with guidance on clustering methods. Additionally, I would like to thank Bernardo Marques (Ph.D) for his availability and advice.

I want to say a huge and lovely thanks to my husband Ricardo and our daughters, Maria Margarida and Maria Beatriz. Thanks also to all my family and relatives, and last but not least, thanks to "All who have come before me..." (Jonh 10:8).

Abstract

This thesis consists of four related essays on the Economics of long-term care (LTC), exploring two mainstream research issues: public LTC policies and private insurance covering LTC risk.

The first essay provides a comprehensive literature review on the Economics of LTC. We develop a timeline perspective of the evolution of LTC definitions, and we present the main characteristics of the LTC public policies, including a comparison of a wide range of countries on the adopted financing sources, benefits attributed, and out-of-pocket rules applied. We also review an extensive list of theoretical and empirical studies that reveal that there is still an open research agenda to find better explanations for the low demand for private insurance to cover LTC costs.

The second essay develops an analysis of several LTC policies by applying a clustering ensemble technique that combines three unsupervised clustering algorithms: FCM, SOM, and PAM. Using data from 30 OECD countries, this essay aims to find a stable typology of LTC policies. We identify seven different clusters based on four main dimensions: supply, demand, financing, and policy provision and regulation. We test the robustness of our clustering proposal under different algorithm settings and by using COVID-19 data. We highlight the relevant properties of our seven clusters in distinguishing the countries' LTC policies.

The third essay follows Pauly (1990) and extends Zweifel & Strüwe (1996) to present a model that establishes a contract between the two members of a couple establishing informal care effort, private insurance, and internal transfers. The principal is the oldest spouse and the agent is the youngest. We find that the unpredictable duration of the care needs and its associated costs, the agent's risk aversion, and the awareness to protect the spouse from financial constraints derived from the LTC costs are crucial issues in the definition of the contract. We then discuss how our results are aligned with previous empirical findings.

Finally, the fourth essay is an empirical study about the influence of the willingness to take financial risks on an older couple's decision to purchase LTC insurance coverage. We use panel data from married/partnered older people from the USA who participated in the Health and Retirement Study (HRS) survey. Our results demonstrate that older couples who are willing to take risks are more likely to demand LTC insurance. Through several robustness checks, we also show that older couples in the USA recognize the specific nature of the LTC insurance compared to other insurance products.

Overall, this thesis provides several contributions to the Economics of LTC literature, adopting a different perspective on LTC policies and the econometric methods applied. It also provides new insights that should be further extended for a better understanding of the decision to finance LTC costs.

Key words: Long-term care, insurance, intra-family moral hazard, aging, older couples, public policies, clusters, clustering ensemble, economics of long-term care, willingness to take risks.

JEL codes: C38, D19, D81, D86, G52, I10, I13, J14, J18

Resumo

Esta tese é composta por quatro ensaios interrelacionados no âmbito da Economia de Cuidados de Longa Duração (LTC), explorando dois dos seus principais domínios de investigação: políticas públicas de LTC e seguro privado para cobertura de custos em LTC.

O primeiro ensaio desenvolve uma ampla revisão da literatura da Economia de LTC. Analisam-se de forma evolutiva as definições de LTC e apresentam-se as principais características das suas políticas públicas, incluindo-se uma comparação de países mundiais no que se refere às suas fontes de financiamento, benefícios atribuídos, e regras aplicadas para pagamento de serviços. Procedem-se também à revisão de uma extensiva lista de estudos teóricos e empíricos que revela oportunidades de investigação para compreender a reduzida procura de seguro privado de LTC.

O segundo ensaio analisa diversas políticas de LTC através da aplicação do método de *clustering ensemble* que combina três algoritmos não supervisionados: FCM, SOM, e PAM. Tendo por base dados de 30 países da OCDE, este ensaio visa identificar uma tipologia sólida de políticas de LTC. Identificam-se sete diferentes *clusters* com base em quatro dimensões: oferta, procura, financiamento, implementação e regulamentação de políticas. Testou-se a robustez desta proposta de *clusters* utilizando-se diferentes definições dos algoritmos e com dados relativos à COVID-19. Ressaltam-se propriedades relevantes da proposta de sete clusters para a diferenciação das políticas de LTC dos países.

O terceiro ensaio baseia-se em Pauly (1990) e complementa Zweifel & Strüwe (1996) para apresentar um modelo que estabelece um contrato entre membros de um casal, determinando o esforço associado aos cuidados informais, a compra de seguro privado e as transferências internas. O principal é o esposo mais velho e o agente é o mais jovem. Verificou-se que a imprevisibilidade da duração, os custos de LTC, a aversão ao risco do agente, e a preocupação em proteger o esposo de restrições financeiras que decorrem do LTC, são questões cruciais na definição do contrato. Posteriormente, discutiu-se de que forma os resultados encontrados estão alinhados com estudos empíricos anteriores.

Por último, o quarto ensaio é um estudo empírico sobre a influência da disposição a riscos financeiros na decisão do casal em comprar seguro de cobertura de custos de LTC. Utilizaram-se dados em painel de indivíduos idosos casados ou com parceiros, participantes no inquérito *Health and Retirement Study* desenvolvido nos EUA. Os resultados sugerem que os casais idosos que têm disposição ao risco provavelmente decidem comprar o seguro LTC. Através de diversos testes de robustez, verificou-se que os casais idosos nos EUA reconhecem características específicas do seguro LTC comparativamente a outros produtos de seguros.

No geral, a tese proporciona diversas contribuições para a literatura da Economia de LTC, adotando uma perspetiva diferenciadora das políticas de LTC e dos métodos econométricos aplicados. Proporciona ainda contributos inovadores que poderão ser desenvolvidos posteriormente para melhor conhecimento da decisão de financiamento dos custos em LTC.

Palavras-chave: Cuidados de longa duração, seguro, risco moral intrafamiliar, envelhecimento, casais idosos, políticas públicas, agrupamento de dados, combinação de agrupamentos de dados, economia de cuidados de longa duração, disposição a riscos.

Classificação JEL: C38, D19, D81, D86, G52, I10, I13, J14, J18

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Chapter 1

Introduction

The aging of the global population has become an increasingly central topic in economic research. Over the past century, human longevity has risen dramatically, transforming into a worldwide phenomenon that has extended even to developing nations (United Nations, 2019). This demographic shift presents profound economic and social challenges. In many countries, the age structure of the population has undergone significant changes. A growing proportion of elderly individuals, coupled with a declining share of working-age people relative to retirees, marks a critical transformation. However, increases in life expectancy do not always translate into more years lived in good health. As a result, societies face rising levels of old-age dependency and a growing demand for personal and long-term care (LTC) services, driven by disabilities, chronic conditions, and age-related illnesses. In the United States, nearly 56% of individuals aged 65 and older experience disabilities that necessitate LTC services. On average, these individuals require assistance for approximately three years, with 22% needing support for even longer durations (Johnson & Dey, 2022). This demographic transition has far-reaching implications for economic growth and demands careful analysis from governments, academics, businesses, civil society, and families, each playing a vital role in shaping economic decisions. Moreover, evolving dynamics in gender roles and family support structures have intensified pressure on LTC systems, prompting the need for new welfare policies, restructured healthcare systems, labor market adaptations, and revised public budgets.

Over the past three decades, the discipline of Economics has increasingly focused on the extensive implications of LTC, giving rise to a specialized sub-field: the Economics of LTC. In a recent systematic review, Bell & Lemmon (2023) identified and ranked the sixteen most frequently studied topics within this domain. This thesis seeks to contribute to the ongoing development of the field by introducing novel approaches and innovative methodologies to explore two of these prominent research areas: public LTC policies and private insurance mechanisms for LTC coverage. These themes are examined through four interconnected essays. The first two essays concentrate on public policy analysis, while the latter two shift focus to the private insurance perspective. Our research aims to provide a comprehensive typology of national LTC policies using advanced statistical techniques, including clustering algorithms. Additionally, we investigate the decision-making processes of older couples regarding LTC insurance, with particular attention to their financial risk preferences and how these influence coverage choices.

The first essay, presented in Chapter 2 and titled "The Economics of Long-Term Care", adopts a historical perspective to trace the evolution of the LTC concept and its growing relevance in contemporary society. Through a timeline-based analysis and supporting data, we highlight how LTC has become a critical component of modern welfare systems. We examine the key determinants of both demand and supply in the LTC sector, emphasizing how demographic and social transformations are placing increasing pressure on public budgets and investment strategies. The chapter also reviews the main attributes of public LTC policies, focusing on benefit structures, out-of-pocket payment rules, and the various financing mechanisms in place.

Special attention is given to one of these mechanisms: the role of private insurance in covering LTC costs. In this context, we revisit the intra-family moral hazard issue first introduced by Pauly (1990), and review both theoretical and empirical literature that seeks to explain the persistently low demand for private LTC insurance.

The second essay, presented in Chapter 3 and titled "Clustering long-term care policies", addresses the need for a more systematic and data-driven classification of LTC policy models. While previous studies have proposed various typologies by grouping countries based on selected features, most rely heavily on descriptive and qualitative analyses, with limited application of clustering methodologies. This essay contributes by developing and applying a robust clustering technique to derive a stable typology of LTC policies. Using data from 30 OECD countries spanning 2016 to 2019, we analyze ten variables grouped into four key dimensions: (i) supply, (ii) demand, (iii) financing, and (iv) policy provision and regulation. We implement a clustering ensemble approach that integrates the outputs of three unsupervised algorithms, Fuzzy C-Means (FCM), Self-Organizing Maps (SOM), and Partitioning Around Medoids (PAM), to identify seven distinct LTC policy typologies. To validate our clustering solution, we assess its performance using internal criteria, and evaluate its consistency by measuring the degree of agreement with the solutions proposed by algorithms. Robustness checks confirm the reliability of our proposed typology, offering a valuable framework for comparative policy analysis.

The third essay, presented in Chapter 4 and titled "Older couples and long-term care coverage - a theoretical approach", builds on the foundational work of Pauly (1990) and extends the model proposed by Zweifel & Strüwe (1996). We develop a theoretical framework that formalizes the intra-couple dynamics surrounding informal care provision, private LTC insurance, and internal financial transfers. Using Principal-Agent theory, we model the relationship between spouses, where the older spouse acts as the principal and the younger as the agent. The principal offers a contract specifying the agent's informal care effort, which is observable and optimally determined by the principal. The agent then decides whether to accept the proposed terms. We analyze the impact of exogenous shocks to key variables, including the mean and variance of LTC costs, the generosity of public LTC benefits, and the agent's coefficient of absolute risk aversion. Through comparative statics, we find that uncertainty in care duration, financial exposure to LTC costs, and the agent's risk preferences are critical factors influencing contract outcomes. Our findings align with existing empirical evidence and offer new insights into the behavioral and financial dimensions of LTC decision-making within households.

The fourth essay, presented in Chapter 5 and titled "*Mine* and *my* spouse's preferences for risk-taking: how do older couples decide to insure their dependency costs?", offers an empirical investigation into the relationship between financial risk preferences and the decision to purchase private LTC insurance among older married or partnered individuals. Using panel data from the Health and Retirement Study (HRS) in the United States (USA), we employ multi-level mixed-effects logistic regression models to estimate the impact of the financial respondent's willingness to take financial risks on the likelihood of LTC insurance coverage. We hypothesize that greater risk aversion is associated with a higher probability of purchasing LTC insurance. Our findings reveal a statistically significant positive relationship between willingness to take financial risks and the odds of holding private LTC insurance. Robustness checks, conducted through alternative specifications of both independent and dependent variables, confirm the consistency of our results. Interestingly, similar effects are observed in the context of life insurance coverage, whereas the analysis of health insurance decisions yields opposite results. We discuss several potential explanations for these contrasting outcomes.

Finally, Chapter 6 concludes the thesis by synthesizing the main findings across all four essays and proposing avenues for future research in the Economics of Long-Term Care.

Chapter 2

The Economics of Long-Term Care

2.1 Introduction

People live increasingly longer, but often with added limitations. The decline in mortality and fertility rates led to changes in demographic structures, fostering the need for new policies, public programs, and services that tackle the challenges of extended living with increased health deterioration and higher social and economic needs. Significant events in the last centuries, such as the Industrial Revolution, urbanization, post-World War II, and population growth, had already enhanced the need for more comprehensive welfare policies, but long-term care (LTC) as a specific social risk was seldom discussed (Österle & Rothgang, 2021). The development of LTC awareness started in the 1980's, gaining traction in the 1990's, when developed countries included systematic coverage for LTC needs in their welfare system. More recently, less developed countries have also been adopting more structured LTC policies. Still, LTC remains less institutionalized than other welfare policies across the world (Ranci & Pavolini, 2013).

The economics science has also shown increased interest in LTC, mainly as a branch of Health Economics. Norton (2000), Cremer et al. (2012), Siciliani (2013), and Bell & Lemmon (2023) presented structured reviews of LTC studies but without highlighting any consistent formalized concepts and theories. We analyze the determinants of LTC demand and supply, and the main funding mechanisms used to cover LTC costs. We start by confronting the alternative LTC concepts and their evolution over time. We then review countries' LTC policies highlighting the financing options, benefits provided, and out-of-pocket rules imposed to finance LTC expenses. LTC is a challenge for social and health care policies, as well as to public finances, given the pressure coming from an increased demand for LTC and the associated costs (World Health Organization, 2021a). On the financing side, we focus on the decision to purchase private insurance and how that decision is shaped when taken by older couples. We conclude by highlighting the main key topics and some limitations for further work.

2.2 The concept

Longevity has been steadily increasing, leading to novel economic and social challenges such as higher levels of old-age dependency and the need for more personal care services for the elderly. LTC encompasses multidisciplinary approaches, multidimensional interventions, and holistic policies around care. The primary purpose of LTC is not to address acute healthcare needs but to improve health through the provision of health and social care that maintains individuals' capacities and delays or makes their deterioration more bearable (Bell & Lemmon, 2023; Norton, 2000; de la Maisonnette & Martins, 2013). Consequently, the model of provision and financing that addresses long-term care is bound to be different from that focused on mainstream health care. In addition, the family is often the primary provider of the necessary services, mainly through informal care delivered by spouses, relatives, or children (Cremer et al.,

2017). This unpaid work is provided in the beneficiary's house and sometimes complemented by home care and community social services. The increased use of nursing home care services has been highlighting the need to adequately measure the opportunity costs associated with these services and study how consumers make their decisions.

Formal definitions of LTC have evolved as LTC became more comprehensive. Doty et al. (1985) defined LTC as "health, social, and residential services provided to chronically disabled persons over an extended period". Institute of Medicine (1986) evoked that LTC is to those "who need assistance continuously because of physical or mental disability", mentioning the settings where care may be provided: "in an institution, the home, or the community, and include informal services provided by family or friends as well as formal services provided by professionals or agencies".

WHO Ageing and Health Programme and Milbank Memorial Fund (2000) described the two sources of care provision, formal and informal, but also explained that LTC acts "to ensure that a person who is not fully capable of self-care can maintain the highest possible quality of life, according to their individual preferences, with the most significant possible degree of independence, autonomy, participation, personal fulfillment, and human dignity". Colombo et al. (2011) emphasized the intrinsic role of LTC in helping to perform activities of daily living (ADL): "a range of services required by persons with a reduced degree of functional capacity, physical or cognitive, and who are consequently dependent for an extended period on help with basic activities of daily living". European Commission (2013) defined LTC as a range of services and assistance for persons who, over an extended period, depend on help, and emphasized which are the ADL and Instrumental Activities of Daily Living (IADL) included on the basic services provided under LTC¹.

World Health Organization (2015) focused on the definition of healthy aging, ensuring that LTC guarantees "a level of functional ability consistent with their basic rights, fundamental freedoms, and human dignity". World Health Organization (2022) presented a broader concept aimed at all ages: "Long-term care includes a broad range of personal, social, and medical services and support that ensure people with, or at risk of, a significant loss of intrinsic capacity (due to mental or physical illness and disability) can maintain a level of functional ability consistent with their basic rights and human dignity."

In sum, LTC began to be associated with the range of social, health, and residential services (Doty et al., 1985; Institute of Medicine, 1986). WHO Ageing and Health Programme and Milbank Memorial Fund (2000) was the first to include an individual's independence, autonomy, participation, personal fulfillment, and human dignity as an important component of it. World Health Organization (2015) focused on LTC within the older population and reinforced its role in guaranteeing fundamental rights, individual freedoms, and human dignity. The services included in LTC policies began as just supporting functional limitations to later include services that prevent, reduce, and rehabilitate individuals (World Health Organization, 2022). Colombo et al. (2011) supported a more comprehensive vision of LTC and its policies, by reviewing an extended and heterogeneous group of world countries' policies and public interventions.

2.3 The economic determinants of long-term care

There is a scarce formalization of concepts, theories, and tools that help frame the economics of LTC as a discipline, even though LTC has become an essential branch of Health Economics (Norton, 2000; Bell & Lemmon, 2023). The following subsections describe the main economic determinants of LTC demand, supply, and market equilibrium.

¹ADL is defined as "self-care activities that a person must perform every day, such as bathing, dressing, eating, getting in and out of bed or a chair, moving around, using the toilet, controlling bladder and bowel functions" and IADL as "activities related to independent living and include preparing meals, managing money, shopping for groceries or personal items, performing light or heavy housework, and using a telephone."

2.3.1 Demand

Demand for LTC arises from the achievements in reducing mortality and increasing longevity, although with added morbidity. OECD projections suggest that most countries will face a negative variation in total population in the next 40 years but a positive variation in the 65 years or older population, with Japan being the exception (see Table 2.1). The primary determinant of demand for care is an individual's physical and mental health status (Norton, 2000). Aging-related issues are closely related to people's health status and their demographic characteristics, such as age, gender, race, and prevalence of long-standing and chronic conditions (Norton, 2000; Klimaviciute & Pestieau, 2022). People live, on average, 81 years ($sd=2,32$) but only approximately 18 healthy years after they turn 60. Almost three full years are lived in poor health, requiring care and support. United Nations - Department of Economic and Social Affairs (2023) estimates more than 46% of people aged 60 or more years have disabilities, and more than 250 million older people experience moderate to severe disability. Across OECD countries, on average, 15 people per 1000 population were estimated to have dementia in 2021, while the forecast for 2040 shows an increase to 22 people per 1000 population. Dementia causes a gradual deterioration of individual functional capacity and social relations and is one of the most common reasons people demand LTC. Countries such as the Czech Republic, Estonia, Finland, Hungary, Italy, Japan, Latvia, Lithuania, Poland, Portugal, Slovak Republic, and Slovenia will soon have a dementia prevalence of at least 25 people per 1000 population (OECD, 2023c).

The demand for LTC is also determined by political, social, cultural, financial, and economic factors. LTC demand is influenced by the availability of quality market services but mainly by the unpaid family care provided by children, spouses, and other relatives. Diverse social and economic forces shape how the demand for informal and formal care is operated (Norton, 2000). Family members' availability to provide care, women's participation in the labor market and their wage level, family structure, and geographical proximity are strong determinants of the amount of formal care effectively demanded. Furthermore, the individual's ability and willingness to pay for formal LTC at a given price depends on the opportunity cost of informal care, the relative price of formal care services, individual earnings and assets, the magnitude of the impairments, individual preferences, the availability of care services, and the cost of the required care. The elderly, when demanding formal care services such as a nursing home, observe price but may have difficulty evaluating the quality of care. Contrary to the demand for acute healthcare services, LTC demand is often not time-sensitive since LTC is not an acute need but a long-lasting condition (Norton, 2000).

The old-age dependency ratio, which measures the number of individuals aged 65 and over per 100 working-age people (defined as those aged 20 to 64) is a relevant indicator for the aggregate demand. Table 2.1 shows that, until 2075, the old-age dependency ratio will increase in all analyzed countries, particularly in the southern European countries, such as Greece, Portugal, Italy, and Spain, but also in Asian countries, namely Japan and South Korea. The increased number of dependent elderly associated with lower availability of informal care and lower number of people working implies that the higher demand for care should also come at a higher cost (Martinez-Lacoba et al., 2021).

2.3.2 Supply

The supply of LTC can be done through informal arrangements, based on family support without direct payment, or through formal settings, when care is provided in institutions against payment. Determinants of LTC supply are intrinsically related to family structure, which is still the primary LTC supplier, but also to public policy.

Changes in family values, the increasing rate of female participation in the labor market, and the increasing number of people living alone are the main factors that contribute to a decline in informal care supply. Formal LTC availability is closely related to a country's public

Table 2.1: LTC: Demand side

Country	Δ Population 2020-2060		Life expectancy at birth (2019)	Old age dependency ratio		Nr. of healthy life years at age 60 (2019)
	Total (n)	$\geq 65y$ (n)		2020	2075	
Australia	14881192	4007636	83,04	27,70	48,40	18,98
Austria	1044207	1150788	81,65	31,30	63,10	18,35
Belgium	1327672	1093541	81,42	33,10	54,00	18,17
Canada	15456234	6554296	82,24	29,80	54,50	18,99
Czech Republic	7117	919952	79,13	33,80	55,60	16,32
Denmark	588117	444475	81,32	34,90	53,40	18,23
Estonia	-656	132464	78,88	34,90	59,00	17,29
Finland	-190141	368376	81,61	40,10	54,70	18,46
France	2537138	5937492	82,48	37,30	55,80	19,70
Germany	1153357	5418123	81,72	36,50	63,10	18,47
Greece	-2380476	502552	81,10	37,80	75,20	18,44
Hungary	-607510	644290	76,44	33,40	57,60	15,30
Ireland	1112420	943588	81,84	25,00	50,90	18,58
Italy	-4188883	4551542	82,97	39,50	67,00	18,91
Japan	-33306425	-623733	84,26	52,00	75,30	20,39
South Korea	-9219186	10530791	83,30	23,60	78,80	19,81
Latvia	-548915	57239	75,38	35,50	52,00	15,64
Lithuania	-635742	201818	75,99	34,70	50,70	15,92
Luxembourg	314847	158726	82,41	22,30	47,10	18,52
Netherlands	2730897	1642595	81,79	34,30	59,70	18,44
Norway	724010	796407	82,62	29,60	51,20	18,46
Poland	-5046259	3823051	78,27	30,50	73,30	16,84
Portugal	-1132071	737950	81,57	38,60	77,60	18,65
Slovak Republic	-438830	652858	78,23	26,50	58,00	16,57
Slovenia	-52863	201780	81,31	34,70	60,20	17,83
Spain	3934700	6210327	83,22	32,80	70,40	19,20
Sweden	1879235	1057681	82,40	35,90	51,60	18,86
Switzerland	1243566	1265942	83,45	31,30	58,10	19,52
United Kingdom	4532490	6503100	81,40	32,00	53,00	18,25
United States	72971543	39849405	78,5	28,40	49,30	16,35
Mean	2289693	3524502	80,99	33,26	59,29	18,11
SD	15463947	7378507	2,32	5,75	9,29	1,28

Sources: Population 2020 data (OECD, 2023e); Population 2060 data (OECD, 2023g); Life expectancy years (World Health Organization, 2023b); Old age dependency ratio data (OECD, 2023f); Healthy life years (World Health Organization, 2023a).

policies and governance, and the chosen investment in accessibility to care, resources, and benefits. According to the OECD (see Table 2.2), the total spending on LTC as a share of GDP (calculated as the sum of health care and social services and all financing schemes available, including governments, voluntary schemes, and household expenditures) ranges between 0,03% and 4,06%. In Europe, East and Southern countries have the lowest share - Slovak Republic (0,03%), Latvia (0,59%), Greece (0,15%), Italy (0,90%), Portugal (0,92%), and Spain (0,93%), while the Northern countries have the highest share of LTC spending - Netherlands (4,06%), Sweden (3,39%), and Norway (3,71%). In Asia and the USA, the total LTC spending follows similar patterns of central European countries, with a higher share in Japan (2,03%) and a lower share in South Korea (1,07%) and the USA (1,34%). The highest component of total LTC spending is still public, accounting for an average of 1,39% of GDP across the selected

Table 2.2: LTC: Supply side

Country	Total LTC spending as share of GDP (2019)			Government LTC spending as share of GDP (2019)	Private LTC spending as share of GDP (2019)	Out-of-pocket LTC spending as share of GDP (2019)	Formal LTC workers per 100 population aged 65y+ (2019)	Nr. of LTC recipients aged 65y+ (2019)		Pop. 50y+ who reports to be informal careers (in %; 2017)
	Health	Social	Sum					in institutions	at home	
Australia	1,14	0,15	1,28	1,27	0,007	0,007	6,20	237259	333303	11,20
Austria	1,53		1,53	1,14	0,033	0,357	4,20			19,20
Belgium	2,50	0,71	3,21	2,31	0,062	0,841	5,51	120604	168026	18,40
Canada	2,22		2,22	1,68	0,077	0,463	3,40	253099	514800	
Czech Republic	1,02	0,65	1,67	1,48	0,186	0,003	3,79	54902	198175	19,70
Denmark	2,17	1,05	3,21	2,98	0,005	0,228	7,80	38781	125579	15,20
Estonia	0,64	0,06	0,70	0,40	0,002	0,294	5,40	11785	14879	10,80
Finland	1,59	0,78	2,37	2,10		0,276	7,91	51934	111213	
France	1,75	0,63	2,38	1,87	0,005	0,510	2,42	546869	789056	17,50
Germany	2,25		2,25	1,58	0,093	0,582	5,40	742366	2547404	17,00
Greece	0,13	0,01	0,15	0,14	0,006		0,35			6,60
Hungary	0,25	0,35	0,60	0,21	0,018	0,021	1,90	56591	165376	
Ireland	1,46		1,46	1,23	0,025	0,211	3,80	22331		6,70
Italy	0,90		0,90	0,67	0,004	0,226	3,74		858896	10,30
Japan	2,03		2,03	1,84	0,021	0,165	6,70	945900		
South Korea	1,07		1,07	0,75		0,321	4,30	210284	532274	
Latvia	0,33	0,26	0,59	0,48	0,001	0,109	1,30	1684		
Lithuania	0,53	0,62	1,15	0,98	0,018	0,130	1,11	69441	147523	
Luxembourg	1,04	0,33	1,36	1,11	0,018	0,226	7,30	4757	6509	12,10
Netherlands	2,83	1,23	4,06	3,82		0,238	8,00	137630	249455	16,80
Norway	3,10	0,61	3,71	3,43		0,278	12,40	37522	100807	
Poland	0,43		0,43	0,41	0,019	0,003	0,57	56977		8,40
Portugal	0,45	0,47	0,92	0,45	0,006	0,466	0,80	27614	14697	9,40
Slovak Republic	0,03		0,03	0,03			1,40	30059	38982	
Slovenia	0,87	0,40	1,27	0,94	0,008	0,326	2,37	18967	30286	14,00
Spain	0,86	0,07	0,93	0,78	0,009	0,144	4,80	202780	844137	13,10
Sweden	2,86	0,53	3,39	3,16		0,227	11,90	86314	242701	9,20
Switzerland	2,41	0,18	2,60	1,76	0,062	0,750	8,30	87562	280035	15,20
United Kingdom	1,92	0,43	2,35	1,60	0,183	0,568				18,20
United States	1,34		1,34	1,00	0,064	0,273	5,20	926842	4082987	7,00
Mean	1,39	0,48	1,70	1,39	0,039	0,294	4,77	191571	539004	13,14
SD	0,88	0,32	1,07	0,99	0,052	0,213	3,16	277606	943101	4,37

Sources: Total LTC spending as a share of GDP (2019) data (OECD, 2023d); Government, Private, and Out-of-pocket spending as a share of GDP (2019) includes health and social spending (OECD, 2023d). Government spending includes government schemes, social health insurance, compulsory private insurance, and compulsory medical savings accounts. Private spending includes voluntary health insurance, non-profit institutions financing schemes and enterprise financing schemes. Out-of-pocket includes direct payment for care goods and services from the households' primary income or savings (OECD et al., 2017). Formal LTC workers "are defined as paid staff – typically nurses and personal carers – who provide care and/or assistance to people limited in their daily activities at home or in institutions, excluding hospitals" and data are from OECD (2021). Data from Australia (year 2016); Austria (year 2011); Denmark (year 2018); Portugal (year 2012). Number of LTC recipients in institutions data are from OECD (b) and at home OECD (a). LTC recipients at institutions data from the USA (year 2020). LTC recipients at home data from Canada (year 2016); Slovak Republic (year 2021); USA (year 2017). Informal careers aged than 50 years (OECD, 2019a). Blanks are due to unavailable data.

OECD countries in 2019. Private and out-of-pocket contributions have the lowest weight, on average, 0,04% and 0,29% of GDP, respectively, while the total spending is 1,70% (see Table 2.2). Across the studied OECD countries, the balance between public, private, and out-of-pocket spending on LTC is heterogeneous. The main financing source of LTC in % of GDP is public funds, but in some countries there is shared financing between public financing, compulsory schemes, private insurance, and out-of-pocket payments (e.g., Canada, Estonia, Portugal, United Kingdom), while in others, we denote a much higher public financing share (e.g., Czech Republic, Finland, Norway, Poland).

LTC suppliers can offer their services in people’s homes or in formal care institutions, namely residential homes, nursing homes, community services, and hospitals. Both informal and formal providers face challenges derived from the changing work-family balance, the heterogeneity in training and education to perform care tasks, the high intensity (in hours dedicated to) of formal and care work, the unequal work conditions, the low wages, and the heterogeneous professionalization of care workers across countries (Norton, 2000; Klimaviciute & Pestieau, 2022; Bell & Lemmon, 2023). Table 2.2 shows the number of LTC recipients and workers available in LTC settings. On average, we observe 4,77 workers per 100 older people, but with high heterogeneity across countries ($sd=3,16$). The highest ratio is found in the European Nordic countries, Norway and Sweden, where the ratio is almost 12 workers per 100 elderly. As a measure of supply, it reflects public investment and countries’ orientations on LTC policy. Furthermore, nearly 10,7% of people aged over 65 years received long-term care, either at home or in long-term care facilities, in the OECD countries in 2019 (OECD, 2021). Most LTC has been provided at the elderly’s homes instead of in institutions. OECD (2021) show that the proportion of LTC recipients aged 65 and over who received care at home was approximately 68%. Table 2.2 confirms that there is a higher number of older people who receive care at home rather than in an institution.

The cost of providing LTC is high² since it is labor intensive and affected by slow technological change and productivity gains (Klimaviciute & Pestieau, 2022). In our sample, the Czech Republic has the highest percentage of informal carers, with 19,70% of people aged 50 years reporting that they provide informal care, while in Greece, only 6,60% report being informal caregivers. This measure shows, on average, that 13,14% of people over 50 years are caregivers ($sd=4,37$), but with high heterogeneity across OECD countries.

2.3.3 Market equilibrium

For LTC, market equilibrium balances the factors that drive individuals’ choices, the availability of informal and formal services, opportunity costs, and the increased number of older adults who require support to overcome dependence-associated needs.

Informal networks or formal care settings, such as nursing homes, rehabilitative services, and community settings, are the leading suppliers of care in this market. However, as people age and have more needs for ADL and IADL coverage, the balance between paid and unpaid care, institutional and community settings, and other issues related to supply, yield new market equilibria at higher prices (Bell & Lemmon, 2023).

Limited public budgets for LTC and scarce long-run investments in LTC have both also molded the equilibrium between increasingly high demand and (costly) supply of LTC services. Norton (2000) argued that the ratio between LTC expenditures and demand may be more relevant at the end-of-life because LTC is one “future cost” under which one additional year of life is more expensive, and it is dependent on the individual’s longevity. Lakdawalla & Philipson (2002) argued that aging may decrease the demand for formal care if it raises the supply of non-market (informal) care services provided by healthier spouses.

²According to Genworth Cost of Care Survey (2023), the monthly median cost of nursing home care in the USA is \$9733 for a private room, \$6292 for home health aide, and \$5720 for homemaker services community.

Males tend to have lower longevity, and it is more likely that they will end up benefiting from spousal care. However, women’s added longevity may be spent in widowhood conditions and under worse health status, which may raise the demand for formal care.

Governments influence on market equilibrium has been related to the definition of policies and rules. A set of diverse measures have been implemented, such as heterogeneous eligibility criteria based on high clinical needs, limited availability of benefits to older people and informal caregivers, regulation of the services available, the existence of long waiting lists to benefit from public support, and the definition of new financing tools. Siciliani (2013) suggested that a scenario of more aged people encourages for-profit providers to enter the care market, and impact the quality of care provision and the equilibrium of the market shared with the non-profit sector. Across OECD countries, progressive competition and marketization of the care sector have been identified, with a significant proportion of care delivered by for-profit entities, specifically over the last 30 years (Corlet Walker et al., 2022).

In sum, the LTC market equilibrium depends on factors such as the available informal help, individual earnings, the magnitude of the health impairments, the extent of need-related services to overcome disabilities, preferences about type of care, market prices, the competitive nature of LTC formal services, and availability of public assistance.

2.4 LTC policies: comparing financing sources, benefits, and out-of-pocket rules

Bell & Lemmon (2023) listed the most studied topics within the economics of LTC and LTC policies were identified as number four. LTC policies and programs can be structured around dimensions such as eligibility criteria, financing sources, benefits available (in cash and in-kind), and the rules applied to define out-of-pocket (OOP) payment by users. Each country establishes different degrees of medical needs to determine eligibility for health and social care services, but also distinct age-related criteria to classify individuals as needing LTC and benefiting public support. For instance, in South Korea, the LTC system considers people aged 65 years or older eligible for all types of LTC, but eligibility for those under 65 is restricted to age-related LTC needs, such as individuals with geriatric diseases (Jeon & Kwon, 2017). In Austria, eligibility requirements for cash benefits are decided by a doctor through an ADL and IADL assessment, which follows federal guidelines. The criterium is the need for LTC services for at least 65 hours per month for a period exceeding six months³.

Table 2.3 classifies the countries according to their main LTC financing type, the public financing sources adopted, the most commonly attributed benefits, and the applied out-of-pocket rules. We classify the countries according to the public sources used to finance LTC: i) countries that finance LTC policy mainly through tax-based schema; ii) countries that mainly use a tax-based system but complement it with other financing instruments; and iii) countries that have social long-term care insurance as the primary financing source.

Some countries finance their LTC policies through tax revenues obtained from both general and local taxation. In Italy, the cash-for-care benefit program (Indennità di Accompagnamento) is paid by social security and financed by general taxation. In Spain, the funding of LTC is shared by the central and the regional governments (Deusdad et al., 2016). Social care and health care beds in hospitals and geriatric units are financed by general taxes (Costa-Font & Courbage, 2012; Bernal-Delgado et al., 2018). In Sweden, taxes, particularly local taxes, are the leading financing source of LTC, covering around 90% of the cost of health and social care (Schön & Heap, 2018; European Commission, 2019). In the UK, funding comes primarily from general taxation, based on a mix of central and local taxes (European Commission, 2019).

³Please see other criteria applied on European countries on the MISSOC, the "Mutual Information System on Social Protection" available at <https://www.missoc.org/>.

Table 2.3: Countries LTC type of financing, public sources, main benefit, and OOP rule applied.

Country	Type of financing	Public sources of the financing	Main benefit applied	OOP rule
Australia	Tax-based	General taxation (Commonwealth of Australia, 2021)	In-kind (Commonwealth of Australia, 2021)	Income and assets (Commonwealth of Australia, 2021)
Austria	Tax-based (mix)	Social care: General taxation (Florian et al., 2018) Health care: Social Health Insurance (Fink, 2018)	In-cash (European Commission, 2019)Fink (2018)	Income (Florian et al., 2018)
Belgium	Tax-based (mix)	Social contributions. General taxation (European Commission, 2019)	In-kind (European Commission, 2019)	Income and degree of care (European Commission, 2019)
Canada	Tax-based	General taxation (Woolley, 2023)	In-kind (Flood et al., 2021)	Income and assets (Woolley, 2023)
Czech Republic	Tax-based (mix)	Social care: General taxation. Health care: Social Health Insurance (Jiráková, 2018)	In-kind (European Commission, 2019)	Income (European Commission, 2019)
Denmark	Tax-based	General taxation (Kvist, 2018)	In-kind (European Commission, 2019)	Income (Roostgard & Langins, 2021)
Estonia	Tax-based (mix)	General taxation. Social health insurance (Paat & Merilain, 2010; European Commission, 2019)	In-cash (European Commission, 2019)	Income (Lannes & Tarum, 2020)
Finland	Tax-based	General taxation (Kalliomaa-Puha & Kangas, 2018)	In-kind (Johansson, 2010)	Income (European Commission, 2019)
France	Tax-based (mix)	Social contributions and taxes (Blanche Le Bihan, 2018)	In-cash (Arrighi et al., 2015)	Income (European Commission, 2019)
Germany	Social insurance	Social insurance: payroll taxes (Gerlinger, 2018) Social care: General taxation (Federal Ministry of Health, 2017)	In-cash (Federal Ministry of Health, 2017)	Degree of care and type of benefit (Gerlinger, 2020)
Greece	Tax-based (mix)	General taxation. Social Health insurance (Ziomas et al., 2018)	In-kind (OECD, 2011)	Income and assets (Economou, 2018)
Hungary	Tax-based (mix)	Social care: General taxation. Health care: Social Health Insurance (Gal, 2018)	In-kind (European Commission, 2019)	Income and assets (European Commission, 2019)
Ireland	Tax-based (mix)	General taxation. Payroll taxes (European Commission, 2019)	In-kind (European Commission, 2019)	Income and assets (European Commission, 2019)
Italy	Tax-based	Health and Social care: General taxation (Matteo et al., 2018)	In-cash (Matteo et al., 2018)	Income (Gori et al., 2016)
Japan	Social insurance	Social contributions. General taxation (Yamada & Arai, 2020)	In-kind (Shimizutani, 2014)	Income (Lin & Imanaka, 2020)

Table 2.3: Countries LTC type of financing, public sources, main benefit, and OOP rule applied (cont.)

Country	Type of financing	Public sources of the financing	Main benefit applied	OOP rule
South Korea	Social insurance	Social Health insurance. General taxation (Jeon & Kwon, 2017)	In-kind (Jeon & Kwon, 2017)	Income (Jeon & Kwon, 2017)
Latvia	Tax-based (mix)	General taxation (Gulbe, 2010)	In-kind (European Commission, 2019)	Income (European Commission, 2019)
Lithuania	Tax-based (mix)	General taxation. Social Health insurance (European Commission, 2019)	In-kind (European Commission, 2019)	Income and assets (Marcinkowska, 2010)
Luxembourg	Social insurance	Social contributions. General taxation (European Commission, 2019)	In-kind (Luxembourg Government, 2023)	Income and assets (The Government of Grand Duchy of Luxembourg, 2023)
Netherlands	Social insurance	Social insurance: payroll taxes. General taxation (European Commission, 2019)	In-kind (Kelders & de Vaan, 2018)	Income and assets (European Commission, 2019)
Norway	Tax-based	General taxation (Grødem, 2018)	In-kind (Grødem, 2018)	Income (Grødem, 2018)
Poland	Tax-based (mix)	General taxation. Social Health insurance (Costa-Font & Raut, 2022)	In-kind (European Commission, 2019)	Income (Costa-Font & Raut, 2022)
Portugal	Tax-based (mix)	General taxation. Social gambling and betting. Payroll taxes (Lopes et al., 2018; Cardoso, 2019)	In-kind (European Commission, 2019)	Income and assets (Instituto da Segurança Social I.P., 2019)
Slovak Republic	Tax-based (mix)	Social care: General taxation. Health care: Social Health Insurance (Schmahl, 2022)	In-kind (Schmahl, 2022)	Income (Gerbery & Bednárík, 2018; Schmahl, 2022)
Slovenia	Social insurance	Social insurance: payroll taxes. General taxation (Poldrugovac, 2023)	In-kind (Euro Careers, 2023)	Income and assets (European Commission, 2019)
Spain	Tax-based	General taxation (Rodríguez-Cabrero et al., 2018)	In-kind (European Commission, 2019)	Income and assets (Rodríguez-Cabrero et al., 2018)
Sweden	Tax-based	General taxation (Schön & Heap, 2018)	In-kind (Schön & Heap, 2018)	Income (European Commission, 2019)
Switzerland	Tax-based (mix)	Social care: General taxation. Health care: Social Health Insurance (Trein, 2018)	In-kind (Trein, 2018)	Income and assets (Costa-Font & Raut, 2022)
United Kingdom	Tax-based	General taxation (European Commission, 2019)	In-kind (European Commission, 2019)	Income and assets (Glendinning, 2018)
United States	Tax-based (mix)	Medicaid: Tax revenue. Medicare: payroll taxes (Howes, 2018)	In-kind (Medicaid.gov, 2023)	Income (Medicaid.gov, 2023)

Note: Social health insurance: financing scheme defined by the government with the aim to become a source of revenue for health financing. It could be from employers' contributions, and by law, it is mandatory to make these contributions. Social contributions: contributions shared by the employee and the employer, which will be used for public benefits. General taxation: general taxes are collected by governments to ensure the provision of public services (to protect human rights). Payroll taxes: a defined percentage that comes from an employee's salary, and governments use it to fund public programs. Social long-term care insurance is a compulsory insurance system funded by the defined contributions of workers and their employers. It aims to provide quasi-universal coverage. Latvia's type of financing derives from the European Observatory on Health Systems and Policies (2022), which attributes two sources of financing: State budget and local governments.

Health care provided by the National Health Service (NHS) is mainly financed by taxation and, in a minor part, by income taxes from employers and employees (Costa-Font & Courbage, 2012; Cylus et al., 2015).

A second group of countries adopts a mix of sources to finance LTC expenses, using mostly taxes but also other financial contributions. The USA uses general Federal and State revenues to finance Medicaid - the national LTC program that pays 44% of long-term care services and support, but payroll income taxes from both employers and employees and, in a smaller percentage, general Federal revenues also finance Medicare Part A and B, which pays for 23,4% of LTSS (Rice et al., 2020). Austria has a LTC policy that is structured around health and social care. General taxes finance social care and a social health insurance scheme finances health care (Florian et al., 2018). France is an example of a public LTC tax-based mix scheme financed by social security funds (Costa-Font & Courbage, 2012). APA (Allocation Personnalisée à l'Autonomie), the primary French LTC policy, is financed by local general taxes and by the National Solidarity Fund for Autonomy, which is funded by employees' social insurance contributions and taxes (Joel et al., 2010). Finally, Portugal's LTC policy of the Rede Nacional de Cuidados Continuados Integrados (RNCCI) is financed jointly by the State Budget of Health and Social ministries (financed by general and local taxation) and by the profits from social gambling and betting (Lopes et al., 2018; Costa-Font & Courbage, 2012).

The last group includes countries that finance LTC policies mainly through social LTC insurance systems. In the Netherlands, the country that first introduced a specific public LTC insurance, the financing source is contributions to a separate system for long-term care. The Long-term Care Act is a statutory social insurance scheme financed by income-dependent payroll tax premiums. Germany has a separate social insurance program to attend to LTC needs that is financed through income-related contributions (payroll taxes) (Bakx et al., 2015). Germany also uses tax revenues to cover social assistance costs (Federal Ministry of Health, 2017). Social insurance schemes have also been adopted in Japan and South Korea. Japan divides the financing of LTC costs by social insurance contributions determined based on income (45%), general taxation (45%; the national government pays 25%, prefecture 12,5%, and municipalities 12,5%). South Korea has a mandatory social premium contribution to finance 60-65% of LTC costs and complements the financing with tax subsidies to pay for another 20%.

LTC benefits to help deal with ADLs, IADLs, and social needs are usually divided into in-kind and in-cash types (see Table 2.3 column 4). In-kind benefits are services delivered directly to the beneficiaries, while cash benefits consist of money allowances given by public entities. Ikegami & Campbell (2002) identified the pros and cons of both types. In-kind benefits have the advantage of not imposing limitations on the number of treatments. Only professionals can decide what is needed, and the out-of-pocket purchase of additional services is restricted. However, difficulties related to the definition of the available care services, cost control, fairness in access, and the distribution of the services and co-payments are common. Cash benefits give users the freedom to choose the providers and type of care but have the disadvantage of being a financial source not only for the elderly in need but (also) for the entire household, creating incentives for manipulation of the level of informal care provided. Except for Japan, where only in-kind benefits are provided, all analyzed countries combine in-kind and cash transfers. Austria, Estonia, France, Germany, and Italy rely more on cash than in-kind benefits.

Table 2.3 also lists the adopted out-of-pocket rules. The government adopts out-of-pocket contributions to complement and limit public financing sources, to reduce unwarranted use of care by controlling the moral hazard, to reduce the welfare losses from public financing, and to regulate access to LTC services and programs (Manning & Marquis, 1996; Pozo-Rubio et al., 2020; Tenand et al., 2021). In all covered countries, users must co-finance their care needs. Out-of-pocket payments are mandatory even in countries with the highest public LTC expenses as a share of GDP (e.g., Netherlands, Sweden). Each country defines the rules regulating out-

of-pocket payments according to different user earnings parameters. We can group countries based on LTC out-of-pocket payments as follows: i) countries that only consider users' income accounting the household earnings (USA, Austria, Czech Republic, Italy, Japan, and Sweden); ii) countries that consider users' income and assets, including financial assets, properties and investments (Portugal, Spain, Netherlands, United Kingdom, and Lithuania); iii) countries that consider only the needs and the services required. Germany defines the amount to be paid by users based on user vulnerability level, specifically depending on the total cost of their care and their level of need (Curry et al., 2019; Brugiavini et al., 2017).

2.5 Funding LTC: public and private options

Long-term care needs are one of the main financial risks faced by the elderly (Bueren, 2023). Previous research has identified that long-term care has been financed through a mix of public and private funds that balance the nature and extent of risk-pooling (Wittenberg et al., 2007). On one side, public support is provided through the definition of LTC programs, funding sources, the provision of services, and the mix of in-kind and in-cash benefits. On the other side, the elderly finance their own needs or pool LTC needs by contributing to public schemes, using private funds such as out-of-pocket payments, own savings, housing equity, and purchasing voluntary private insurance policies. Generically, the LTC costs are covered by the combination of public sources, users' own means and private insurance. The discussion of LTC financing is still an open issue and more research is needed. The uncertainty on the length of care that needs to be provided, the high cost of the required services, and the ideal combination between formal and informal care are just some of the dimensions that require further analysis (Gori, 2019).

The bulk of LTC is informal and provided by close family and relatives, having an indirect effect on public finances (Cremer et al., 2012). The level of family support impacts labor market participation and health and financial costs for caregivers, being unequally prevalent across countries. New issues arise if the option to finance and provide care is mainly delegated to the informal care component because family care is not a "free lunch" and associated costs emerge from it.

Governments provide support and benefits financed by general tax revenues and social insurance schemes funded by payroll contributions. Care is supplied based on needs-based but also depending on income and assets rules to guarantee principles of public financial sustainability and equality (Wittenberg et al., 2007)⁴.

Individuals may use their savings to fund their LTC, namely financial investments, housing equity value, and social and private pensions (Wittenberg et al., 2007). Accumulated savings to cover care costs can be inefficient due to the uncertainties about costs, the incidence and degree of need, and the possibility of lowering the current household's consumption. When countries apply mean-tested eligibility rules or limit State pensions, higher personal savings can make the person ineligible to be covered by public insurance, pushing individuals to rely even more on their savings to pay for their future care needs (Costa-Font, 2010; Costa-Font & Courbage, 2015; Comas-Herrera, 2020).

Voluntary private long-term care insurance (LTC insurance) has been studied for the last thirty years as a substitute or complement to public LTC insurance. Private insurance can be triggered after a medical assessment confirms impairments and associated needs. The benefit is collected either by cash that directly finances the expenditures on care or by reimbursement of incurred LTC costs. However, very little private LTC insurance is currently purchased. France and the USA are the two most important markets for voluntary private long-term care insurance. Still, in the USA, in 2010, only about 11% of the population aged 55 and older was covered

⁴To complement this information, please see Table 2.3

by private LTC insurance (Hirth et al., 2019). In France, 15% of people aged over 40 years hold private insurance (Mosca et al., 2016). In Germany, only 4% of the population purchased additional private LTC insurance to supplement their mandatory public LTC insurance coverage (Nadash et al., 2017). This financial mechanism is nearly absent in other countries.

Previous studies have identified supply and demand factors that justify the low uptake of private LTC insurance. From the supply side, high prices of LTC insurance policies, the difficulty to insure inter-temporal risks with a high lag between the insurance taking and the (unpredictable) use of the policy benefit, asymmetric information between insurance company and beneficiary, imperfect competition in the insurance market, and high administrative costs, are all recognized factors that explain the low purchase (Pestieau & Ponthière, 2010; Van Houtven et al., 2015; Klimaviciute, 2017; Klimaviciute & Pestieau, 2020). On the demand side, some social-demographic features likely contribute to the decision to purchase insurance. Being a woman, higher income, higher education, and having expectations about worse future health conditions explain a higher demand for LTC insurance. Low demand for LTC insurance is related to other factors, such as individual misjudgment of the probability of becoming dependent, poor information about long-term care insurance coverage and misunderstanding and expectation to be eligible for government support, the option for self-insurance by using their savings, and trust into family solidarity (Brown & Finkelstein, 2007; Pestieau & Ponthière, 2010; Costa-Font, 2010; Van Houtven et al., 2015).

In sum, the economic theory explains that the low purchase of LTC insurance is associated with two information problems that lead to adverse selection and moral hazard. Adverse selection is mainly related to the trade-off between purchasing a private policy and getting public insurance support, e.g., social insurance can act as a reason to avoid purchasing private insurance (Sloan & Norton, 1997). Pauly (1990) discusses a particular form of moral hazard in private long-term care insurance - the intra-family moral hazard (Please see Subsection 2.5.1).

2.5.1 Intra-family moral hazard: theoretical and empirical findings

Pauly (1990) explains that rational older people may not demand LTC insurance due to intra-family moral hazard (IFMH). He suggests that the children can have lower incentives to become caregivers if the parents own a private LTC insurance policy. Children put less effort into providing care, pushing for formal care services, such as nursing home care, whose costs are covered by insurance. On the other side, parents prefer to be cared for by their informal network, which includes their children. Hence, they refrain from purchasing private insurance to cover LTC costs and strategically use bequests to influence and incentivize children to care for them.

Studies on intra-family moral hazard found divergent results depending on the nature of insurance benefits, the motives to supply informal care, and the context under analysis (Courbage et al., 2018b). Building on Pauly (1990), Zweifel and Strüwe constructed a theoretical model based on a principal-agent framework, highlighting an inter-generational interaction where the parent is the principal trying to control the agent's (the child) behavior. Zweifel & Strüwe (1996) mentioned two instruments used by parents to shape inter-generational relationships: bequest and LTC insurance. They concluded that when the parents use both instruments to control the child's effort, they purchase less LTC insurance. Zweifel & Strüwe (1998) concluded that the amount of care the children provide, specifically those with lower wage rates, decreases when parents purchase an additional unit of LTC insurance. An ambiguous effect was found when the children's wage exceeded the net price of formal services used to cover LTC needs. Courbage & Zweifel (2011) developed a two-sided inter-generational moral hazard model, where the parent and the child are modeled as players in a non-cooperative game. The parent decides the amount of LTC insurance and the child's caregiver effort. Parents value final wealth for their use but also value the wealth transfer to the child, possibly conditional on the amount of received caregiving. From the child's perspective, LTC insurance could protect parents' final

wealth. Klimaviciute (2017) compared fixed and proportional insurance benefits and concluded that IFMH is limited when the benefits were fixed, i.e. the child reduces the care provision less drastically⁵.

Xu & Zweifel (2014) examined whether data from China support the theoretical predictions derived in Courbage & Zweifel (2011). They confirmed the existence of bilateral inter-generational moral hazard in which parents purchased less LTC coverage if the child made more effort. Mellor (2001) concluded that expectations of receiving family care appeared to deter the poorest individuals from purchasing insurance in the USA. In contrast, these expectations did not affect those with higher wealth and potentially higher bequests. In France, Courbage & Roudaut (2008) found no evidence of IFMH, given that individuals purchased LTC insurance not only to preserve bequests and income but also to reduce the burden on potential informal caregivers. Courbage et al. (2018b) compared Spain and Italy’s public insurance schemes⁶, showing that, in Italy, public LTC insurance had a positive impact on informal care, but the opposite was found in Spain. Regarding the effect of private LTC insurance on informal care, significant opposite results were also found for the two countries, but only when informal care was defined as informal care for IADL. In that case, private LTC insurance positively impacted the reception of informal care in Italy and negatively in Spain.

2.5.2 Privately insured LTC costs: how do older couples decide?

Pauly (1990) explained that “the elderly with a surviving spouse sharing the same household” is a more complex case as “impoverishing one’s spouse, rather than one’s children, seems to be the major fear of many married elderly”. The study of couples’ decision to insure LTC costs has been scarce and has mainly adopted a more traditional perspective of a bargaining process between the two spouses (Tennyson et al., 2022), although some studies assumed that LTC insurance purchase was a joint decision (Hirth et al., 2019).

Klimaviciute (2019) proposed a theoretical model of LTC decision in the context of elderly spouses, arguing that financial decisions such as acquiring private insurance influence both spouses’ level of wealth and their ability to cover LTC costs. In that context, deciding to purchase insurance is a couple’s decision, but with specific effects on each individual. Joint LTC policies are a possible insurance option, modeled by Zweifel (2020). A simultaneous decision to acquire LTC insurance between the older member of the couple and the partner seemed to mitigate the IFMH effect.

Caro et al. (2010) showed that the primary respondent⁷ odds of LTC insurance uptake are positive and significantly related to both spouses nursing home expectation, higher education level, and higher net worth and income. Haag (2020) studied whether a spouse is a substitute for LTC insurance coverage. Using cross-section data from the USA Health and Retirement Study (HRS), the author found that marriage significantly impacted individuals’ decision to purchase LTC insurance, being more of a complement than a substitute for LTC insurance. Tennyson et al. (2022) used panel data from the HRS to capture the spouse’s relative influence on the household’s decision to purchase LTC insurance, concluding that the respondents’ probability of having LTC insurance coverage was higher when they were older, had more education, a higher level of net wealth, were retired, and had health insurance coverage. Moreover, if the husband had the “final say”, the likelihood of LTC insurance purchase was lower for the couple and specifically for the wife.

⁵Fixed LTC benefit type is typical in the French market, and it is characterized by fixed monthly cash benefit insurance payments, which start being paid after the insured is medically recognized as dependent. It can be used in any way the beneficiary decides, even transferred to the family. Proportional benefits reflect the LTC insurance benefits prevalent in the USA, where they take the form of reimbursement for incurred LTC expenditures.

⁶In Spain, the public benefit is predominantly in-kind, and in Italy, it is in cash.

⁷Primary respondents are those who, between the two couple members, answered the surveys’ financial questions.

2.6 Concluding remarks

Researchers have been showing increased interest in the study of LTC, but many key topics are still puzzling. The weak private financing market and public policies' comprehensiveness are two of them. LTC is financed and provided through different mechanisms across the world. Individual choices are closely related to personal, household, family, cultural, economic, and the range of welfare policies ruling in each country. Different orientations regarding LTC organization, financing mechanisms, and eligibility rules yield heterogeneous systems with specific institutional features. Given the aging population, the expected change in the supply of informal care, the low uptake of private LTC insurance, the heterogeneous public investment in LTC, as well as the issues around financing, organization, and provision of LTC to all citizens are crucial topics for academics and policymakers.

We reviewed the different financing sources adopted by countries to understand the role of public intervention and how each country calls individuals to contribute to their own LTC costs. Governmental rules on how much individuals should contribute to finance their LTC costs are distinctive features of LTC systems. Previous research revealed that private LTC insurance may be an essential financial tool to cover LTC costs. However, related factors have been identified as determining insurance demand and supply, some deriving from intra-family behavior. Under the contemporaneous dynamics of social, demographic, and familiar systems, characterized by higher life expectancy, health-related factors associated with the longevity of the population, lower number of children, who also live further away from their parents, the decision to finance and provide LTC has to be framed within the two spouses dynamics.

We acknowledge that there are several unexplored research issues within the economics of LTC. First, researchers should apply formal bibliometric methods to analyze bibliographic inputs. Second, researchers should use software or formal methods to develop, group, and summarize the existing research. Third, our review found diverse issues and open questions among the theoretical and empirical literature. In this thesis, we focus mainly on those related to policies and insurance.

Chapter 3

Clustering long-term care policies

3.1 Introduction

Increased longevity triggered novel economic and social challenges, such as higher levels of old-age dependency and the need for specialized services for the elderly (United Nations, 2019). Individuals with disabilities need long-term care (LTC) services to tackle chronic diseases or other physical or mental limitations for extended periods, placing additional pressure on support systems.

LTC is increasingly important in facing these challenges. In the USA, almost 56% of people 65 years or older develop a disability that requires LTC services for, on average, three years. For 22% of those, that need lasts even longer (Johnson & Dey, 2022). Aging, together with changes in family structure, such as higher female labor force participation, prompted the emergence of more institutionalized providers of care that can replace family and friends as the main source of LTC, even in countries where filial duty is culturally strong. Addressing this potentially unaffordable and uninsurable "new social risk" requires a more structural approach, distinct from the ones used for the "old social risks" - poverty, unemployment, and health (Ranci & Pavolini, 2013; Comanje, 2014).

LTC policies are very diverse across countries. Each country has defined its LTC strategy according to intrinsic cultural, institutional, social, health, and economic norms and constraints. LTC choices yield variations in services, access rules, supply organization, funding sources, and governance structure. Still, regardless of this heterogeneity, it is possible to distinguish clusters of countries with similar LTC approaches.

In this paper, we address some of the limitations faced to cluster LTC policies, such as methodological vulnerabilities and limited comprehensiveness of included variables and countries. We review the proposed LTC clustering typologies resulting from different methodological and institutional approaches and discuss the robustness and stability of the identified clusters, as well as the need to include other demographic, financial, and organizational factors. We then propose a typology of LTC policies that covers more countries and includes more variables, using a clustering ensemble model that combines three unsupervised clustering methods - Fuzzy c-Means (FCM), Self-Organizing Maps (SOM), and Partitioning Around Medoids (PAM). We select the optimal cluster partitioning from each method (FCM, SOM, PAM) based on a plethora of internal and external criteria. We finally use Tukey's 'Honest Significant Difference' method to validate seven significantly differentiated and independent clusters.

This paper is organized as follows: next, we review the different proposals of LTC typologies, with a particular focus on those that use clustering techniques. Section 3.3 describes the applied clustering method techniques (FCM, SOM, and PAM) and internal and external evaluation criteria. In section 3.4, we present the methodology, data, variables, and descriptive statistics. Section 3.5 discusses the results, followed by robustness checks. We conclude by discussing our main findings.

3.2 Literature review

World Health Organization (2021b) states that a "long-term care system encompasses all organizations, people and actions aiming to promote, maintain or improve well-being, health and functional ability for individuals with limitations in intrinsic capacity". Across countries, LTC policies diverge in the adopted financing mechanisms, the criteria applied to determine who benefits and the type of benefits provided, and the nature of formal and informal care structure that supports individuals with limitations. We found thirty-four papers clustering LTC policies published between 1998 and 2022, covering sixty-one world countries, mainly from Europe. Several different LTC policy typologies were proposed, highlighting the difficulty in identifying consistent similarities across countries¹.

The proposed LTC typologies can be summarized according to different perspectives such as: i) based on the welfare policies, such as social insurance and health care systems (e.g. Pacolet et al. (1998); Lamura et al. (2007); Camacho et al. (2008); Greve (2017)); ii) based on the Colombo et al. (2011) which distinguished countries according to whether the entitlement to LTC benefits is universal or means-tested and whether LTC coverage is through a single system, or multiple benefits, services and programs. This approach was followed by several authors such as Feng & Glinskaya (2019), Barber et al. (2021), and Karagiannidou & Wittenberg (2022); iii) based on the Kraus et al. (2010), which highlighted the need to adopt methodological advancements on clustering study; iv) clusters based on the use of formal care (European Commission, 2013); v) based on the actors involved, highlighting the role of family and public entities (Fuino et al., 2020) and vi) based on the countries LTC labor market and the migrants' role (Simonazzi, 2009; Bettio & Verashchagina, 2012; Leone et al., 2014).

3.2.1 Clustering analysis on study LTC policies

Clustering methods were applied in only eight of the thirty-four papers (23,53%): Kautto (2002), Lamura et al. (2007), Kraus et al. (2010), Saraceno & Keck (2010), Damiani et al. (2011), Halásková et al. (2017), and Ariaans et al. (2021)².

Kautto (2002) clustered LTC policies according to the availability of in-kind and in-cash benefits. Three different LTC clusters were identified using analysis of boxplots, hierarchical clustering, and K-means: a "service approach", characterized by high service intensity and average or high cash transfers; a "transfer approach", characterized by high cash transfers, and average or low service; and a residual "third group", characterized by low service and low cash transfers.

Lamura et al. (2007) applied hierarchical clustering to twenty-one European countries, using as criteria health-related demand for care, socioeconomic needs, and (in)formal care provision. Five clusters were established: i) "standard care mix", characterized by medium formal and informal care provision and medium demand; ii) "public Nordic", with lower availability of informal care but a more robust public formal care; iii) "family-based", which attributed higher risk of poverty in older age and low public effort; iv) "transition", characterized by higher informal care availability, and lower income inequalities; and finally v) "Baltic", with a higher propensity for private care.

Kraus et al. (2010) derived two typologies from two distinct cluster analyses. The first applied the K-means clustering algorithm to variables related to the organization and financing of the provision of LTC. Four clusters were identified, covering twenty-one countries: Cluster 1 - Scandinavian and Continental countries, characterized by profound organizational depth and high levels of financial generosity; Cluster 2 - Intermediate case, characterized by medium organizational depth and medium financial generosity; Clusters 3 and 4 share low levels of

¹In Appendix 3.8.1 we present a synthesis of these publications, the respective cluster attributed to each country, and the main used methods.

²Kraus et al. (2010) includes two distinct typologies.

financial generosity, but differ significantly in terms of organizational depth, more developed for Cluster 3. The second typology focused on the financing and use of care. A factor analysis was performed to select the main factors, and K-means clustering with Euclidean distance was applied. The following clusters were identified: Cluster 1 included countries with low share of private LTC spending, high informal care use and support, and low public spending to elderly; Cluster 2, countries with low share of private LTC spending, low informal care use and high support, high public spending to elderly; Cluster 3, countries with high share of private LTC spending, high informal care and support, medium public spending to elderly; and Cluster 4, countries with high share of private LTC spending, high informal care use and low support, low public spending to elderly.

Saraceno & Keck (2010) built on the fuzzy-set configuration of elderly social policies. Countries were ranked according to the relative distribution of minimum non-contributory pension as a share of average net income and people in institutional care as a share of the population 65+. Four groups were identified: i) high degree de-familism and high minimum pension, ii) low degree de-familism and high minimum pension, iii) high degree de-familism and low minimum pension, and iv) low degree de-familism and low minimum pension.

Damiani et al. (2011) studied twenty-seven European countries using a multiple-factor analysis (MFA) that included the alignment between old age-related expenditure and elderly needs and level of formal care. Four clusters emerged: Group 1 - High alignment between old age-related expenditure and elderly needs and low formal care; Group 2 - Low alignment between old age-related expenditure and elderly needs and inadequate formal care; Group 3 - High alignment between old age-related expenditure and elderly needs and high formal care, and Group 4 - Low alignment between old age-related expenditure and elderly needs and high formal care.

Halásková et al. (2017) evaluated the provision and financing of long-term care using data from 2008 and 2013 for selected OECD countries. Three clusters were defined using principal component analysis and two-step cluster analysis, combining non-hierarchical (K-means) and hierarchical cluster analyses: Cluster 1 had the lowest total LTC expenditures as a percentage of GDP and the highest expense in institutions; Cluster 2 also had lower LTC expenditures as a percentage of GDP, high expenditures in institutions, and lower values in the total number of LTC recipients aged 65+ as a percentage of total LTC recipients; Cluster 3 had the highest total number of LTC recipients aged 65+ as a percentage of total LTC recipients and the highest total LTC expenditures as a percentage of GDP. The quality of the clusters was assessed by Silhouette measure of cohesion and separation.

Finally, Ariaans et al. (2021) innovated by considering both quantitative and institutional data and by adopting multi-cluster analysis, instead of single-cluster, based on K-means partitioning and agglomerative analysis, using either z- or range-standardized variables, Gower and squared Euclidean distance as measures of dissimilarity, as well as average and Wards algorithm as linkage methods. The first and second-best results were selected by the stopping rules of Caliński-Harabasz, Duda-Hart, and Dendrograms. Two cluster solutions were proposed, clustering OECD countries around nine or six clusters. The latter contained: Cluster 1: Residual public system; Cluster 2: Private supply system; Cluster 3: Public supply system; Cluster 4: Evolving public supply system; Cluster 5: Need-based supply system; and Cluster 6: Evolving private need-based system.

In sum, our review highlighted the opportunity to contribute to this literature by studying LTC policies beyond their welfare characteristics. As referred by Timonen (2005), "Welfare State classifications are of limited usefulness in trying to understand variation among systems of long-term care, because the field of social care is argued to be inherently more complex and varied". Additionally, we verified that studies adopted extensive use of qualitative, institutional-based, and descriptive methods, which are complex and subjective by nature, but limited use of quantitative methods and robust empirical strategies. Kraus et al. (2010) and Ariaans et al. (2021) highlighted the need to study LTC systems using a more complete approach that uses

both qualitative and quantitative information. Fischer et al. (2021) also pointed to the need to properly tackle methodological issues, such as the lack of transparency in the specification of criteria and underlying procedures and methods. It is now widely accepted that new methods to perform comprehensive LTC policy clustering are needed. The scarce usage of clustering methods in studying LTC policies has been attributed to the limited availability of quantitative data, particularly data that can be easily compared across countries.

3.3 Cluster analysis

Data clustering, or cluster analysis, is an optimization technique that finds a coherent organization of objects in a given dataset by identifying and quantifying similarities or dissimilarities between objects (Wu et al., 2015; Hashemi et al., 2023). It assesses if the objects can be summarized meaningfully in a relatively small number of groups or clusters, identifying k groups based on a chosen measure of similarity such that the similarities are high among the objects in the same group and low across objects in different groups (Duda et al., 2001). Jain (2010) identifies three main applications for cluster analysis: i) underlying data structure, helping to gain insight into data, generate hypotheses, detect anomalies, and identifying salient features; ii) natural classification by distinguishing the degree of similarity among data, forms or organisms, and iii) compression data, which is used for organizing and summarizing the data through cluster prototypes. As a significant branch of unsupervised learning, cluster analysis does not require external knowledge of types or category labels, managing only unlabeled data. The absence of category information distinguishes it from classification or discriminant analysis, both used in supervised learning (Jain, 2010).

Cluster analysis techniques can rely on different methods: hierarchical, partitional-based, density-based, and artificial neural networks (Khanchouch et al., 2015; Wierchoń & Kłopotek, 2018).

Hierarchical clustering algorithms are a sequence of partitions that recursively find nested clusters. Starting with all data points in one cluster, it recursively divides them into smaller clusters. It can be done either in agglomerative mode, i.e., from bottom to top, or in divisive mode, i.e., from top to bottom. A dendrogram is a particular type of tree structure that provides a picture of hierarchical clustering, enabling the researcher to see how objects are being merged into clusters or split into successive levels of proximity (Jain & Dubes, 1988; Jain, 2010).

The nonhierarchical methods use partitional clustering algorithms to find clusters as partitions of the data without imposing a hierarchical structure. In the partitioning method, the k is given by the researcher, and the algorithm is run several times with different values of k (Leonard & Rousseeuw, 2005). Algorithms classify the data into k groups, so that each group contains at least one object, and each object belongs to only one group.

The density-based methods define clusters detecting dense regions in the data space. It identifies clusters based on a cloud of points with higher density, where the neighborhoods are defined by a threshold of distance or number of nearest neighbors (Ester et al., 1996). The most used is the density-based clustering algorithm which assumes that regions with high density constitute clusters, each one separated by regions with low density (Leonard & Rousseeuw, 2005).

Finally, the artificial neural networks (ANNs) clustering method consists of layers of nodes that follow an unsupervised, biologically inspired learning approach. Specifically, the interconnected neurons network takes in a set of input data points and then outputs data incrementally based on each input, the weights of the network’s connections and underlying patterns in the data (Polanco et al., 2001; Sarkar, 2018).

In this paper we use three unsupervised clustering algorithms: from the nonhierarchical or partitioning method, we apply Fuzzy c-Means (FCM) and Partitioning Around Medoids (PAM),

and from ANNs, we apply the Self-Organizing Maps (SOM). We present them in the following section.

3.3.1 Fuzzy c-Means

The Fuzzy c-Means (FCM) is a partitioning clustering algorithm first studied by Dunn (1973) and later improved by Bezdek (1973, 1981). The algorithm is based on fuzzy set theory (Zadeh, 1965) that assumes that within a space of points X there is a generic element denoted by x , such that $X=x$. A membership function $f_A(x)$ associates an actual number in the interval $[0,1]$ to each X . The value of $f_A(x)$ at x represents the grade of membership of x in A .

This partitioning algorithm is a soft clustering method because each data point belongs to a cluster with a certain probability, i.e., a membership value. The FCM clustering algorithm finds the optimal solution for clusters by minimizing the objective function by iteratively updating the cluster centers and the membership matrix. It introduces the possibility of every object belonging to different clusters throughout a membership weight between 0 (absolutely doesn't belong) and 1 (absolutely belong). FCM minimizes the weighted within-group sum of squared errors through the coefficient m (Cebeci et al., 2022).

We follow Cebeci et al. (2022) and implement FCM clustering whose overall aim is to minimize the following objective function³:

$$J(\mathbf{X}; \mathbf{U}, \mathbf{V}) = \sum_{i=1}^n u_{ij}^m \|x_i - v_j\|^2 \quad (3.1)$$

subject to the constraints:

$$u_{ij} = [0, 1]$$

$$0 \leq \sum_{i=1}^n u_{ij} \leq n$$

$$\sum_{j=1}^k u_{ij} = 1;$$

$$\text{such that: } 1 \leq i \leq n \quad 1 \leq j \leq k \quad 1 \leq k < n$$

where $\mathbf{X}$ is the set of the selected variables; $\mathbf{U}$ is a membership fuzzy matrix computed from dataset $\mathbf{X}$, such that: $\mathbf{U}=[u_{ij}]$; $\mathbf{V}$ is a vector of cluster prototypes, such that: $\mathbf{V}=[v_1, v_2, \dots, v_k]$; n is the number of objects; k is the number of partitions or clusters and j is the prototype cluster, i.e., is the centroid used as the basis of calculation of distances. u_{ik} is the membership value of i^{th} object belongs to k^{th} cluster; x_i is the data points vector; v_k is the vector of centroids or prototypes. The fuzziness coefficient m specifies the amount of 'fuzziness' of the clustering output showing good results with $1, 5 \leq m \leq 2, 5$ (Wierzchoń & Kłopotek, 2018).

FCM is highly efficient with small-scale data. Issues arise when the dimensions of the problem are large and when the data have many outliers. Slow convergence or divergence results can emerge in the absence of proper initial centers selection (Deng, 2020; Hashemi et al., 2023; Liew et al., 2000). Saraceno & Keck (2010) recognized the fuzzy set characteristics of social policy configurations and highlighted the interest in applying soft algorithms, such as FCM, instead of hard clustering algorithms⁴. FCM is often applied in regional and country typologies, public policies design and government performance indicators (Harris et al., 1993; Huh et al., 2018; Precious, 2020; Kim & Im, 2019), healthcare and medical diagnosis and segmentation (Wu et al., 2015; Krasnov et al., 2023; Setiawan et al., 2023).

³In Appendix 3.8.2, we present how the algorithm is implemented.

⁴The partitioning algorithm of K-means is a hard clustering method because it implies m close to 1 and forces that each point belongs to only one cluster (Wierzchoń & Kłopotek, 2018).

3.3.2 Self-Organizing Maps

The Self-Organizing Map (SOM) neural network, also called Kohonen neural network, is an ANN-based unsupervised learning algorithm (Kohonen, 1997). The SOM reduces high-dimensional data (input layer) into a two-dimensional grid (output layer) using the concept of neurons. It yields an orderly feature map (Polanco et al., 2001; Lu & Segall, 2013) geometrically organized as a grid that retains the natural relationship among input patterns, i.e., similar data are placed next to each other and close data belong to the same or neighboring clusters (Ilbeigipour et al., 2022).

This approach is divided into competitive and cooperative phases. SOM’s competitive and iterative process starts with random weights. The aim is to know which neuron has the closest weighting vector to the input data vector by calculating the linear distance (e.g., Euclidean distance) between the weightings of each neuron and input data several times. A cooperative process follows, based on updating the weighting vectors of the winning and neighboring neurons (topologically close neurons). The SOM can be applied using online and batch algorithms (Kohonen, 2001). The main difference between them is that the update of the winning unit(s) in the online algorithm is done after each object is presented. In contrast, in the batch algorithm, all input data are presented to the neurons and only after the neurons’ weights are updated⁵.

The batch SOM offers several advantages over the conventional online SOM method. According to Kohonen (2013), the batch version does not involve any learning-rate parameter and its convergence is faster and safer. Since the weight updates are not recursive, there is no dependence upon the order in which the input records are presented. The neurons are connected to adjacent neurons by a neighborhood relationship, defining a map’s structure, which most commonly is 2-dimensional grids under hexagonal and rectangular typologies. Under the latter, a neuron has four one-neighbor neurons, while under the former, a neuron has six one-neighbor neurons. Kohonen (2001) highlighted that the hexagonal lattice for mappings yields more stable, well-oriented, and less ambiguous results.

Kohonen (2013) mentioned the main application areas of the SOM method: geosciences and geospatial analysis (Bação et al., 2005; Duarte et al., 2023), spatiotemporal diffusion patterns (Augustijn & Zurita-Milla, 2013), hospital, health and medical decision-making (Basara & Yuan, 2008; Wickramasinghe et al., 2011; Pourkia et al., 2019; Ilbeigipour et al., 2022), environmental studies (Vlaovic et al., 2023), planning and political sciences (Chung et al., 2018; Karaatli et al., 2020), and grouping countries (Melin et al., 2020).

3.3.3 Partitioning Around Medoids

Leonard & Rousseeuw (2005) proposed a clustering procedure called Partition Around Medoids (PAM) or k-medoids algorithm. PAM applies a partitioning (clustering) of the data into k clusters based on “around medoids” (Maechler, 2022). To obtain clusters, the PAM method selects objects (called representative objects) in the dataset $X = x_1, x_2, \dots, x_N$ with N data points. Instead of taking the mean value of the object in a cluster as a reference point (as occurs in the case of K-means), PAM uses the medoid, which is the most centrally located object in a cluster (i.e., is a point in the cluster whose dissimilarities with all other points in the cluster is minimum).

The PAM algorithm consists of two phases. In the BUILD phase, an initial clustering is obtained by the successive selection of representative objects. In the SWAP phase, the goal is to improve the set of representative objects and, therefore, the clustering. All possible combinations of representative and nonrepresentative points are analyzed, and the quality of the

⁵In this case, all samples are presented, the distance values of each winning neuron are stored and the average is calculated. Only then is the weight value of each neuron updated (Wehrens & Kruisselbrink, 2018). That process is repeated a certain number of times. Please see Appendix 3.8.3 for a description of how the algorithm is implemented.

resulting clustering is calculated for each pair. A cost function is derived C which includes the sum of costs incurred when a nonrepresentative point replaces a representative point (Leonard & Rousseeuw, 2005; Jin & Han, 2016). The PAM objective function relates to C as the sum of the distances from each object to its closest medoid:

$$Cost = \sum_{i=1}^N \min_{1 \leq j \leq K} D(x_i, m_j) \quad (3.2)$$

where x_i are data points to be clustered with $X = x_1, \dots, x_N$, m_j are the medoids such that $M \subset X$, K is the number of clusters, D is the distance metric from each object x_i to its nearest medoid m_j ⁶.

The PAM method is more efficient for small datasets. Medoids are robust representations of the cluster centers and are less sensitive to outliers (because extreme values easily influence a mean) than other cluster profiles, such as the cluster means of K-means. It is particularly more appropriate for cases when the data are fuzzy, and both continuous and categorical variables coexist (Botyarov & Miller, 2022; Maechler, 2022; Setiawan et al., 2023). It has been used in health care research (Mushtaq et al., 2018; Shokri et al., 2023), world countries index (Wang et al., 2023a), and operations research, particularly in the choice of location of service centers (Wierzchoń & Kłopotek, 2018).

3.3.4 Principal Component Analysis applied to the clustering methods of FCM, SOM, and PAM

Principal component analysis (PCA) is a mathematical technique developed by Karl Pearson as a descriptive and data-reduction method (Jolliffe, 2002). PCA transforms the original set of correlated variables (p) into a linear combination of a set of pairwise mutually orthogonal or uncorrelated variables, the principal components, that account for most of the variance of the original set (m), such that $m < p$ (Jolliffe, 2002; Cangelosi & Goriely, 2007). The principal components are ordered so that the first principal component explains most of the data variance. Subsequent components embody the linear combinations that explain the maximal sample variance not explained by the previous combinations. As long as they remain orthogonal, the variables do not have a relationship amongst them (Cangelosi & Goriely, 2007).

Cumulative percentage of total variation is a criterion applied to determine the number of the principal components selected (Jolliffe, 2002). Each eigenvalue represents the level of variation explained by the associated principal component (PC), and the number of PCs is the smallest value of m for which the cumulative percentage varies between 70% or 90% (Jolliffe, 2002).

PCA has been applied in diverse fields such as ecology, economic geography, and regional analysis, determining clusters of industries and agglomeration economies, finance, psychology, meteorology, oceanography, health care, and zoology (Cangelosi & Goriely, 2007; Pääkkönen & Seppälä, 2014; Marques & Alves, 2020; Tsoulfidis & Athanasiadis, 2022; Setiawan et al., 2023). Menger et al. (2019) applied PCA with clustering ensemble modeling, and previous studies use PCA with FCM (Wang et al., 2019; Setiawan et al., 2023), SOM (Daneshpajouh et al., 2017; Ahmad et al., 2019), and PAM (Irwansyah et al., 2020; Ramadan et al., 2020).

3.3.5 Optimal number of clusters and similarity of sets

The evaluation of clustering methods involves determining the optimal number of clusters and the partitions that best feature the data (Jain & Dubes, 1988). To get the optimal result, clustering validity indexes are built based on clusters' compactness and separability. While compactness measures the closeness of the cluster elements, separability measures how distinct

⁶Please see Appendix 3.8.4 for a description of how the algorithm is implemented.

or well-separated a cluster is. Clustering validity combines both criteria and is assessed by internal and external measures.

The internal clustering evaluation measures how the clustering obtained from an algorithm fits the data and the clustering is compared only with the result itself. The external criteria validate the clustering output by comparing the degree to which two partitions of n objects agree with each other (Jain & Dubes, 1988).

In this essay, we apply the internal criteria of Silhouette Width (Rousseeuw, 1987), Caliński-Harabasz Index (Caliński & Harabasz, 1974), Davies-Bouldin Index (Davies & Bouldin, 1979) and Dunn Index (Dunn, 1973). For external validity, we apply Simple Matching, Rand Index, Hubert and Arabie adjusted Rand Index, and Jaccard Index⁷.

For each observation i , the Silhouette Width (SW_i) is calculated based on the difference between a_i (the average distance of observation i to other points in the cluster) and b_i (the minimum average distance to points in another cluster), divided by the maximum distance among a_i and b_i (Maechler, 2022):

$$SW(i) = \frac{b_i - a_i}{\max(a_i, b_i)} \quad (3.3)$$

An overall measure of the goodness of clustering can be obtained by computing the average silhouette coefficient (ASW) of all points. The rationale behind the ASW analysis is to study the separation distance between the resulting clusters, using the formula:

$$ASW = \frac{1}{n} \sum_{i=1}^n SW(i) \quad (3.4)$$

Both ASW and the $SW(i)$ vary between $[-1, 1]$. A value close to 1 suggests the observations are well-matched to the current clusters. A value close to -1, indicates that $a_i > b_i$ and that observations have a better fit with closest neighboring clusters. A value of 0 suggests the observations have a fit close to a border between clusters. In this case, the maximum SW partition is considered optimal. By applying the average silhouette width, we distinguish ‘clear-cut’ from ‘weak’ clusters (Rousseeuw, 1987). For each partition, we also calculate the percentage of observations (countries) with $ASW > 0,5$ and with $ASW < 0$. We include both measures as additional selection criteria.

The Caliński-Harabasz index (CH) applied by Desgraupes (2017) is computed following Caliński & Harabasz (1974). It integrates a ratio of the inter-cluster dispersion or the between-group dispersion (BGSS) and the intra-cluster dispersion or the within-cluster sum of squares (WGSS) for a given partition of K clusters. It is calculated by:

$$CH = \frac{N - K}{K - 1} \times \frac{BGSS}{WGSS} \quad (3.5)$$

where N is the total number of observations and K the total number of clusters. A higher CH index value means higher cluster quality. Caliński-Harabasz index indicates how well-separated and dense the clusters are (Awong & Zielinska, 2023).

The Davies-Bouldin index (DB) applied by Desgraupes (2017) follows Davies & Bouldin (1979) and is the average similarity measure of each cluster with the cluster most similar to

⁷The Caliński-Harabasz, Davies-Bouldin, Silhouette Width, and Dunn indexes are the most well-known and used internal criteria (Liu et al., 2010; Vendramin et al., 2010; Rendón et al., 2011; Hassani & Seidl, 2016; Daneshpajouh et al., 2017; Ilbeigipour et al., 2022; Marques & Alves, 2020; Chair et al., 2016; Wierchoń & Kłopotek, 2018; Renjith et al., 2022). The most used tests for external validity are Rand, adjusted Rand, the Jaccard coefficient, and the Fowlkes and Mallows measure. Milligan & Cooper (1986) concluded that Hubert and Arabie adjusted Rank indexes were better suited for comparisons across hierarchy levels, while Jaccard index has the same performance pattern as the Fowlkes and Mallows measure. Morey and Agresti adjusted Rand and Jaccard appear to have the most desirable properties.

it (M_K). It calculates the similarity between clusters as a sum of two intra-cluster dispersions (mean distance of the points belonging to a cluster) divided by the distance between the centers of all clusters. It is computed by:

$$DB = \frac{1}{K} \times \sum_{K=1}^K M_K \quad (3.6)$$

Small values of DB correspond to compact clusters and centers far away from each other. Therefore, the cluster partition that minimizes DB is taken as optimal, while higher values indicate that clusters may be overlapping or poorly separated (Bolshakova & Azuaje, 2003; Awong & Zielinska, 2023). This index considers the ‘within-class’ and ‘between-class’ similarities to show how well-separated and distinct the clusters are.

The Dunn index (DI) is the minimum inter-cluster distance (d_{min}), i.e., the smallest distance between any two cluster centroids, divided by the highest intra-cluster distance (d_{max}), i.e., the largest distance between any two points in any cluster (Dunn, 1974; Desgraupes, 2017):

$$DI = \frac{d_{min}}{d_{max}} \quad (3.7)$$

A higher Dunn index indicates better clustering results, meaning compact (observations within the same cluster are close to each other), well-separated, with minimal overlap (observations in different clusters are far apart).

The Simple Matching Coefficient (SM) is an external validation measure calculated by the proportion of matching characteristics relative to the overall count of attributes in consideration and is based on the following equation:

$$SM = \frac{A}{Total} \quad (3.8)$$

where A is the number of similar attributes and $Total$ is the total attributes under comparison (Verma & Aggarwal, 2019).

The Rand index (RI) computes a similarity measure between two proposals (e.g., assignments from FCM vs. other clustering proposals) by considering all pairs of samples and counting pairs assigned in the same or different clusters by both methods. It is calculated by:

$$RI = \frac{TP + TN}{TP + TN + FN + FP} \quad (3.9)$$

where TP is the number of true positives (pairs that were correctly grouped), TN is the number of true negatives (pairs that were correctly not grouped), FP is the number of false positives, and FN is the number of false negatives.

Hubert and Arabie’s adjusted Rand index (ARI) is a measure of the similarity between two clusters based on the Rand Index, but that applies a correction for the presence of agreement by chance. It is given by:

$$ARI = \frac{TP + TN - n_c}{TP + TN + FN + FP - n_c} \quad (3.10)$$

where TP is the number of true positives (pairs that were correctly grouped), TN is the number of true negatives (pairs that were correctly not grouped), FP is the number of false positives, FN is the number of false negatives, and, n_c adjusts the index to include chance.

The Jaccard index (JI) is a measure of similarity between two clusters, but it reflects the number of unique elements common to both proposals divided by the total number of unique elements in both proposals:

$$JI = \frac{TP}{TP + FP + FN} \quad (3.11)$$

These indexes have been found to provide the best properties and take values between 0 (total disagreement) and 1 (total agreement) (Milligan & Cooper, 1985, 1986).

In addition, we perform the Pearson’s Chi² Test for external validation, for which, under the null hypothesis, the expected values (the cluster proposal obtained from our clustering) and the observed values (the cluster proposals from the algorithms) are independent.

3.3.6 Clustering Ensemble Modeling

Clustering ensemble is an unsupervised learning tool that combines several clustering algorithms to get a final optimal partition. Intuitively, it combines the outputs of several clustering algorithms, applying a decision function to achieve a more accurate and stable final clustering output (Al-Shaqsi & Wang, 2010). It has three phases: ensemble member generation, consensus function, and evaluation (Alqurashi & Wang, 2018). Ensemble member generation is implemented by applying different clustering algorithms on the same dataset. The algorithms should be as different from each other as possible because a high level of diversity captures different information about the data and can help to improve the ensemble’s performance. A consensus function is then used to aggregate each algorithm clustering results. Kuncheva (2014) lists three consensus patterns: unanimity, simple majority, and plurality. The unanimity rule requires that an object is included in a specific cluster only if all used algorithms agree. In the case of the simple majority, the object is classified as part of a cluster if a majority of the clustering algorithms propose the same classification label. The plurality method evokes a diversity of clustering methods and broadly applies the majority vote, i.e., assigns an object to a cluster label that is the highest proposed among the methods used to cluster the dataset. Note that because initial cluster labels are arbitrary and symbolic, the clustering ensemble has a matching step where it is necessary to operate the matching labels, i.e., making a correspondence between labels (Golalipour et al., 2021). Finally, in the evaluation phase, the quality of the final clustering result is assessed using internal and external validity criteria (Alqurashi & Wang, 2018; Al-Shaqsi & Wang, 2010).

Several advantages of using clustering ensemble have been established when compared to single data clustering algorithms: i) it is possible to get a more accurate and objective outcome from the combination of multiple partitions (Menger et al., 2019); ii) it produces good data partitioning even in divergent conditions, and the clustering results are more robust and stable (Jain, 2010; Nazari et al., 2017); iii) it can be applied in different ways, namely: a) using different clustering algorithms, b) using the same clustering algorithm with different values of parameters or initializations, and c) combining different data and clustering algorithms (Jain, 2010).

From the disadvantages of clustering ensemble modeling, we highlight the difficulty of combining the results from several partitioning. At this point, it becomes necessary to re-label partitions since the initial labels attributed are virtual (Golalipour et al., 2021).

Clustering ensemble methods have been applied in Health Economics and health care, as well as in the business and finance sectors (Greene et al., 2004; Menger et al., 2019; Marques & Alves, 2020; Pelka, 2019)⁸.

3.3.7 Testing the Clustering Ensemble Modeling method

We use the clustering ensemble method to combine the results from three clustering algorithms, FCM, SOM, and PAM, thus increasing the robustness, accuracy, and precision of

⁸Please see Appendix 3.8.6 to see how the clustering ensemble modeling is implemented.

the proposed clusters. To assess the performance of this method when applied to study LTC policies, we use Ariaans et al. (2021)’s data⁹.

We calculate the Average Silhouette width, the Caliński-Harabasz index, the Davies-Bouldin index, and the Dunn index for Ariaans et al. (2021)’s cluster solutions K=4, K=6, K=9, and for a proposed clustering of K=6 obtained by applying the clustering ensemble modeling¹⁰. Table 3.1 presents the internal criteria for each solution.

Table 3.1: Comparison of the internal criteria obtained based on Ariaans et al. (2021) cluster solutions and our approach using the clustering ensemble modeling.

Internal Criteria	Ariaans et al. (2021) (K=4)	Ariaans et al. (2021) (K=6)	Ariaans et al. (2021) (K=9)	Ariaans et al. (2021) with clustering ensemble modeling (K=6)
Average Silhouette Width	0,14	-0,09	-	-0,09
Calinski-Harabaz index	2,97	3,58	4,82	1,86
Davies-Bouldin index	2,35	1,88	1,70	0,96
Dunn index	0,016	0,016	0,017	0,016

Notes: Data are from the Ariaans et al. (2021). Data on LTC expenditure health, LTC recipients beds, LTC recipients institutions, private expenditure (health) share, life expectancy, and perceived health status are imputed. N=25 countries. "-" is absent due to clusters with only one country. Ariaans et al. (2021) with clustering ensemble method (K=6) was run from partitions K=2 to K=9, and includes as inputs the PC1 to PC6. SOM adopts a hexagonal grid. Bold entries represent the optimal value by each internal criteria.

From Table 3.1 we observe best results of Average Silhouette width with K=4 of Ariaans et al. (2021), Caliński-Harabasz index for K=9 Ariaans et al. (2021); Davies-Bouldin index (minimum values) for Ariaans et al. (2021) with clustering ensemble method (K=6), and Dunn index for K=9 Ariaans et al. (2021).

Ariaans et al. (2021) methodological proposal was K=9, but the authors also argued that the cluster solution K=6 "might prove more useful for, e.g., quantitative outcome analysis". Our clustering ensemble modeling identified, at first sight, the best clustering at K=6. Compared with Ariaans et al. (2021) K=6, our cluster solution K=6 exhibits better results for the Davies-Bouldin index and similar values at Average Silhouette width and Dunn index. Davies-Bouldin index’s better results indicate compact clusters and centers far away from each other, but the lowest Caliński-Harabasz index suggests weakly separated clusters.

Ariaans et al. (2021) represented a methodological advancement in clustering LTC policies, relying on multiple cluster solutions analyses and not solely on one cluster analysis, and included more OECD economies, many of which were excluded in previous research. By applying our clustering method, we identified six clusters based exclusively on method application. Our clustering exhibited better internal properties on one criterion out of 4 and similar on 2 criteria out of 4. Importantly, our final cluster solution did not rely on subjective choices.

As can be observed from those results, our clustering ensemble modeling, when applied to the OECD countries’ LTC data, demonstrates good clustering properties in identifying the best clustering solution, and it yields good performance when applied to our data.

3.4 Methodological strategy

3.4.1 Data and Variables

Our data cover 30 OECD countries between 2016 and 2019, the largest data ever used in this type of study. We select a wide range of variables and dimensions to assess and compare

⁹We thank the authors for their availability to share the dataset and Stata code.

¹⁰Please see Appendix 3.8.7 to get information on all procedure.

LTC policies. We structure the variables around four main dimensions: i) supply, ii) demand, iii) financing, and iv) policy provision and regulation. These dimensions were defined based on the review available in Appendix 3.8.1 and include ten indicators (nine quantitative and one qualitative). Our data have the following advantages: i) higher number and diversity of countries analyzed, bringing more heterogeneity into the analysis; ii) the data cover the main dimensions selected in previous studies, while previously ignored dimensions are also included; iii) we use data from sources that are comparable, iv) both quantitative and qualitative indicators are used, and v) quantitative measures are prioritized over qualitative ones to avoid subjective interpretations. Short definitions, descriptions of the variables, years covered, and sources are provided in Table 3.2¹¹.

The supply dimension encompasses three variables: the availability of beds in formal settings, the proportion of health and social-paid workers, and household size. LTC beds is a measure of countries' resources. Damiani et al. (2011) applied PCA analysis and integrated beds in institutions as one factor of formal care within the supply domain. Our variable integrates data from OECD Health Statistics (2023d), which measures the establishments primarily engaged in providing residential long-term care by including the beds from residential and nursing care facilities.

The variable health and social care workers measures the supply of formal care. It is the ratio between health and social workers and total activity workers. Even though this variable is not LTC sector-specific, it is a proxy for the size and involvement of the professional care sector and the availability of formal services within a country. The lack of standardization in qualification and educational requirements for the health and social workforce across countries, particularly in the LTC sector, is a strong limitation to its interpretation (OECD, 2020).

Household size aims to capture the presence of a spouse and children in the household. This variable is a proxy for the supply of informal care provided by the close family network or, reversely, the demand for formal care services when the informal network is absent or unavailable. Co-resident caregivers provide about two-thirds of all informal care hours across Europe and the USA, and the presence of children could impact the household's care priorities (Barczyk & Kredler, 2019; United Nations, 2017). Lamura et al. (2007) included the proportion of extended households (including three or more adults and dependent children) as a proxy for informal care provision in their clustering model.

Two variables represent demand. The female employment rate proxies for formal care and we assume that higher female employment could imply a higher demand for formal care. The women's role in care provision is well documented. However, new social dynamics related to women's labor and social participation have changed their current and future roles in providing informal care, and we aim to capture this in our model. Lamura et al. (2007) included the employment rate of women aged 55-64, i.e., the age group most family careers belong to.

The second demand variable is the total population life expectancy at birth. Higher life expectancy should lead to higher LTC demand as additional life years are likely to have been achieved with increased limitations. Ariaans et al. (2021) included this measure to capture the performance of the LTC system arguing that this indicator captures the quality of LTC services.

The third dimension covers financing. Halásková et al. (2017) and Damiani et al. (2011) included social and health LTC costs in their clustering exercise. Ariaans et al. (2021) comprised the LTC (health) expenditure per capita and the private (voluntary and out-of-pocket) expenditure as a percentage of total expenditure. To capture LTC financing sources across countries, we include two measures: i) government LTC spending and ii) private LTC spending, both as a share of GDP. Following Kraus et al. (2010), we adjust these measures to the mean share of the population 65 years and older.

¹¹Data manipulation and analysis were performed using R programming language and RStudio to integrate the development environment (R Core Team, 2021). The specific packages used in this research are described in Appendix 3.8.5.

Table 3.2: Description of the variables

Dimension	Variable	Description and Measurement		Time period	Source
Supply	LTC beds	Beds in residential long-term care facilities per 1000 population aged 65+	Average number	2016-2019	OECD Health Statistics (2023d); Greece: Ziomas et al. (2018), Eurostat (2023); Portugal: European Commission (2019)
	Health and social workers	Ratio between the number of persons employed on human health and social work activities, by the number of total population on activity (both in thousands)*100	Average ratio in %	2016-2019	OECD (2023a)
	Household size	Number of members in a household	Average number	2017	United Nations (2017)
Demand	Female employment rate	Female population aged 15 that supply labor for the production of goods and services	Average %	2016-2019	World Bank (2023)
	Life expectancy at birth	Total population life expectancy at birth	Average years	2016-2019	OECD Health Statistics (2023b)
Financing	Government LTC spending	Government expenditure on LTC as a share of GDP, divided by the mean share of the population aged 65+	Average %	2016-2019	Own calculation based on OECD Health Statistics (2023a)
	Private LTC spending	Voluntary insurance and out-of-pocket expenditures on LTC as a share of GDP, divided by the mean share of the population aged 65+	Average %	2016-2019	Own calculation based on OECD Health Statistics (2023a)
Policy provision and regulation	Mean-testing for benefits	Mean-testing applied to obtain any benefit, either in-cash or in-kind	Binary. 0: no; 1: yes	2018	Ariaans et al. (2021); Canada: Feng & Glin-skaya (2019) and national expert; Hungary: Gyarmati (2019); Portugal: Instituto da Segurança Social I.P. (2024)
	Elderly income inequality	Gini coefficient of population aged 65+	Continuous. 0: equality; 1: inequality	2016 or until 2019	OECD (2019b)
	Elderly self-health status evaluation	Percentage of population aged 65+ who report their health to be 'good/very good'	Average %	2016-2019	OECD Health Statistics (2023c)

Notes: LTC Beds per 1000 elderly include long-term nursing care facilities and other residential long-term care facilities and exclude beds in hospitals dedicated to long-term care and beds in residential settings such as adapted housing that can be considered people's homes. Greece beds data are own calculations based on the sum of the sheltered boarding houses for old people with mental health problems, public psychiatric hospitals for the long-term care of chronically mentally ill persons, and non-profit and for-profit residential care homes for the elderly (Ziomas et al., 2018), and the mean (2016-2019) of long-term care beds in nursing and residential care facilities (Eurostat, 2023). According to European Commission (2019), the public LTC in Portugal is provided through residential structures for the elderly (ERPI - Estrutura Residencial para Pessoas Idosas) and Long-term Care National Network (RNCCI - "Rede Nacional de Cuidados Continuados Integrados"). Beds data for Portugal respects to 2017 and is based on the sum of the beds within RNCCI (2017), including the total number of beds on the National Health Service (SNS), Charities including Holy Houses of Mercy and other IPSS, private sector, and the number of agreements (2017) between the Government and the non-profit entities (European Commission, 2019), since these agreements reveal the allocation of financial contributions by the public social security to the non-profit providers, which are the main managers of the nursing homes (around 70%) and where 80% of elderly people receive care (Veloso, 2017). Health and social workers are calculated based on available years. Government and private LTC spending includes the sum of mean values of health and social (social expenditure when data are available). Government LTC spending and private LTC spending are both measures of share of GDP, and they were divided by the mean share of the population 65 years and over between 2016 and 2019. Government spending includes government schemes, social health insurance, compulsory private insurance, and compulsory medical savings accounts. Private spending includes voluntary health insurance, non-profit institutions financing schemes, enterprise financing schemes, and out-of-pocket (OECD et al., 2017). '65+' indicates population 65 years old and over.

The fourth dimension is related to how each country provides and regulates LTC policy, benefits, and services. We consider three measures: first, whether a country has any mean-testing rule to exclude individuals from access to in-kind and in-cash benefits. Generally, countries' eligibility criteria combine different rules (e.g., the USA and UK adopt entry rules for public support based on means-tested eligibility), and it is a proxy for regulation of access to the public LTC system benefits. Kautto (2002) examined how countries balance their strategies of benefits-in-kind ('service effort') and in-cash ('transfer effort'). For example, Spain requires means-tested criteria for in-kind and cash benefits (European Commission, 2019), while France combines eligibility criteria with the cash benefit APA amount, which varies according to the elderly's level of dependency and financial resources (European Commission, 2019). The second measure is the elderly income inequality, measured through the Gini coefficient for people over 65. The coefficient ranges from 0, perfect equality, to 1, maximal inequality. By measuring the elderly's income inequality, we are including an indicator of the welfare state support in each country and the income distribution across the elderly population (Wu et al., 2020). Inequality at older ages has been moderate in the OECD, but there are substantial country differences, reflecting countries' efforts on the distribution of household disposable income OECD (2019b). Lamura et al. (2007) also explored this socio-economic dimension through the proportion of older people at risk of poverty. The last variable is the elderly's self-reported health status. Ariaans et al. (2021) used this variable to evaluate the LTC system's performance, while Damiani et al. (2011) included people aged 65 self-perceived health.

The selected variables are almost exclusively quantitative and are collected for an unprecedented number of countries. They cover the main characteristics of LTC policies. We also define them considering the adjustment between the country's demographic structure and the relative investment in covering the elderly population's LTC needs. Still, we recognize that these variables have limitations.

First, using data from more heterogeneous countries raises additional concerns about comparability and consistency. For example, data from Portugal and Greece on the number of beds in formal care settings are scarce or absent. We had to construct both countries' data based on OECD (2023b). This reflects the trade-off between considering a less diverse range of countries or fewer variables.

Second, we decided not to use any imputation procedures. Using imputation could have increased the number of countries and variability of LTC systems but would also have raised additional methodological concerns.

Third, the LTC workforce plays different roles and often has different qualifications across countries.

Fourth, we integrated the elderly self-evaluation of health status, a subjective indicator strongly correlated with intrinsic cultural and individual beliefs and self-perception of the disability (Damiani et al., 2011; Schulmann & Leichsenring, 2014).

3.4.2 Descriptive statistics

Table 3.3 presents descriptive statistics. The mean number of LTC beds in residential LTC facilities per 1000 elderly people is 43 beds (sd=19,21), and almost 10,75% of the active population are workers in social and health care activities. About 55,09% of the women are employed, and each household has, on average, 2,39 members (sd=0,19). Life expectancy at birth is, on average, 81 years (sd=2,42). Public expenditures on LTC services and programs adjusted to the elderly people of each country are, on average, 0,07% of GDP, while private costs are, on average, 0,02% of GDP. The mean-testing rules to attribute any benefit, in cash or in-kind, is considered in 57% of the countries. The Gini coefficient among the elderly is, on average, 0,29 (sd=0,05), which indicates low inequality in the income distribution in our

sample. Approximately 43% of older people evaluate their health as being in good or very-good status, with high variability.

Table 3.3: Descriptive statistics (N=30)

Variable	Mean	SD	Min.	Max.
LTC beds per 1000 elderly people	43,00	19,21	4,31	82,30
Health and social workers	10,75	4,26	4,37	21,11
Household size	2,39	0,19	2,10	2,90
Female employment rate	55,09	5,64	40,93	70,39
Life expectancy at birth	80,98	2,42	75,15	84,25
Government LTC spending	0,07	0,05	0,002	0,20
Private LTC spending	0,02	0,01	0,0001	0,05
Mean-testing for benefits	0,57	0,50	0	1
Elderly income inequality	0,29	0,05	0,18	0,42
Elderly self-health status evaluation	42,80	20,65	7,55	79,85

Notes: Data sources are described in Table 3.2. Data covered the period 2016-2019 (N=30). Own coding scheme. Standard deviation (SD). Number of countries (N).

Table 3.4 presents summary statistics by country. The average number of beds per 1000 elderly people in LTC residential services is the highest in Luxembourg (82,30) and the lowest in Portugal (4,31). The formal labor supply for health and social activities is the highest in Norway, almost 16 percentage points larger than in Poland, the lowest. The measure of household size is relatively similar across the sample, with a mean value of 2,39 (sd=0,19). On average, 60% of the women are involved in the labor market in European Nordic countries (Norway), central Europe (Switzerland), North America (Canada), and Australia, while only 40% in Italy and Greece. The average life expectancy at birth is nearly 81 years (sd=2,42). Japan has the highest average life expectancy (84 years), while Latvia and Lithuania have the lowest (75 years). Public expenditures are, on average, 0,07% of GDP, having a maximum in the Netherlands (0,20) and a minimum in the Slovak Republic (0,002). Private expense values are very similar across countries; however, Belgium, Switzerland, and the United Kingdom have higher values (around 0,04% of GDP), and the Slovak Republic (0,0001%) lower. Mean-testing rules are present in nearly half of the 30 countries. The income inequality of older people is higher in South Korea and the USA (on average, 0,41) and lower in the Czech Republic (0,18). Self-evaluation of health status collects higher scores in Canada, Australia, and the USA, where more than 70% of respondents classify it as good or very good, while Lithuania has the lowest (7,55%).

3.4.3 Preprocessing data

One risk of cluster analysis is that the data do not have natural grouping tendencies. We computed the Hopkins statistic to measure the clustering tendency of our sample. The Hopkins statistic ranges from 0 (uniformly distributed data) to 1 (highly clusterable data), with 0,5 representing randomly distributed data. We compute this statistic for our standardized measures using Euclidean distance, and we get a value of Hopkins statistic 0,97 (p-value=0,00), which is indicative of the high likelihood of the existence of significant clusters (Menger et al., 2019).

We also perform the Pearson correlation matrix to measure the linear correlation between each pairwise combination of continuous variables. Figure 3.1 shows, in general, a moderate correlation between the variables selected. We observe, however, a strong positive correlation between health care and social care workers and government LTC expenses (0,89), as well as with the elderly's self-evaluated health status (0,73). Elderly self-evaluated health status is also positively correlated with LTC beds (0,53) and life expectancy (0,55). Government spending is negatively correlated with household size (-0,56) and positively with female labor participa-

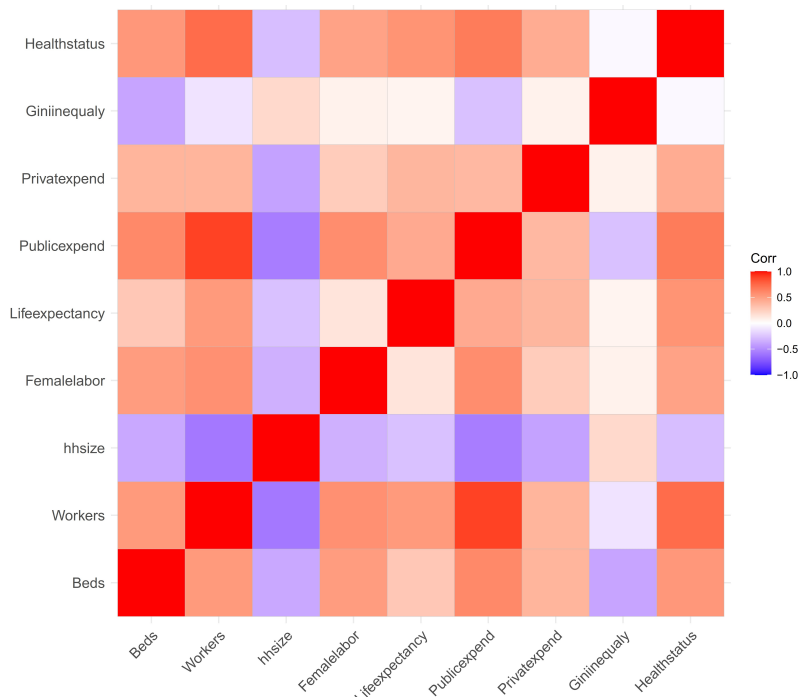
Table 3.4: Descriptive statistics, by country (N=30)

Country	LTC beds per 1000 elderly people	Health and social workers	Household size	Female employ- ment rate	Total population life expectancy at birth	Government LTC spending	Private LTC spending	Mean- testing for benefits	Elderly income inequality	Elderly self-health status evaluation
Australia	51,48	13,31	2,5	60,17	82,63	0,08	0,001	1	0,33	74,00
Austria	45,25	10,33	2,3	56,06	81,83	0,06	0,02	1	0,26	44,70
Belgium	69,35	13,11	2,3	48,96	81,73	0,13	0,05	1	0,22	54,25
Canada	54,03	11,44	2,3	61,51	82,03	0,10	0,03	1	0,29	79,85
Czech Republic	36,38	6,48	2,3	52,38	79,15	0,07	0,01	0	0,18	26,03
Denmark	41,03	17,50	2,1	57,68	81,13	0,15	0,01	0	0,23	57,13
Estonia	36,30	6,13	2,3	57,42	78,48	0,02	0,01	1	0,28	17,65
Finland	56,53	16,24	2,1	55,63	81,78	0,10	0,01	0	0,23	47,60
France	50,50	13,96	2,3	51,40	82,80	0,10	0,03	1	0,27	42,03
Germany	54,30	13,17	2,1	56,01	81,10	0,07	0,03	0	0,26	41,78
Greece	7,94	5,63	2,4	44,07	81,63	0,01	0,0002	1	0,28	39,80
Hungary	45,50	6,74	2,4	48,46	76,23	0,01	0,002	1	0,25	19,00
Ireland	47,33	12,68	2,7	55,88	82,23	0,09	0,02	0	0,28	67,73
Italy	19,90	7,76	2,4	40,93	83,38	0,03	0,01	1	0,31	38,95
Japan	25,15	12,52	2,4	51,75	84,25	0,07	0,01	0	0,35	25,70
South Korea	24,48	7,50	2,5	53,23	82,78	0,05	0,02	0	0,42	22,55
Latvia	13,58	5,52	2,4	55,42	75,15	0,02	0,01	0	0,34	10,63
Lithuania	37,53	6,88	2,4	56,32	75,80	0,05	0,01	0	0,34	7,55
Luxembourg	82,30	10,44	2,4	55,03	82,45	0,07	0,02	1	0,29	46,73
Netherlands	73,90	15,38	2,3	59,10	81,90	0,20	0,01	1	0,24	60,75
Norway	45,48	21,11	2,2	61,84	82,75	0,19	0,02	0	0,22	64,88
Poland	11,68	4,37	2,8	48,35	77,88	0,02	0,001	0	0,25	20,08
Portugal	4,31	8,16	2,6	54,21	81,58	0,02	0,02	0	0,35	13,85
Slovak Republic	50,18	5,73	2,9	52,47	77,45	0,002	0,0001	1	0,20	21,70
Slovenia	52,75	6,42	2,5	57,47	81,38	0,05	0,02	1	0,25	34,88
Spain	43,93	7,52	2,6	52,69	83,60	0,04	0,01	1	0,30	42,55
Sweden	68,50	17,02	2,2	70,39	82,68	0,16	0,01	0	0,30	61,40
Switzerland	64,53	13,68	2,2	62,84	83,80	0,10	0,04	1	0,30	66,53
United Kingdom	44,35	12,27	2,3	57,94	81,15	0,09	0,04	1	0,34	56,50
United States	31,65	13,43	2,6	57,09	78,70	0,06	0,02	1	0,41	77,35
Mean	43,00	10,75	2,39	55,09	80,98	0,07	0,02	0,57	0,29	42,80
SD	19,21	4,26	0,19	5,64	2,42	0,05	0,01	0,50	0,05	20,65

Notes: Data sources are described in Table 3.2. Data covered the period 2016-2019 (N=30). Own coding scheme. Number of countries (N).

tion (0,58) and health status (0,66). Household size is negatively correlated with most other variables (LTC beds, health and social workers, female employed, life expectancy, government and private expenses, and health status) and only has a positive and weak correlation with the Gini inequality coefficient (0,20). Private spending is negatively correlated with household size (-0,40) and positively with self-rated health (0,43).

Figure 3.1: Pearson correlation coefficients between pairwise variables



Notes: Data sources are described in Table 3.2. Data covered the period 2016-2019 (N=30). Data are unstandardized.

Principal Component Analysis (PCA) is then implemented to select the most significant features from our ten attributes. PCA improves the accuracy of clustering techniques by reducing the number of variables before applying cluster algorithms. The PCA process reduces the multidimensionality of the data and extracts meaningful components that explain most of the variability in the dataset. Our data include nine continuous and one binary variable. To handle such mixed data, we perform a PCA adjusted to the mixture of numerical and categorical variables¹².

Table 3.5 shows the eigenvalues with the proportion variance and the cumulative proportion variance. The proportion variance of the principal component 1 (PC1) of 43,82 indicates that PC1 can explain 44% of the data variance. PC2 can explain 14,38%. The cumulative proportion of variance reached the criterion of variation between 70% or 90% for PC3 (Jolliffe, 2002). We retain five components that account for 87,41% of the total variance of our dataset.

Next, we implement a Varimax rotation procedure (Kaiser, 1958) to improve the interpretation of these five components without adversely affecting the proportion of cumulative inertia. The Varimax rotation maximizes the loading of a predictor variable on one component and produces a ranked series of factors. Table 3.6 shows the results of the Varimax rotation for the five principal components as well as the amount of variance explained by each component. PC1 has the highest variance and the rotated principal components still contained 87,41% of the total inertia¹³.

¹²PCA technique is not scale invariant, which requires standardizing the original data to get comparable data and then proceeding with the PCA on the transformed data (Setiawan et al., 2023).

¹³We also plotted (please see Figures on Appendix 3.8.8) the squared loadings.

Table 3.5: Eigenvalues, proportion variance and cumulative percentage of total variation, by component

Principal Component	Eigenvalue	Proportion	Cumulative
dimension 1	4,38	43,82	43,82
dimension 2	1,44	14,38	58,20
dimension 3	1,27	12,70	70,90
dimension 4	0,87	8,66	79,56
dimension 5	0,78	7,85	87,41
dimension 6	0,44	4,42	91,83
dimension 7	0,37	3,75	95,58
dimension 8	0,22	2,24	97,82
dimension 9	0,13	1,32	99,14
dimension 10	0,09	0,86	100

Notes: Data sources are described in Table 3.2. Data covered the period 2016-2019 (N=30). Continuous data standardized.

Table 3.6: Variance of the rotated PCs

Principal Component	Variance	Proportion
dimension 1	2,44	24,38
dimension 2	1,41	14,12
dimension 3	1,37	13,70
dimension 4	2,05	20,47
dimension 5	1,47	14,74

Notes: Data sources are described in Table 3.2. Data sources are described in Table 3.2. Data covered the period 2016-2019 (N=30). Continuous data standardized.

The following step is analyzing the link between the variables (numerical or categorical) and the principal components, using squared loadings as coordinates¹⁴. Table 3.7 presents the rotated squared loadings and those five principal components. The health and social workers, LTC beds, government LTC spending and female employment rate are strong variables within PC1. Mean-testing for benefits is linked after rotation to PC2, with all other variables with lower loadings. Similarly, the elderly income inequality mainly loads PC3, for which self-rated health status has very low importance. PC4 rotated squared loadings are higher for life expectancy at birth (0,81) and almost absent for elderly inequality income. For PC5, either household size (0,57) or private LTC spending (0,62) contribute the most, with the last one being slightly high correlated. The mean testing rules and income inequality are both variables with low influence on PC5.

The first component has the highest loading with female employment rate, but also with two measures of the supply: LTC beds and workers, respectively, 0,39 and 0,37 loadings. This suggests that PC1 is related to the availability of informal care and also exhibits a strong relation with the supply domain, which seems to indicate complementarity in both formal and informal care. The second component PC2 gives more weight to mean-testing for benefits, which could be related to access and regulation of the LTC policy. The third component PC3 is related to elderly income inequality and could be oriented to the countries 'policies organization, welfare policies and alignment to elderly needs. For PC4, life expectancy at birth is of higher importance, which can be interpreted as a proxy for demand and also policy implementation.

¹⁴For numerical variables, squared loadings are squared correlations, and for categorical variables, squared loadings are correlation ratios.

PC5 is mainly correlated with private LTC spending, but also with very close loading absolute value from the household size measure. This component relates to the financing questions, specifically those associated with voluntary insurance purchasing and OOP spending, and is intrinsically related to the possibility of guaranteeing one's care based on family support.

Based on this, our selected five PCs express the following topics: PC1: demand for formal care; PC2: access regulation; PC3: social protection; PC4: demand and policy implementation; PC5: financing LTC through private spending. These PCs are used under the clustering algorithm¹⁵.

Table 3.7: Rotated squared loadings

Variable	PC1	PC2	PC3	PC4	PC5
LTC beds	0,39	0,18	0,18	0,03	0,06
Health and social workers	0,37	0,04	0,03	0,40	0,08
Household size	0,06	0,06	0,08	0,04	0,57
Female employment rate	0,86	0,01	0,01	0,001	0,02
Life expectancy at birth	0,000001	0,01	0,005	0,81	0,03
Government LTC spending	0,41	0,03	0,10	0,28	0,08
Private LTC spending	0,03	0,10	0,03	0,05	0,62
Mean-testing for benefits	0,01	0,89	0,003	0,004	0,0003
Elderly income inequality	0,00002	0,003	0,92	0,0003	0,0001
Elderly self-health status evaluation	0,31	0,10	0,00002	0,44	0,01

Notes: Data sources are described in Table 3.2. Data covered the period 2016-2019 (N=30). Continuous data standardized. Bold means the highest loadings. Principal Component (PC).

3.5 Results

PC1 to PC5 components are used as inputs for the three algorithms in the clustering analysis. Table 3.8 shows the results for the clustering algorithms, FCM, SOM, and PAM, evaluated by internal criteria. The column optimal cluster shows how many times each partition is first or second best.

We verify that each algorithm points to a different optimal number of partitions: FCM proposes $K = 9$, SOM proposes $K = 5$, and PAM proposes $K = 7$. This demonstrates nonmajority and nonconsensus on the optimal number of clusters proposed by the algorithms. Hence, following the Clustering Ensemble modeling described in Appendix 3.8.6, we take the maximum value of the Average Silhouette Width as our decision metric. Across the algorithms, the maximum absolute value of the Average Silhouette Width is observed on the PAM algorithm $K = 7$ (0,30).

In complement, we analyze plots (Figures 3.2, 3.3; 3.4 and 3.5) about each internal evaluation. On the y-axis we assign the score values and on the x-axis the corresponding partition from $K = 2$ to $K = 9$. We can see that the ASW values from PAM increase as the number of K increases, reaching the maximum at $K = 7$. In contrast, for SOM, these values start increasing but the curve inverts at $K = 6$. Higher Caliński-Harabasz values indicate better clustering partition. For the FCM algorithm, we observe a peak at $K = 5$ with a score of 8,09, while for the SOM, the maximum is reached at $K = 6$, and for PAM, $K = 7$ score of 8,32 is the

¹⁵Complementary note: we test our algorithms without PCA process, and we observe that the FCM, SOM and PAM proposals pointed by majority voting to $K = 2$. When we apply our original features to the algorithms' calculations, we use correlated features that seem to be less informative. We have 10 features to explain 30 observations, and that could be a case of a too large number of features (high dimensionality), where clustering algorithms become less effective, the noise increases, and the distance metrics calculations become less meaningful (Golalipour et al., 2021).

maximum value. Davies-Bouldin hints that better clustering is found at minimum values, and scores fluctuate around 2,15 to 0,45.

Table 3.8: Internal evaluation criteria, by algorithm and cluster partitions (K)

Algorithm	Cluster partitions (K)	ASW	ASW > 0,5	ASW < 0	CH	DB	DI	Optimal cluster	$\sum$ 1st Best	$\sum$ 2nd Best
FCM	2	0,14	0,00	6,67	6,06	2,08	0,14	1	1	0
	3	0,14	0,00	6,67	6,06	2,08	0,14	1	1	0
	4	0,21	0,00	13,33	8,03	1,48	0,28	2	0	2
	5	0,22	3,33	13,33	8,09	1,15	0,39	3	2	1
	6	0,20	10,00	20,00	6,91	1,07	0,26	0	0	0
	7	0,19	13,33	30,00	6,26	0,69	0,26	1	0	1
	8	0,27	26,67	20,00	7,44	0,51	0,26	3	2	1
	9	0,28	26,67	16,67	7,98	0,52	0,33	4	2	2
SOM	2	0,12	0,00	13,33	5,72	2,15	0,23	3	1	2
	3	0,18	0,00	10,00	7,34	1,53	0,20	3	1	2
	4	0,16	3,33	13,33	6,88	1,17	0,21	2	1	1
	5	0,18	0,00	10,00	7,77	1,16	0,23	5	2	3
	6	0,17	0,00	16,67	8,02	1,24	0,18	2	1	1
	7	0,04	0,00	33,33	5,12	1,09	0,18	1	0	1
	8	0,16	3,33	26,67	6,52	0,96	0,23	3	2	1
	9	0,03	3,33	36,67	5,10	1,09	0,23	3	1	2
PAM	2	0,13	0,00	10,00	5,02	2,12	0,14	1	0	1
	3	0,16	0,00	6,67	6,01	1,68	0,14	1	1	0
	4	0,19	6,67	13,33	6,74	1,30	0,16	1	0	1
	5	0,21	6,67	10,00	6,81	1,18	0,30	1	0	1
	6	0,23	13,33	13,33	6,45	0,89	0,30	0	0	0
	7	0,30	20,00	6,67	8,32	0,68	0,46	5	4	1
	8	0,27	20,00	10,00	7,63	0,64	0,36	4	0	4
	9	0,27	23,33	10,00	7,49	0,45	0,36	4	2	2

Notes: Data sources are described in Table 3.2. Data covered the period 2016-2019 ($N=30$) and included as inputs PC1 to PC5. Optimal values of the internal criteria: Average Silhouette width (ASW) (maximum), the Calinski-Harabaz index (CH) (maximum), the Davies-Bouldin index (DB) (minimum), and the Dunn index (DI) (maximum). Bold means higher sum and identifies the optimal cluster partition on each algorithm. The ASW coefficients are the average of the countries' silhouette scores for each country. $\sum$ is the sum of times each partition is the 1st (first) or the 2nd (second) best.

The three algorithms have close Davies-Bouldin scores, and at $K = 5$, all the score algorithms are around 1,5. Finally, the Dunn index expresses very close values from partitions 2 to 9 on the SOM, while FCM and PAM reach maximums at $K = 5$ and $K = 7$, respectively. From the results of Table 3.8 and also our analyses of respective plots, we reinforce our clustering $K = 7$.

After we perform the correspondence between the FCM, SOM, and PAM assigned clusters labels to each country, we calculate the external evaluation of the $K = 7$ solution. Table 3.9 shows a Simple Matching coefficient of 80% in FCM, i.e., 80% of the countries are equally clustered by the FCM and cluster ensemble $K = 7$. In the SOM, this similarity is around 70%, and PAM reveals 77%. The Rand Index indicates that 91% of the pairs were correctly assigned, either in positive or negative groupings. The FCM vs Clustering Ensemble pairs collect the highest value of RI. The adjusted Rand Index is similar to the Rand Index but considers chance. The value decreases in all combinations but remains the highest on FCM. The Jaccard index collects close results in the three cases with higher indexes in FCM and SOM, respectively, 0,49 and 0,47, and decreases to 0,40 in PAM. We also perform the Chi² test of independence and reject the null hypothesis of statistical independence between the assignments from our clustering ensemble $K = 7$ and those from FCM, SOM, and PAM. We conclude that the expected values (the cluster obtained from the clustering ensemble) and the observed values (the cluster proposals from the algorithms) are dependent, which is indicative of the similarity between FCM, SOM and PAM vs. Clustering Ensemble, corroborating the external criteria.

Figure 3.2: Average Silhouette Width score

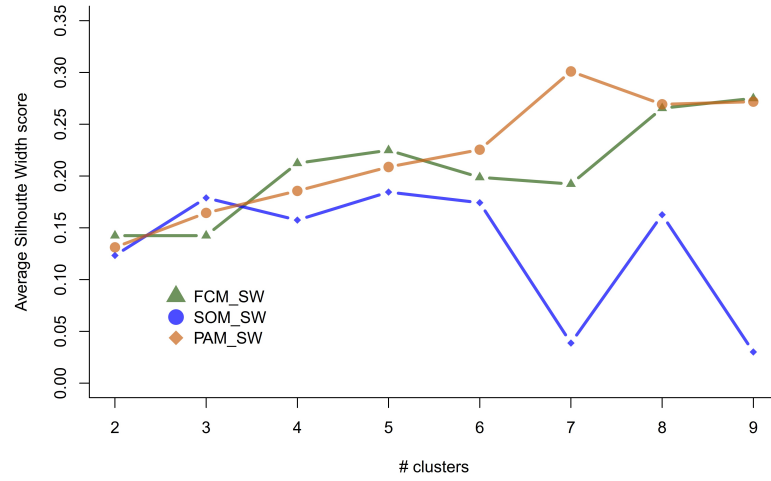


Figure 3.3: Caliński-Harabasz Index score

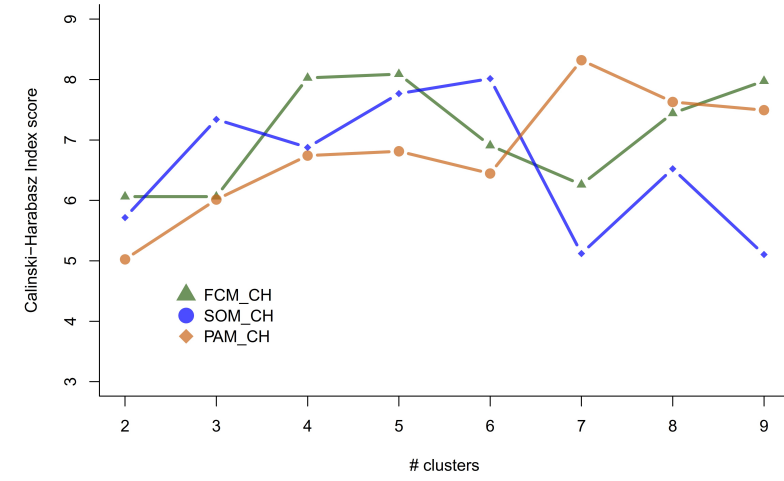


Figure 3.4: Davies-Bouldin Index score

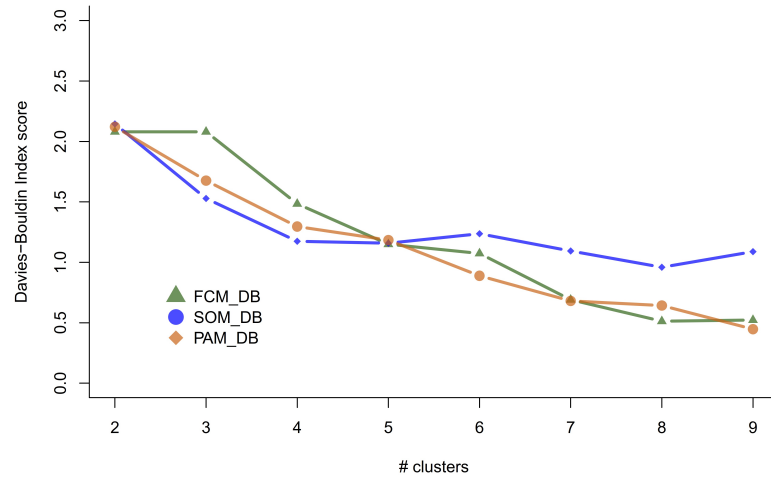
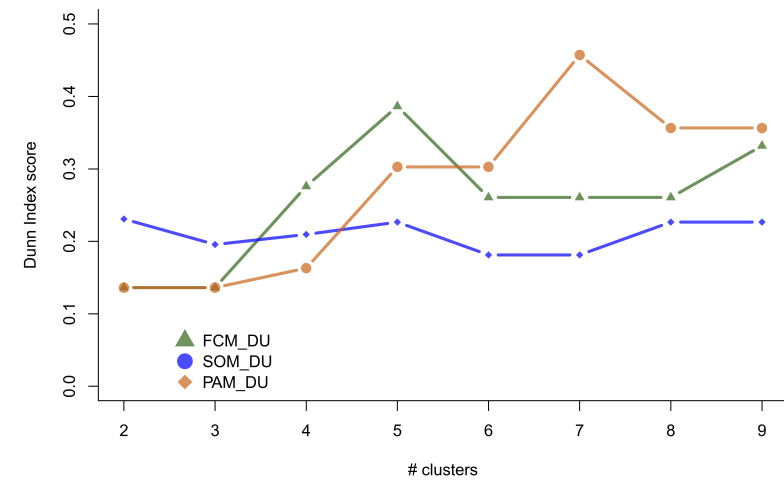


Figure 3.5: Dunn Index score



Notes: Data sources are described in Table 3.2. Data covered the period 2016-2019 (N=30) and included as inputs the PC1 to PC5.

Table 3.9: Similarity of cluster ensemble LTC typologies $K = 7$, with FCM, SOM, and PAM partitions and external criteria

	K	Ensemble						
		1	2	3	4	5	6	7
FCM	1	57%	0%	0%	0%	0%	0%	67%
	2	0%	100%	0%	0%	25%	0%	0%
	3	14%	0%	100%	0%	0%	0%	0%
	4	0%	0%	0%	100%	0%	0%	0%
	5	0%	0%	0%	0%	75%	0%	0%
	6	0%	0%	0%	0%	0%	100%	0%
	7	29%	0%	0%	0%	0%	0%	33%
	SM	80%						
	RI	0,91						
	ARI	0,61						
	JI	0,49						
	Chi ²	131,61***						
SOM	1	86%	0%	0%	0%	0%	0%	0%
	2	0%	100%	0%	50%	0%	0%	0%
	3	0%	0%	80%	0%	0%	100%	0%
	4	0%	0%	0%	25%	0%	0%	0%
	5	0%	0%	0%	0%	100%	0%	67%
	6	0%	0%	20%	0%	0%	0%	0%
	7	14%	0%	0%	25%	0%	0%	33%
	SM	70%						
	RI	0,89						
	ARI	0,57						
	JI	0,47						
	Chi ²	94,86***						
PAM	1	100%	0%	20%	0%	25%	0%	33%
	2	0%	60%	0%	0%	0%	0%	0%
	3	0%	0%	80%	25%	0%	0%	0%
	4	0%	40%	0%	75%	0%	0%	0%
	5	0%	0%	0%	0%	50%	0%	0%
	6	0%	0%	0%	0%	0%	100%	0%
	7	0%	0%	0%	0%	25%	0%	67%
	SM	77%						
	RI	0,87						
	ARI	0,49						
	JI	0,40						
	Chi ²	111,18***						

Notes: Data sources are described in Table 3.2. Data covered the period 2016-2019 (N=30) and included as inputs the PC1 to PC5. The Simple Matching (SM) method is obtained directly from the elements of cross-tabulation and computed as the sum of similar LTC model classification (elements in the diagonal) divided by the total number of elements. Rand index (RI), Hubert and Arabie's Adjusted Rand index (ARI), and Jaccard index (JI). We also test the independence from the clustering ensemble output for each clustering method (FCM, SOM, and PAM) through Pearson's Chi² independence test. Statistical significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

3.5.1 Validation of cluster solution $K = 7$

We evaluate if the seven proposed clusters are significantly different and independent under three methods: i) we perform the F-statistic ratio for one-way ANOVA for each variable to evaluate how much the respective variable is distinct across clusters; ii) we compare the clusters' significance difference by applying a Tukey test, and iii) we evaluate the correlation between each variable and the clusters to verify which variables have more contribution on each cluster.

F-statistic values are presented in Table 3.10¹⁶ and respective p-value. There are significant differences in all variables means across clusters at $p\text{-value} \leq 0,05$.

Table 3.10: F-statistic values and p-values by variable

Variables	F-value	p-value
LTC beds	3,39	0,02
Health and social workers	7,58	0,00
Household size	3,33	0,02
Female employment rate	3,16	0,02
Life expectancy at birth	11,78	0,00
Government LTC spending	5,71	0,00
Private LTC spending	8,30	0,00
Mean-testing for benefits	2,77	0,04
Elderly income inequality	4,75	0,00
Elderly self-health status evaluation	7,04	0,00

Notes: Data sources are described in Table 3.2. Data covered the period 2016-2019 (N=30). Data are unstandardized.

To complement, we compute the Tukey HSD test to identify which cluster pairs are significantly different based on the variables' means¹⁷. Table 3.11 presents the results obtained for each variable, and we complement it with plots about the countries and their mean values by cluster and variable, available on the Appendix 3.8.9.

Cluster 1 includes seven European countries, mainly from central Europe: Austria, Belgium, France, Germany, Luxembourg, Switzerland, and the UK. It is the largest cluster, including 23,3% of the countries in our sample. This cluster has the highest mean value of LTC beds available for the elderly (58,65; $sd=14,01$), being significantly different from Cluster 5. It also exhibits the highest average private LTC spending (0,03; $sd=0,01$), being significantly different from Clusters 2, 3, 4, 5, and 6. Countries belonging to Cluster 1 are, among all clusters, those that apply more mean-tested rules to rule out access to public benefits (86%), and it differs significantly from Cluster 4 (at $p\text{-value}=0,06$). All considered, we label Cluster 1 as "High supply of resources and high private financing".

This cluster composition is aligned with previous studies. Lamura et al. (2007) included Austria, Belgium, France, Germany, and the UK in the same group, while Saraceno & Keck (2010) also included Luxembourg and put Germany and the UK together. Within the countries of Cluster 1, Switzerland is the one fewer times included in LTC typologies studies, but Halásková et al. (2017) integrated Switzerland, Luxembourg, and Germany within the same cluster "Cluster 3 - highest total LTC expenditures as a percentage of GDP; the higher total number of LTC recipients aged 65+ as a percentage of total LTC recipients". Leichsenring (2021) classified Austria, France, Germany, Switzerland, and the UK as "Subsidiary LTC regime".

¹⁶F-statistic: Variation between clusters means/Variation within clusters

¹⁷The Tukey HSD test takes the fitted ANOVA as an argument. We compute Tukey HSD by performing multiple pairwise comparisons between the means of variables across the seven clusters. For the mean-testing of the binary variable, we perform a logistic regression and then calculate the least square means, and through the Tukey HSD Test, we generate contrasts for all pairwise comparisons among estimated marginal mean (Yujiao & Zhiyong, 2017).

Table 3.11: LTC clusters and Tukey test

Variable	Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5	Cluster 6	Cluster 7
LTC beds per 1000 elderly people	58,65(14,01) (Cl. 5)	54,57(16,99)	39,28(16,66)	44,85(8,62)	24,23(14,98) (Cl. 1)	25,55(16,94)	27,60(25,00)
Health and social workers	12,42(1,49) (Cl. 3)	14,36(1,80) (Cl. 3, 6)	5,88(0,92) (Cl. 1, 2, 4)	15,33(6,25) (Cl. 3, 5, 6)	8,36(2,93) (Cl. 4)	6,20(0,96) (Cl. 2, 4)	9,03(2,11)
Household size	2,27(0,10) (Cl. 3)	2,46(0,21)	2,58(0,26) (Cl. 1, 4)	2,18(0,10) (Cl. 3)	2,45(0,10)	2,40(0,00)	2,47(0,15)
Female employment rate	55,46(4,47)	60,53(5,76) (Cl. 5)	52,83(4,53)	56,88(3,96)	47,36(5,77) (Cl. 2)	55,87(0,64)	56,32(4,52)
Life expectancy at birth	82,12(0,97) (Cl. 3, 6)	81,63(1,67) (Cl. 3, 6)	78,28(1,92) (Cl. 1, 2, 5, 7)	81,20(1,52) (Cl. 6)	83,21(1,12) (Cl. 3, 6)	75,48(0,46) (Cl. 1, 2, 4, 5, 7)	82,13(0,61) (Cl. 3, 6)
Government LTC spending	0,09(0,02)	0,12(0,06) (Cl. 3, 5)	0,02(0,02) (Cl. 2, 4)	0,13(0,05) (Cl. 3, 5)	0,04(0,02) (Cl. 2, 4)	0,04(0,02)	0,06(0,04)
Private LTC spending	0,03(0,01) (Cl. 2, 3, 4, 5, 6)	0,01(0,01) (Cl. 1)	0,01(0,01) (Cl. 1)	0,01(0,00) (Cl. 1)	0,01(0,00) (Cl. 1)	0,01(0,00) (Cl. 1)	0,02(0,00)
Mean-testing for benefits	0,86(0,38)	0,60(0,55)	0,80(0,45)	0,00(0,00)	0,75(0,50)	0,00(0,00)	0,33(0,58)
Elderly income inequality	0,28(0,04)	0,31(0,06) (Cl. 4)	0,25(0,03) (Cl. 7)	0,22(0,02) (Cl. 2, 6, 7)	0,31(0,03)	0,34(0,00) (Cl. 4)	0,35(0,06) (Cl. 3, 4)
Elderly self-health status evaluation	50,36(9,15) (Cl. 3, 6)	68,25(7,40) (Cl. 3, 5, 6)	22,66(6,99) (Cl. 1, 2)	48,91(16,81) (Cl. 6)	36,75(7,53) (Cl. 2)	9,09(2,17) (Cl. 1, 2, 4)	38,75(35,86)
Countries	[n=7] Austria, Belgium, France, Germany, Luxembourg, Switzerland, UK	[n=5] Australia, Ireland, Netherlands, Sweden, USA	[n=5] Estonia, Hungary, Poland, Slovak Republic, Slovenia	[n=4] Czech Republic, Denmark, Finland, Norway	[n=4] Greece, Italy, Japan, Spain	[n=2] Latvia, Lithuania	[n=3] Canada, South Korea, Portugal

Notes: Data sources are described in Table 3.2. Data covered the period 2016-2019 (N=30), using the original variables (unstandardized). "n=" is the Number of countries and is an absolute number. For each variable was computed the Tukey HSD test for the comparison of means per pair of LTC clusters, and the results show significance at $p\text{-value} \leq 0,05$. From the Tukey HSD test to the binary variable Mean-testing benefit, we get a significance between Cluster 1 and 4 at the $p\text{-value}=0,06$. Each variable presents, on the first row, the mean and the standard deviation in brackets, and on the second row, inside brackets, "Cl." indicates the pairwise clusters that are statistically different.

Damiani et al. (2011) based on the formal care available and alignment between elderly needs and expenditures found a cluster very similar to our Cluster 1, labeled as "High alignment between old age-related expenditure and elderly needs and low formal care." The analysis of LTC under the principles of health care systems grouped the UK as a Beveridge-oriented system of social protection and France and Germany Bismarck systems (Pacolet et al., 1998), but as discussed, the classification of LTC as typical health care systems has limitations. From plots in Appendix 3.8.9, we verify that all seven countries have close mean values on LTC workers, life expectancy at birth, and public LTC spending.

Cluster 2 integrates five countries from three different world regions: Australia, Ireland, Netherlands, Sweden, and the United States. This cluster exhibits the highest female employment rate and elderly self-health status evaluation, being significantly different from Clusters 3, 5, and 6. High female social roles in the labor market may indicate lower availability of informal care and higher demand for formal care. The elderly in these countries revealed high self-evaluation of health status, which may result from long-run investment in public health and social care, an idea reinforced by the verification that this is the cluster with the second highest public LTC spending, being significantly different from Cluster 3 and 5. Plots show that this measure separates the Netherlands and Sweden from all countries of the cluster and places Cluster 2 closer to Cluster 4 (see Appendix 3.8.9). Cluster 2 also distinguishes itself from Cluster 1 in private financing spending. LTC workers' average is the second highest, significantly different from Clusters 3 and 6. Life expectancy mean values are similar for all countries except for the USA. Cluster 2 is labeled as "High supply, high demand for formal care, and strong policy oriented" given their high availability of LTC workers, female labor market participation and their elderly population's high self-rated health. Sweden and the Netherlands are often included in the same cluster in previous LTC typologies (Kraus et al., 2010; Saraceno & Keck, 2010; Damiani et al., 2011; Halásková et al., 2017; Angrisani et al., 2022), even though it is not consensual (Joshua, 2017; Ariaans et al., 2021; Kautto, 2002).

Integrating Australia, Ireland, the USA, the Netherlands, and Sweden in the same cluster is uncommon. Most LTC typologies classified the USA as a regime of means-tested rules, with mixed financing sources, prevailing the private financing to cover their own LTC needs. Sweden and the Netherlands are usually associated with universal coverage, with sources of funding based on general taxes and a social insurance scheme. Still, based on Figures in Appendix 3.8.9, we observe highly similar mean values on self-rated health, female labor, and LTC workers.

Cluster 3 comprises five Eastern Europe: Estonia, Hungary, Poland, Slovak Republic, and Slovenia. This cluster has the lowest mean percentage of health and social workers across the total population (5,88; sd=0,92), and this mean is significantly different from Clusters 1, 2, and 4. It also shows the lowest share of public and private LTC, respectively, 0,02 and 0,01 (sd=0,02 and 0,01). According to Appendix 3.8.9, we verify that the countries in this cluster have consistent shares on both measures. Merely 20% of the individuals classify their health as good or better, which is the second lowest percentage across all clusters. The elderly income inequality coefficient is 0,25 (sd=0,03), the second lowest inequality and a significant difference from Cluster 7. The household size is the highest among our clusters, which suggests that informal care is potentially high. Around 80% of the countries in the cluster impose mean-testing rules to regulate access to any benefit. Cluster 3 is labeled as "Low supply of formal care, low demand, and low public financing".

These East European countries are commonly clustered together. Lamura et al. (2007) grouped Hungary, Poland, Slovak Republic, and Slovenia as a "Transition" cluster. Damiani et al. (2011) grouped Estonia, Hungary, Slovenia, and Slovak Republic as countries that belong to Group 4, "Low alignment between old age-related expenditure and elderly needs and high formal care." At the same time, Poland was classified as "Group 2 - Low alignment between old age-related expenditure and elderly needs and low formal care". Pavolini (2022) divides these countries into two different groups, but both groups have in common the level of State inter-

vention: limited (Estonia, Hungary) and mild (Poland, Slovenia, Slovak). Plots on Appendix 3.8.9 reveal that the mean of LTC workers and public LTC spending are similar for all the five countries of this Cluster. Overall, we conclude that this cluster is characterized by countries with weak LTC structures, in which the necessary care is provided mainly in an informal setting, with formal care being limited.

Cluster 4 includes four European countries: the Czech Republic, Denmark, Finland, and Norway. The dominant features are the highest presence of health and social workers (15,33; sd=6,25) and the highest government spending (0,13; sd=0,05). In the case of LTC workers, plots from Appendix 3.8.9 express a divergence of the mean value of the Czech Republic from all other countries. For public spending, the countries' mean values are distributed from 0,07 in the Czech Republic to 0,19 in Norway. None of these countries integrate a mean-testing rule in their policies, and they have the lowest elderly inequality (0,22; sd=0,02), which is significantly different from Clusters 2, 6, and 7. The household composition is, on average, 2,18 elements (sd=0,10), which makes it the cluster with the lowest number of people within a household. Cluster 4 is labeled as "High supply for formal care, high public financing, and high equal distribution policies", given their higher availability of workers and high public investment. Conversely, they share small household sizes, absent mean-testing rules, and have the lowest unequal income distribution.

The Czech Republic is seldom in a cluster with most Nordic European countries. Denmark, Finland, and Norway are often classified together. From the social insurance branch, they are classified as a "Beveridge oriented system of social protection/Long term care included in present systems of social protection" (Pacolet et al., 1998), while from a coverage domain, they are classified as "Universal coverage within a single system" (Colombo et al., 2011). However, Ariaans et al. (2021) and Damiani et al. (2011) do not cluster them together and highlight their dissimilarities. Damiani et al. (2011) grouped Denmark and Finland as countries with high alignment between expenditure and elderly needs and low formal care, while Norway has high formal care. The Czech Republic has low alignment and low formal care. Based on Ariaans et al. (2021), the Czech Republic is clustered as a residual public system, Denmark and Norway are more public supply-oriented, while Finland is private. Furthermore, based on Lamura et al. (2007) the Czech Republic and Finland are "Standard-care mix" and Denmark is "Public-Nordic", which is aligned with Pavolini (2022) that classified the Czech Republic and Finland as having decisive State intervention, differing if this was via cash or in-kind benefits.

Cluster 5 includes three countries from the Mediterranean Europe region: Greece, Spain, and Italy, and one from Asia, Japan. This cluster exhibits the lowest female employment rate (47,36; sd=5,77), with a significant difference from Cluster 2. Countries in Cluster 5 have a higher life expectancy at birth, 83,21 years (sd=1,12). The private expenses are, on average, 0,01 (sd=0,01) of the share of GDP, which is aligned with other clusters (2, 3, 4, and 6) but significantly different from Cluster 1. Public LTC spending is similar to Cluster 6, but differs significantly from Clusters 2 and 4. On average, there are 24,23 (14,98) LTC beds per 1000 elderly people, which is the minimum average value across the seven clusters. The mean percentage of health and social workers is 8,36 (sd=2,93), which is the second lowest and differs significantly from Cluster 4. Cluster 5 is labeled as "Low supply of resources, low demand for formal care, high regulation", based on the low availability of LTC residential beds, low female labor participation, highest life expectancy, and high mean-testing rules applied.

Greece and Spain are usually clustered together (Kautto, 2002; Lamura et al., 2007; Damiani et al., 2011), and Italy is often clustered with Spain (Kraus et al., 2010; Saraceno & Keck, 2010). Japan is more unexpected. According to Leichsenring (2021), Italy, Japan, and Spain belong to the "Subsidiary LTC regime," while Greece is an "Emerging (-market) LTC regime." In that respect, we highlight the separability between countries from Cluster 5 and Cluster 7. Portugal has often been grouped with other Mediterranean countries, such as Spain, Italy, or Greece (Simonazzi, 2009; Bettio & Verashchagina, 2012). Japan and South Korea are frequently

grouped and constitute, in some cases, an exclusive cluster (Ariaans et al., 2021; Applebaum et al., 2013; Colombo et al., 2011). However, Leone et al. (2014) and Leichsenring (2021) place them in different groups. The expansion of public funding and the universalization of access to LTC that replaced a previously means-tested system in Spain could justify the joint clustering with Japan (Costa-Font & Vilaplana-Prieto, 2017). From Appendix 3.8.9, we observe their close means on private LTC spending.

Cluster 6 is the smallest cluster, including two European countries, Latvia and Lithuania. This cluster has the lowest self-evaluation of individual health status (9,09; $sd=2,17$), significantly different from the Clusters 1, 2, and 4. People from those countries have a minimum life expectancy at birth (75,48 years; $sd=0,46$) across all clusters, significantly differing from Clusters 1, 2, 4, 5, and 7. The supply of LTC beds is the second lowest across all clusters (25,55; $sd=16,94$). The mean percentage of health and social workers is also the second lowest at 6,20 ($sd=0,96$), significantly differing from Clusters 2 and 4. None of the countries in this cluster has mean-testing rules. Cluster 6 is characterized by "Low demand and low policy implementation", reflecting a younger population, low LTC beds available, and low female labor participation.

Latvia and Lithuania are frequently grouped. Lamura et al. (2007) classify both as an exclusive cluster named "Baltic." Damiani et al. (2011) grouped them on the cluster "low alignment between old age-related expenditure and elderly needs and high formal care". On the other hand, some studies have highlighted some divergences between the countries. Kraus et al. (2010) ranked Latvia with medium organizational depth on their LTC and Lithuania with low organization. To Saraceno & Keck (2010), the main difference between both is that the minimum non-contributory pension available in Latvia is high, but "low" in Lithuania. Pavolini (2022) puts both on different groups, with Latvia's "limited State intervention" and Lithuania's "mild State intervention". Appendix 3.8.9 shows that both countries have very similar mean values for all variables.

Cluster 7 is composed of Canada, South Korea, and Portugal. It has the second-highest average of private spending on LTC (0,02; $sd=0,00$), which denotes higher OOP expenses. These countries have the second highest life expectancy at birth, with very close mean results and a significant difference from Clusters 3 and 6. The maximum income inequality among the elderly belongs to that cluster (0,35; $sd=0,06$), with significant differences from Clusters 3 and 4. South Korea has the highest inequality, and Canada has the lowest. LTC workers variable has mean values of 9,03 ($sd=2,11$) with a maximum of 11,44 (in Canada) and 8,16 (in Portugal). Conversely, the LTC beds have divergent results across the countries, and the measure of self-rated good health also presents wide variations. Cluster 7 can be labeled as "Low supply of resources, weak distribution policies, and high demand" given the high levels of income inequality, low availability of beds in formal care settings, but highest life expectancy at birth.

According to Colombo et al. (2011), Canada and Portugal both have mixed systems, while in South Korea the entitlement is universal coverage within a public LTC insurance model. Canada's mixture of financing methods and subsidiary LTC regime are both characteristics highlighted in Feng & Glinskaya (2019) and Leichsenring et al. (2021), while South Korea was classified as "Universal coverage" and an "Emerging (-market) LTC regime." Pavolini (2022) states that Portugal has a "limited State intervention model", which could reveal characteristics of mixed State and market orientations. Canada, South Korea, and Portugal seem to have similarities with Cluster 5, however, we observe higher female labor participation, higher public investment, and lower mean-testing rules. Portugal has usually been grouped with other Mediterranean countries (Simonazzi, 2009; Saraceno & Keck, 2010; Bettio & Verashchagina, 2012), but the trade-off between high female labor force participation and low formal care resources available has been a particular issue (Bettio & Plantenga, 2004). From Appendix 3.8.9 we observed close mean values around measures of private LTC spending and life expectancy at birth.

Finally, Table 3.12 presents the correlation coefficients between variables within each cluster, allowing us to evaluate which variables have a higher influence on cluster countries (we defined each $K = 7$ cluster as a binary variable). This allows us to answer the following question: How do the country's individual LTC policy characteristics contribute to them being clustered together?

Cluster 1 correlates more with LTC beds and private LTC spending. Cluster 2 has more robust correlations with health and social workers, female employment rate, government spending, and elderly self-evaluation of health. Cluster 3 has a positive and significant correlation with household size, and a negative significant correlation with the number of workers, life expectancy, government spending, and self-rated health. Cluster 4 has positive correlations with workers' availability and government spending and negative with household size, application of mean testing rules, and inequality. Cluster 5 is negatively correlated with the number of beds and female employment and positively correlated with life expectancy. Cluster 6 is negatively correlated with life expectancy and self-rated health. Finally, Cluster 7 is highly correlated with elderly inequality.

Table 3.12: Correlation coefficients between each variable and our cluster solution of $K = 7$

Variables	CL1	CL2	CL3	CL4	CL5	CL6	CL7
LTC beds	0,45	0,27	-0,09	0,04	-0,38	-0,24	-0,27
Health and social workers	0,22	0,38	-0,51	0,42	-0,22	-0,29	-0,13
Household size	-0,35	0,15	0,43	-0,44	0,12	0,01	0,13
Female employment rate	0,04	0,43	-0,18	0,12	-0,54	0,04	0,07
Life expectancy at birth	0,26	0,12	-0,50	0,04	0,36	-0,61	0,16
Government LTC spending	0,15	0,39	-0,46	0,43	-0,29	-0,19	-0,12
Private LTC spending	0,72	-0,11	-0,34	-0,10	-0,32	-0,23	0,21
Mean-testing for benefits	0,32	0,03	0,21	-0,45	0,15	-0,31	-0,16
Elderly income inequality	-0,09	0,20	-0,31	-0,48	0,17	0,27	0,40
Elderly self-health status evaluation	0,20	0,55	-0,44	0,12	-0,12	-0,44	-0,07

Notes: Data sources are described in Table 3.2. Data covered the period 2016-2019 (N=30). All variables are standardized except Mean testing. Bold identifies the correlation coefficient significance at p-value $\leq 0,05$. Calculations were performed using the software Stata SE v.18.0.

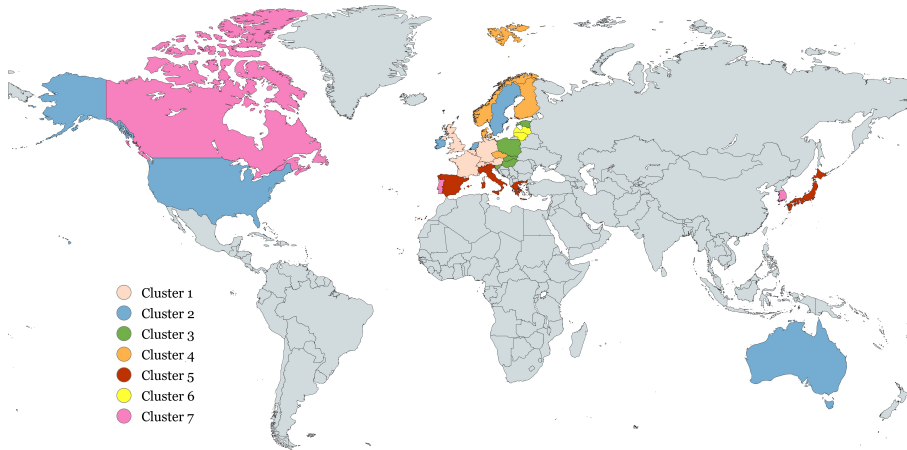
Table 3.13 summarizes the findings from our validation process of the seven clusters. In complement, we also map the clusters to get a visualization of their associated countries, allowing an analysis of the distribution of clusters across the world (Figure 3.6):

Table 3.13: Our cluster solution of $K = 7$ and their main distinctive characteristics

Dimension	Variables	CL1: High supply of resources and high private financing	CL2: High supply, high demand for formal care, and strong policy oriented	CL3: Low supply of formal care, low demand, and low public financing	CL4: High supply for formal care, high public financing, and high distribution policies	CL5: Low supply of resources, low demand for formal care, high regulation	CL6: Low demand and low policy implementation	CL7: Low supply of resources, weak distribution policies, and high demand
Supply	LTC beds	+				-		-
	Health and social workers			-	+		-	
	Household size			+	-			
Demand	Female employment rate		+			-		+
	Life expectancy at birth			-		+	-	
Financing	Government LTC spending		+	-	+			
	Private LTC spending	+						
Policy provision and regulation	Mean-testing for benefits	+			-			
	Elderly income inequality				-			+
	Elderly self-health status evaluation		+				-	
Countries		[n=7] Austria, Belgium, France, Germany, Luxembourg, Switzerland, UK	[n=5] Australia, Ireland, Netherlands, Sweden, USA	[n=5] Estonia, Hungary, Poland, Slovak Republic, Slovenia	[n=4] Czech Republic, Denmark, Finland, Norway	[n=4] Greece, Italy, Japan, Spain	[n=2] Latvia, Lithuania	[n=3] Canada, South Korea, Portugal

Notes: "+" / "-" means a strong/weak characteristic observed even at mean values and also on correlations.

Figure 3.6: Visualization of the seven clusters on the world map



Notes: Map modelled by <https://www.mapchart.net/world.html>. Colors legend: Cluster 1: High supply of resources and high private financing (apricot); Cluster 2: High supply, high demand for formal care, and strong policy oriented (blue); Cluster 3: Low supply of formal care, low demand, and low public financing (green); Cluster 4: High supply for formal care, high public financing, and high equal distribution policies (orange); Cluster 5: Low supply of resources, low demand for formal care, high regulation (red); Cluster 6: Low demand and low policy implementation (yellow); Cluster 7: Low supply of resources, weak distribution policies, and high demand (pink).

3.6 Robustness checks

In this section, we implement some robustness checks. We change some of the algorithm parameters and analyze six cases of clustering proposals' results. We also evaluate the percentage of similarity across countries between our original $K = 7$ proposal and the cases obtained

from the previous robustness check. The third robustness exercise applies the method of sub-sampling, where a subset of our sample data is randomly selected and analyzed. Finally, we perform an additional robustness test by using COVID-19 data.

3.6.1 Changing algorithms parameters

The first robustness check analysis tests how changing algorithm parameters of the three algorithms, FCM, SOM, and PAM, could impact the proposed clustering.

First, our FCM algorithm works under soft clustering terms with a default fuzziness coefficient $m = 2$. Under this coefficient, the algorithm assigns each data point (i.e., country) to each cluster but with an associated weight, allowing each country to belong to different clusters with varying degrees. As m approaches 1, the clustering tends to become crisp (i.e., it performs K-means, which is a hard clustering, given that each data point belongs to only one cluster or partition). When it goes to infinity, the clustering becomes fuzziness (Cebeci et al., 2022). To check the stability of our proposal, we define different fuzziness coefficients, keeping all other algorithm settings constant. Yu et al. (2004) explored some rules to define a valid value of the level of fuzziness and concluded that it depends on the data. Following Bezdek’s rule $m = \frac{n}{n-2}$ (Yu et al., 2004) and applying it to our data we get $m = 1,1$, while based on the Winkler et al. (2015) rule $m = 1 + \frac{2}{N_{inputs}}$, where N_{inputs} is the feature space, we get $m = 1,2$.

Second, our SOM algorithm from Kohonen (2001) applied the hexagonal lattice for mappings, and it is more effective for visual display and allows getting more stable, well-oriented, and less ambiguous results. However, the lattice type can also be rectangular or even irregular. We test our data using a rectangular grid that applies four neighbor neurons instead of six neighbor neurons. It implies observing how our results change when we reduce the number of interactions with other neurons.

Third, the PAM algorithm will be tested by changing the metric to determine object-object dissimilarity. The Manhattan distance is applied, as opposed to the Euclidean distance. We aim to compare the cluster proposal obtained from the Manhattan distance since it is also used in the clustering research and is calculated by summing the horizontal and vertical distances between observations, which gives less weight to outliers and has higher sensitivity power (Botyarov & Miller, 2022).

We test the following cases:

i) Case 1: $m = 2,5$, which implies a higher fuzziness of our data. After running the three algorithms of the clustering ensemble modeling, the proposal clustering division becomes: FCM optimal number of cluster partitions is assigned to $K = 9$; SOM proposes $K = 5$, while PAM assigned $K = 7$. Since the consensus rule is not applied, we observe the partition with the highest ASW. PAM $K = 7$ has the highest value (0,30). However, when we proceed with the correspondence between the assigned clusters attributed to each country to get a unique ensemble classification, we found empty clusters on FCM partitions¹⁸. We accept the best partition $K = 5$, and from the Tukey test, we observe that all variables, except the household size and the income inequality, have pairwise clusters with significant differences.

ii) Case 2: $m = 1,5$ reduces the fuzziness of our data. FCM proposes the partition $K = 7$, SOM proposes $K = 5$, and PAM $K = 7$. By consensus and majority voting, the best solution is $K = 7$ when the fuzziness coefficient is equal to 1,5. From the Tukey test, all variables have any pairwise cluster with significant difference, except the measure of mean-testing benefit rule.

iii) Case 3: $m = 1,001$ puts the FCM algorithm very close to the K-means algorithm. From the FCM algorithm, $K = 8$ is the optimal number of partitions; SOM proposes $K = 5$,

¹⁸ $K = 9$ also get empty clusters. We test with $K = 6$, and FCM and SOM have empty clusters.

while PAM $K = 7$. Given that PAM $K = 7$ is the partition among all algorithms with the highest ASW, we assume that under a fuzziness coefficient of 1,001, the best partition would be $K = 7$. The Tukey test found significance for all variables across pairwise clusters except for the mean-testing benefit variable.

iv) Case 4: $m = 1, 2$ runs our model under the fuzziest coefficient close to the literature rules. FCM proposes $K = 7$; SOM proposes $K = 5$, and PAM $K = 7$, and by majority, we assume $K = 7$. The Tukey test found significance for all variables across pairwise clusters.

v) Case 5: we (re)run our model, changing the settings of the SOM, *ceteris paribus*. We assume a rectangular grid instead of a hexagonal one. The best partition proposals are from FCM $K = 9$, SOM $K = 5$, and PAM $K = 7$. Applying the highest ASW rule, we get PAM $K = 7$ as the best partition, and from the Tukey test, the insignificance of the mean testing measure remains.

vi) Case 6: we change the distance metric on PAM, and instead of Euclidean distance, we adopt the Manhattan distance, *ceteris paribus*¹⁹. From FCM, the best partition is $K = 9$, SOM proposes $K = 5$, $K = 6$, $K = 8$, and $K = 9$, while PAM proposals $K = 8$ and $K = 9$. From the consensus and majority rule, $K = 9$ is the optimal partition. From the Tukey test, we get significance for all variables across pairwise clusters, except on the household size and mean testing²⁰.

Comparing the changing algorithms parameters

We compute the overall Average Silhouette Width, the Calinski-Harabaz index, the Davies-Bouldin index, and the Dunn index of our cluster $K = 7$ and all cases analyzed. Table 3.14 shows the results. These internal criteria collected from the six cases have very close values. All cases have ASW values close to 0, suggesting the occurrence of countries whose LTC policies are close to the border between clusters. The FCM with $m = 2, 5$ has the highest ASW and CH among all the cases. Given that FCM $m = 2, 5$ allows the higher fuzziest on countries clusters, this characteristic seems to be captured by ASW and CH maximum values. The best value of the DB index is on FCM $m = 1, 2$, while the worst value is on the FCM $m = 2, 5$. Under FCM $m = 1, 2$, we restrict the fuzziest to the theoretical rules, and we observe optimal values in both DB and DI. Around the Dunn Index, all cases have very similar results, with evidence of FCM with $m = 1, 5$ and $m = 1, 2$, which collect a higher value.

From Table 3.14, we also observe the number of partitions proposed by each method and the average size distribution of the proposed clusters. Both are essential clustering indicators for identifying similarities across partitions, but also the cluster's distinctive characteristics (Gates et al., 2019). The majority of the analyzed cases proposed a partition of $K = 7$. Changes in the clustering partition proposal are observed in the results associated with the FCM algorithm tested under the highest fuzziest coefficient m and on the PAM algorithm using Manhattan distance.

Taking a focus on the partitions proposal of $K = 7$, our clustering collects the lowest average number of countries belonging to each cluster (4,80), which is evidence that our $K = 7$ has the potential to identify distinctive characteristics of the country's LTC policies, and does not agglomerate countries. On the opposite, when we impose an FCM with $m = 1, 001$, we get the highest average number of countries clustered together (5,53), suggesting that in our case

¹⁹Euclidean distances are root sum-of-squares of differences, and Manhattan distances are the sum of absolute differences (Maechler, 2022).

²⁰Across all cases, on the mean-testing variable we perform a logistic regression and then calculate the least square means and by Tukey HSD Test we generate contrasts for all pairwise comparisons among estimated marginal mean.

hard partitioning algorithms could produce very highly dense clusters, which could imply lower discriminant power of LTC policies features.

Table 3.14: Cases analyzed based on changing clustering algorithms parameters and their internal criteria evaluation

Cases analyzed	Partition proposed	ASW	CH	DB	DI	Average nº countries
Our proposal of $K=7^a$	$K=7$	-0,22	3,54	2,61	0,07	4,80
FCM, $m=2,5$	$K=5$	0,005	9,27	4,23	0,07	6,47
FCM, $m=1,5$	$K=7$	-0,10	7,44	1,08	0,09	5,33
FCM, $m=1,001$	$K=7$	-0,19	5,46	3,51	0,08	5,53
FCM, $m=1,2$	$K=7$	-0,12	7,56	0,90	0,09	5,47
SOM with rectangular grid	$K=7$	-0,19	3,80	2,74	0,07	4,93
PAM with Manhattan distance	$K=9$	-0,17	5,15	1,66	0,07	3,73

Data sources are described in Table 3.2. Data covered the period 2016-2019 ($N=30$) and included as inputs the PC1 to PC5. Optimal values of the internal criteria: Average Silhouette width (ASW) (maximum), the Calinski-Harabaz index (CH) (maximum), the Davies-Bouldin index (DB) (minimum), and the Dunn index (DI) (maximum). Bold identifies the optimal value on each criteria. Nº of countries is the weighted average number of countries calculated by multiplying each cluster percentage by its value and summing these weights.

^aObtained using FCM with $m=2$; SOM hexagonal; PAM with Euclidean distances. Please see Appendix 3.8.5 to get details.

Comparing our proposal with all the cluster partitions of $K = 7$ using external criteria allows us to observe, from Table 3.15, that our clustering proposal $K = 7$ collects, on average, 64% of similarity with the four other cases. The highest similarity is observed with SOM with the rectangular grid, where it is observed that 97% of our sample countries collected the same cluster in both methods ($K=7$ & SOM with rectangular grid). SOM with a rectangular grid reveals maximum values with all external criteria. All cases collect RI values close to 1, which indicates high agreement between both cluster solutions. JI analyses only the true positives, i.e., countries classified in the same cluster by both methods, revealing moderate overlap between the cases. Finally, the null hypothesis tests the statistical independence of the cases analyzed from Pearson's χ^2 Test. We reject the null to all comparisons, which indicates significant dependence between cases and our $K = 7$, reinforcing that in spite of getting different clustering, those cases still have similarities with our $K = 7$

Table 3.15: Cases analyzed: external criteria comparison

Cases analyzed	SM	RI	ARI	JI	χ^2
Our $K=7$ & FCM, $m=1,5$	0,57	0,88	0,49	0,39	97,00***
Our $K=7$ & FCM, $m=1,001$	0,40	0,91	0,64	0,52	123,74***
Our $K=7$ & FCM, $m=1,2$	0,63	0,89	0,53	0,43	110,32***
Our $K=7$ & SOM with rectangular grid	0,97	0,98	0,92	0,87	168,75***

Data sources are described in Table 3.2. Data covered the period 2016-2019 ($N=30$) and included as inputs the PC1 to PC5. Simple Matching (SM) compares our $K = 7$ cluster solution with each case. Rand index (RI), Hubert and Arabie's Adjusted Rand index (ARI), Jaccard index (JI), and Person χ^2 Test are calculated using clustering previous re-labeling. Bold identifies the optimal value on each criteria. Statistical significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

In sum, we verify that our clustering solution exhibits good properties when compared to other cluster solutions obtained from different algorithm settings. The $K = 7$ clustering proposal is moderately stable, distinguishing the countries' characteristics and does not agglomerate them.

3.6.2 Countries pairwise comparison

The second robustness check evaluates how often each of the previous cases assigned countries to the same cluster. We compare our original $K = 7$ proposal and the cases obtained on the previous robustness check: FCM with $m = 2, 5$; FCM with $m = 1, 5$, FCM with $m = 1, 001$, FCM with $m = 1, 2$, SOM with rectangular grid, and PAM with Manhattan distance. For each country ($N=30$), we calculate how many times it was assigned to the same cluster²¹. Table 3.7 shows a matrix with those comparisons. Since comparisons are symmetric, the table shows the results of comparisons in the upper-right triangle.

The matrix presents, by country pair, the percentage of times each country pair is clustered together. From our review of the countries' LTC policies (please see Appendix 3.8.1), as expected, some pairs are never jointly clustered (0%) by any of the cases, including our model (e.g., Lithuania and Canada). On a maximum, we observe a 100% concordance, i.e., among the seven cases studied, all agree on assigning together the following country pairs: Austria and Belgium; Ireland and Australia; Australia and USA; Austria and France; Belgium and France; Italy and Greece; Ireland and USA; South Korea and Portugal; Latvia and Lithuania; UK and Switzerland. Our typology $K = 7$ captured all these pairs, denoting higher agreement between countries clustered together.

The second higher concordance is observed at 86% agreement rate. We found this concordance percentage on the following 12 country pairs: Germany and Austria, Belgium and Germany, France and Germany, Hungary and Czech Republic, Luxembourg and Austria, Luxembourg and Belgium, France and Luxembourg, Norway and Denmark, Poland and Hungary, Slovak Republic and Hungary, Slovak Republic and Poland, Sweden and the Netherlands. At 86% agreement rate, our typology $K = 7$ only does not cluster together the pair Hungary and the Czech Republic since Hungary belongs to Cluster 3 while the Czech Republic belongs to Cluster 4.

3.6.3 Random sample selection

The third robustness is evaluated by randomly selecting country subsamples from the original dataset. Considering our clustering solution of $K = 7$, we aim to test if it holds when we follow all the procedures of the clustering ensemble modeling, but we randomly disturbed our countries' sample. We test around three cases: i) we impose 3,33% of disturbance on the baseline subsample, which means that we drop one country; ii) we impose 6,67% of disturbance on the baseline subsample, which means dropping two countries; and iii) we impose 10% of disturbance on the baseline subsample, which means dropping three countries.

i) Case 1: 3,33% of disturbance on the baseline subsample.

On a subsample of 29 countries taken at baseline, we assessed the effect of one country less on the final number of clusters proposal, and we analyzed their external validity indexes. We ran a random selection procedure²². We observe the cumulative proportion of variance of the PC5 is 87,67%, and we follow the 5 PCs. From the proposals of FCM, SOM, and PAM, we do not reach a consensus, and we accept the partition PAM $K = 7$, which is the one with the highest ASW. We observe a simple matching coefficient of 83% between our cluster proposal obtained under the random subsample and our original cluster solution of $K = 7$ ²³. Considering both situations, we get the Rand index of 0,92, Hubert and Arabies's adjusted Rand index of 0,66, and a Jaccard index of 0,54. Pearson's Chi² independence test rejects the null hypothesis

²¹Ariaans et al. (2021) adopted a similar procedure to identify the connection between countries and to develop the network of LTC systems.

²²After several times repeated, in order to get a stable result, we accepted the last drop suggestion. In that case, the eliminated country was Estonia.

²³To compare both, we also drop Estonia from our $K = 7$

Figure 3.7: Countries pairwise comparison matrix (in %)

	AU	AT	BE	CA	CZ	DK	EE	FI	FR	DE	GR	HU	IE	IT	JP	KR	LV	LT	LU	NL	NO	PL	PT	SK	SI	ES	SE	CH	UK	US
AU	--	0%	0%	0%	0%	14%	0%	0%	0%	0%	0%	0%	100%	0%	0%	0%	0%	0%	0%	57%	29%	0%	0%	0%	0%	57%	71%	0%	0%	100%
AT		--	100%	43%	0%	0%	0%	14%	100%	86%	0%	0%	0%	0%	0%	0%	0%	0%	86%	0%	0%	0%	0%	14%	57%	0%	0%	71%	71%	0%
BE			--	43%	0%	0%	0%	14%	100%	86%	0%	0%	0%	0%	0%	0%	0%	0%	86%	0%	0%	0%	0%	14%	57%	0%	0%	71%	71%	0%
CA				--	0%	0%	0%	14%	43%	43%	0%	0%	0%	0%	0%	29%	0%	0%	43%	0%	0%	0%	29%	0%	43%	0%	0%	71%	71%	0%
CZ					--	14%	57%	14%	0%	14%	0%	86%	0%	0%	0%	14%	14%	0%	0%	14%	71%	0%	71%	14%	0%	0%	0%	0%	0%	0%
DK						--	0%	14%	0%	0%	0%	0%	14%	0%	0%	0%	0%	0%	0%	57%	86%	0%	0%	0%	0%	14%	43%	0%	0%	14%
EE							--	14%	0%	14%	0%	71%	0%	0%	0%	43%	43%	0%	0%	0%	57%	0%	57%	29%	0%	0%	0%	0%	0%	0%
FI								--	0%	14%	0%	14%	0%	0%	0%	14%	14%	0%	43%	71%	0%	0%	0%	0%	0%	29%	0%	0%	0%	0%
FR									--	86%	0%	0%	0%	0%	0%	0%	0%	0%	86%	0%	0%	0%	0%	14%	57%	0%	0%	71%	71%	0%
DE										--	0%	14%	0%	0%	0%	0%	14%	14%	71%	0%	0%	0%	0%	0%	43%	0%	0%	71%	71%	0%
GR											--	0%	0%	100%	57%	14%	0%	0%	0%	0%	0%	14%	14%	0%	43%	0%	0%	0%	0%	0%
HU												--	0%	0%	0%	0%	14%	14%	0%	0%	0%	86%	29%	86%	29%	0%	0%	0%	0%	0%
IE													--	0%	0%	0%	0%	0%	0%	57%	29%	0%	0%	0%	0%	57%	71%	0%	0%	100%
IT														--	57%	14%	0%	0%	0%	0%	0%	14%	14%	0%	43%	0%	0%	0%	0%	0%
JP															--	57%	0%	0%	0%	0%	0%	14%	57%	0%	0%	43%	0%	0%	0%	0%
KR																--	0%	0%	0%	0%	0%	14%	100%	0%	0%	0%	0%	0%	0%	0%
LV																	--	100%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
LT																		--	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
LU																			--	0%	0%	0%	0%	14%	71%	0%	0%	71%	71%	0%
NL																				--	71%	0%	0%	0%	0%	14%	86%	0%	0%	57%
NO																					--	0%	0%	0%	0%	14%	57%	0%	0%	29%
PL																						--	14%	86%	29%	0%	0%	0%	0%	0%
PT																							--	0%	0%	0%	0%	0%	0%	0%
SK																								--	43%	0%	0%	0%	0%	0%
SI																									--	0%	0%	43%	43%	0%
ES																										--	29%	0%	0%	57%
SE																											--	0%	0%	71%
CH																												--	100%	0%
UK																													--	0%
US																														--

Note: Countries codes are from www.nationsonline.org: AT - Austria; AU - Australia; BE - Belgium; CA - Canada; CH - Switzerland; CZ - Czech Republic; DE - Germany; DK - Denmark; EE - Estonia; ES - Spain; FI - Finland; FR - France; GR - Greece; HU - Hungary; IE - Ireland; IT - Italy; JP - Japan; KR - South Korea; LV - Latvia; LT - Lithuania; LU - Luxembourg; NL - Netherlands; NO - Norway; PL - Poland; PT - Portugal; SE - Sweden; SI - Slovenia; SK - Slovakia; UK - United Kingdom; US - USA.

Clusters with $K = 7$ re-labelled. Blue color means gradient % of times each country pair is clustered together, i.e., higher blue extension indicates higher %, while 0% is uncolored.

of independence between the subsample clustering proposal and our $K = 7$ clustering ($\text{Chi}^2 = 136,33$; $\text{p-value} \leq 0,05$).

ii) Case 2: 6,67% of disturbance on the baseline subsample.

In this second random subsample selection, we apply a disturbance of 6,67%, which eliminates two countries. We accept the random selection proposal of deleting Japan and Poland. At PC5, we get a cumulative proportion of variance of 87,37%, and we follow the 5 PCs. We get a proposal of seven partitions²⁴, and the simple matching coefficient obtained was 75% between our cluster proposal obtained after a random drop of two countries and our original cluster solution of $K = 7$ ²⁵. Considering both situations, we get the Rand index of 0,91, Hubert and Arabies's adjusted Rand index of 0,59, and a Jaccard index of 0,48. Pearson's Chi^2 independence test rejects the null hypothesis of independence between the subsample clustering proposal and our $K = 7$ clustering ($\text{Chi}^2 = 112,85$; $\text{p-value} \leq 0,05$).

iii) Case 3: 10% of disturbance on the baseline subsample.

The last disturbance applied is 10%, which eliminates three countries. From the last random process, we deleted the Czech Republic, Lithuania, and the Netherlands. As before, we get 5 PCs with a cumulative proportion of variance of 87,43%. The proposal number of partition is seven²⁶. We get a simple matching coefficient of 70% between our cluster proposal obtained after a random drop of two countries and our original cluster solution of $K = 7$ ²⁷. The Rand index coefficient obtained is 0,89, Hubert and Arabies's adjusted Rand index is 0,52, and a Jaccard index is 0,41. Pearson's Chi^2 independence test rejects the null hypothesis of independence between the subsample clustering proposal and our $K = 7$ clustering ($\text{Chi}^2 = 101,08$; $\text{p-value} \leq 0,05$).

Our typology resists across the three disturbances tests, which is a good indicator of the robustness of our cluster solution. Our sample of $N=30$ is not large, and by applying up to 10% of disturbance, we are generating higher changes to the baseline subsample. We recognize that one unique country elimination could potentially have a significant impact on the outcome. Still, our clustering proposal is consistent with the number of partitions proposed ($K = 7$). From applying those random disturbances robustness checks, we derive the following relevant findings:

First, analyzing the number of partitions proposed by each method is an essential indicator for identifying similarities across partitions, but also to highlight each cluster's distinctive characteristics (Gates et al., 2019). As expected, the external indices decrease across the three subsamples, but the number of partitions proposed $K = 7$ is kept.

Second, we include countries that were not clustered before, and we still observe good similarity and agreement from our $K = 7$. This reinforces our proposal and guarantees that we i) are covering a wide range of countries, ii) include the main variables that characterize countries' LTC, and iii) cover substantial heterogeneity of the countries' LTC policies and their typologies.

Third, we found that even using a low countries sample ($N=30$) and after imposing high disturbance, we still observe, at minimum, 70% of matching with our $K = 7$ typology. Furthermore, across all cases, we observe a significant Pearson's Chi^2 independence test, accepting and indicating the dependence and similarity between our cluster $K = 7$ and the proposals obtained. Those results reinforce that our $K = 7$ clustering performs a proposal typology to group countries, which remains almost constant and is a valid clustering of OECD countries' LTC policies.

²⁴From the algorithms, we get a proposal of 9 clusters. However, with both 9 and 8 partitions, we have empty clusters.

²⁵To compare both, we also drop Japan and Poland from our $K = 7$

²⁶FCM and PAM propose 8 clusters, but have empty clusters.

²⁷To compare both, we also drop the Czech Republic, Lithuania, and the Netherlands from our $K = 7$.

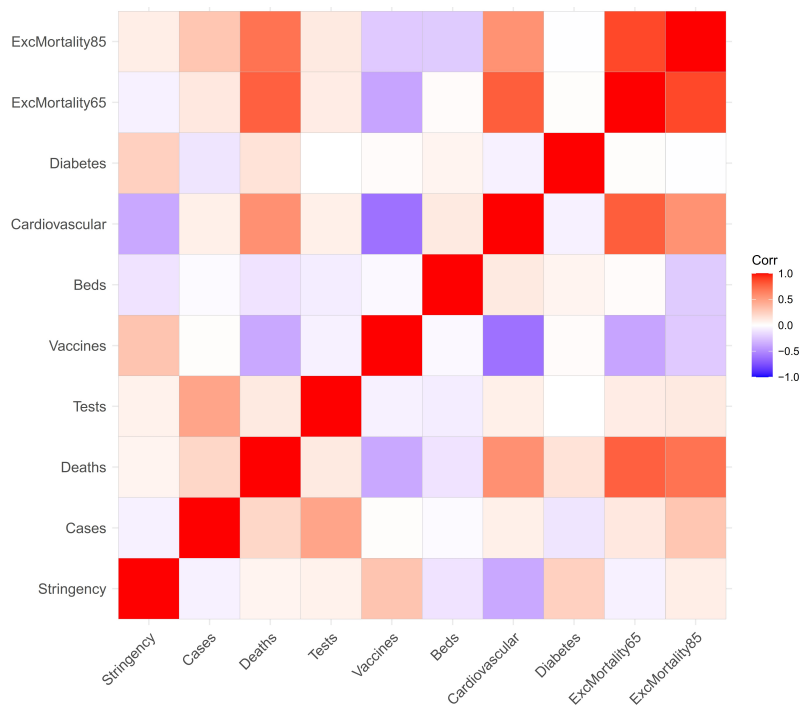
3.6.4 An application using the COVID-19 pandemic

Coronavirus disease (COVID-19) is an infectious disease caused by the SARS-CoV-2 virus. COVID-19 disproportionately impacted older adults, with a particular focus on those in LTC facilities who had medical and social vulnerabilities. The incidence and mortality rates were not homogeneous across countries (Gohari et al., 2022). As an unexpected external shock, we aim to verify if, under the onset of COVID-19, each of the $K = 7$ clusters identified in our previous results exhibits significant differences for health variables influenced by this shock.

Table 3.16 describes the variables used in our analysis. We selected variables related to COVID-19, such as cases, deaths, vaccination, country restrictiveness policies implemented, hospital beds supply, and excess mortality among the elderly. We also included two variables indirectly related to COVID-19: cardiovascular and diabetes death rates in 2017. Both variables had been previously used to cluster countries based on the leading causes of death and health risk factors (İşikhan & Güleç, 2018).

The Hopkins statistic exhibits a value of 0,99 (p-value=0,00), which indicates a high likelihood of the existence of significant clusters. The correlation matrix is presented in Figure 3.8. The highest positive correlated variables are tests and cases (0,47), vaccines and stringency (0,31), cardiovascular deaths and deaths from COVID-19 (0,57), and excess of mortality among people aged 65 and 85 years, and the general deaths occurred (0,78 and 0,70). The highest negative correlations are between cardiovascular deaths and vaccines (-0,61) and excess mortality among people 65+ and vaccines (-0,39).

Figure 3.8: Pearson correlation coefficients between pairwise variables



Notes: Data sources and period are described in Table 3.16. (N=30). Data are unstandardized.

Diverse guidelines and policies were implemented across countries, specifically in the LTC facilities, to limit the spread of COVID-19, such as forbidding and limiting visits. On a range from 0 to 100, on average, the stringency index adopted by countries was 41,31 (sd=5,50) points, which indicates the adoption of similar and not very restrictive measures. The highest restrictive policies were applied in the European Mediterranean countries such as Greece, with a stringency index of 52,74, and Italy (52,43). Estonia registered the lowest stringency index (32,08). The average per million COVID-19 cases were 205342 (sd=66416), while deaths were, on average,

1571 (sd=782). The sum of confirmed COVID-19 cases has a maximum in Slovenia (315399 per million people) and a minimum in Canada (63695 per million people). In comparison, the deaths range from a maximum in Hungary (3169) to a minimum in Japan (240 per million people). On average, the total COVID-19 tests per 1000 people were 1602 (sd=1486), with a maximum in Austria (6939 per 100 people) and a minimum in Japan (124 per 100 people). On average, at least one vaccine dose was administrated in 59% (sd=9,44) of the population. Portugal had the highest vaccination rate (78,60), and the Slovak Republic had the lowest (34,66). The average number of hospital beds per 1000 people was 5,07 (sd=2,60), with a maximum of 13 (Japan) and a minimum of 2 beds (Sweden). On average, the annual number of deaths per 100000 people due to cardiovascular issues is 159 (sd=74,26), reaching a maximum in Latvia (350) and a minimum in Japan (79). Diabetes prevalence, on average, affected 5,95% (sd=1,72) of the adult population, with maximum prevalence in the USA (10,79%) and minimum in Ireland (3,28%). The excess mortality among people aged 65 and 85 years old was, on average, 875 (sd=638) and 396 (sd=269) elderly individuals per million, ranging from a minimum to maximum of -41,23 and -275,94 (Japan) and 2425 and 863 excess deaths (Lithuania)²⁸.

We perform the Tukey HSD test to compare the mean values of each variable across our $K = 7$ clusters. Table 3.17 shows the mean differences across pairs of LTC clusters and the pairwise clusters with significance at p-value $\leq 0,05$.

The COVID-19 pandemic was, across the world, an unexpected shock. Countries adopted and imposed some rules to control the spread of the contagion, and their internal policies collected significant differences among Clusters 3, 4, and 5. In Appendix 3.8.10, we observe that the countries belonging to those clusters reveal the highest and lowest restrictive policies. Concerning the number of total cases, deaths, and tests, we do not verify any significant differences at p-value $\leq 0,05$. However, our $K = 7$ cluster division captures significant differences when we analyze the vaccination rate. Our results show that Cluster 3 statistically differs from most of the other clusters. Clusters 6 and 7 also show significant differences in their mean value of vaccination. The death rate from cardiovascular disease previously to COVID-19 also reveals significant results across all our clusters, which corroborates previous studies (İşikhan & Güleç, 2018) and reaffirms the robustness of our cluster solution. On the excess of mortality among older people, the youngest older people captured higher significance statistical difference, specifically between Cluster 2, 6, and 7.

Table 3.17 shows that our proposed LTC typology has good properties to capture dissimilarities across countries and their LTC characteristics. The unexpected onset, the high intensity of the contagion, and the high infectious rate could be the main reasons behind the difficulty in finding more differences across clusters, specifically in the total cases, deaths, and tests. Since the vaccination was an internal policy defined by the governments, our cluster solution $K = 7$ captured significant differences in these policy orientations. We recognize that our typology $K = 7$ was obtained by taking policy features that reflected the country's previous welfare policies and long-run investments. Using COVID-19, we could verify that significant common policies were implemented, specifically at vaccination, and also previous health conditions were identified across clusters. Both results contributed to the significant distinction of our cluster proposal and their good properties in capturing similarities across countries on LTC domains.

²⁸Please see data from Table 3.16 and in Appendix 3.8.10

Table 3.16: Description of the variables of COVID-19 dataset

Variable	Description and measurement	Time period	Source	Mean	SD	Min.	Max.
Stringency Index	Average government Stringency Index composite (its a measure based on 9 response indicators including school closures, workplace closures, and travel bans, rescaled to a value from 0 to 100 (100 = strictest response)).	03/01/2020 to 13/11/2023	Mathieu et al. (2020)	41,31	5,50	32,08	52,74
Total cases	Average of the total confirmed cases of COVID-19 per 1000000 people. Counts can include probable cases where reported.		Mathieu et al. (2020)	205341,66	66416,88	63695,20	315399,37
Total deaths	Average of the total deaths attributed to COVID-19 per 1000000 people. Counts can include probable deaths where reported.		Mathieu et al. (2020)	1571,13	782,33	240,02	3169,70
Total tests	Average of the total tests for COVID-19 per 1000 people		Hasell et al. (2020)	1602,37	1486,30	124,45	6939,66
Vaccination	Average of the total number of people who received at least one vaccine dose per 100 people		Mathieu et al. (2021)	59,79	9,44	34,66	78,60
Hospital beds	Average of hospital beds per 1000 people (most recent year available since 2010)		Mathieu et al. (2020)	5,07	2,60	2,22	13,05
Cardiovascular	Death rate from cardiovascular disease in 2017 (annual number of deaths per 100000 people)		Mathieu et al. (2020)	159,14	74,26	79,37	350,06
Diabetes	Diabetes prevalence (% of population aged 20 to 79) in 2017		Mathieu et al. (2020)	5,95	1,72	3,28	10,79
Excess mortality people aged 65 years old	Average of excess deaths associated with COVID-19 from all-causes by people 65+ years, both genders and with year of death 2020 and 2021, per million.	2020 and 2021	World Health Organization (2023c)	875,82	637,99	-41,23	2425,36
Excess mortality people aged 85 years old	Average of excess deaths associated with COVID-19 from all-causes by people 85+ years, both genders and with year of death 2020 and 2021, per million.		World Health Organization (2023c)	396,47	268,83	-275,94	863,00

Table 3.17: Tukey test of COVID-19 dataset and our typology of $K = 7$

Variable	CL1: High supply of resources and high private financing	CL2: High supply, high demand for formal care, and strong policy oriented	CL3: Low supply of formal care, low demand, and low public financing	CL4: High supply for formal care, high public financing, and high equal distribution policies	CL5: Low supply of resources, low demand for formal care, high regulation	CL6: Low demand and low policy implementation	CL7: Low supply of resources, weak distribution policies, and high demand
Stringency Index	41,74(4,38)	43,63(4,63)	37,65(3,47) (Cl. 5)	35,84(2,93) (Cl. 5)	47,66(5,99) (Cl. 3, 4)	35,82(0,38)	45,00(4,90)
Total cases	246406(44337)	184848(43369)	191753(88194)	199259(83138)	169379(59785)	257910(3970)	187339(109045)
Total deaths	1604(519)	1227(676)	2302(718)	1187(1079)	1543(882)	2243(73)	945(729)
Total tests	2545(2199)	1007(158)	1428(1788)	2243(1784)	927(585)	1403(123)	861(456)
Vaccination	63,04(3,81) (Cl. 3)	60,01(7,54) (Cl. 3)	45,59(7,62) (Cl. 1, 2, 4, 5, 7)	61,59(5,43) (Cl. 3)	65,39(6,14) (Cl. 3)	51,64(9,71) (Cl. 7)	71,09(6,83) (Cl. 3, 6)
Hospital beds	5,51(1,86)	3,02(0,61)	5,73(1,12)	4,00(1,81)	5,85(4,83)	6,07(0,70)	6,05(5,40)
Cardiovascular	121,80(24,43) (Cl. 3, 6)	125,74(18,04) (Cl. 3, 6)	240,53(53,97) (Cl. 1, 2, 4, 5, 6, 7)	152,52(53,25) (Cl. 3, 6)	116,90(41,58) (Cl. 3, 5)	346,52(5,00) (Cl. 1, 2, 3, 4, 6, 7)	106,48(20,94) (Cl. 3, 6)
Diabetes	5,43(1,49)	5,84(2,87)	6,40(1,48)	6,08(0,67)	5,56(1,19)	4,29(0,88)	8,01(1,62)
Excess mortality people 65y+	688,80(263,21)	560,43(365,17) (Cl. 6)	1418,04(618,92)	634,09(799,99)	897,31(646,48)	2035,86(550,83) (Cl. 2, 7)	454,42(538,81) (Cl. 6)
Excess mortality people 85y+	342,89(160,86)	257,20(196,32)	563,68(168,02)	313,84(221,04)	474,18(501,43)	738,97(175,42)	253,18(323,75)
Countries	[n=7] Austria, Belgium, France, Germany, Luxembourg, Switzerland, UK	[n=5] Australia, Ireland, Netherlands, Sweden, USA	[n=5] Estonia, Hungary, Poland, Slovak Republic, Slovenia	[n=4] Czech Republic, Denmark, Finland, Norway	[n=4] Greece, Italy, Japan, Spain	[n=2] Latvia, Lithuania	[n=3] Canada, South Korea, Portugal

Data sources and time periods are described in Table 3.16. N=30, using the original variables (unstandardized). "n=" is the Number of countries and is an absolute number. For each variable was computed the Tukey HSD test for the comparison of means per pair of LTC clusters, and the results show significance at $p\text{-value} \leq 0,05$. Each variable presents, on the first row, the mean and the standard deviation in brackets, and on the second row inside brackets "Cl." indicates the pairwise clusters that are statistically different.

3.7 Conclusions

Diverse LTC typologies have been proposed, most of them based on institutional analysis and qualitative research methods. These studies have been criticized for their subjectiveness and lack of comprehensiveness in terms of covered countries and data. We address some of these limitations by applying a more robust methodology based on clustering techniques and by including more countries and adopting mainly quantitative variables. By running a clustering ensemble modeling combining optimal partitions proposed by three unsupervised algorithms, we identified a typology that distinguishes seven LTC policy groups encompassing 30 world countries.

The composition of our clusters is, in general, aligned with previous proposals but also differs in some interesting points. Clusters 2 and 4 are the most surprising. Clusters 1, 3, 5, and 6 are generally well-recognized structures of LTC policies. From the countries that have been understudied until now, Cluster 7 brings new insights: Canada and Portugal are both countries that have been less studied on the topic of LTC policies. We tested the robustness of our typology by using exhaustive validation tests. We verified that our cluster solution of $K = 7$ has good statistical properties and remains moderately stable across different algorithm settings. On a second check, a matrix with the percentage of cases that clustered pairs of countries belonging to the same cluster brings robustness to our cluster solution $K = 7$ because we verify that our model captured some of the country's pairs more commonly clustered together. Third, we randomly selected country subsamples, and the results were in agreement with $K = 7$ clusters with good external indices values. Finally, also acting as a case example, we applied our clustering $K = 7$ to the COVID-19 data, and we verified significant differences across clusters in vaccination, which could reveal intra-cluster countries' similarities in the vaccination policy orientations.

Investing in LTC policies is a contemporary challenge for all countries. Even in less developed countries, projections indicate that economic growth and improved well-being and health status will lead to longer lives and the demand for a more inclusive society. Our research provides a new LTC policies typology based on current economic, demographic, and social indicators from more developed world countries, but also takes countries' long-run features about welfare state investments. In a changing world with new dynamics in societies, families, challenges on the financial sustainability of public budgets, and the labor market, applying clustering algorithms to analyze and group the countries' LTC policies could be an opportunity to recognize emerging shared dimensions between countries, to contribute to (future) LTC (re)conceptualization, to identify their distinctive characteristics and their intrinsic relation with healthcare systems and countries welfare principles.

Discussions around the leading LTC providers, their role and integration with family and individual decisions, the public sector position, and the limits of the market intervention are increasingly topics. Recently WHO (2024) claimed the importance of investing in LTC to empower LTC systems, enhance their public governance, the development of countries' strategies that promote sustainable financing, protection of the care workforce, and more needed innovation and research concerning the availability, quality, and distribution of care. An intense debate occurs about how the countries should define the public budget to finance LTC and to what extent the LTC should be an individual concern: Should mandatory public insurance schemes financed by mandatory taxes guarantee the provision of LTC in the long run? Should the citizens be incentivized to demand private insurance policies? Should the States define their strategies to account for a mix of these solutions? Or should free-cost LTC policies be implemented in such a way as to prevent individuals from becoming without resources when facing LTC costs?

Our results provide a better understanding of countries' strategic spending and public policy options, the investments performed on the supply side, and the main rules applied to their LTC

policies. The possibility of including other data sources and periods would allow for testing other LTC dimensions and observing changes in resource allocation. This recognition is an opportunity to enhance the definition of future LTC policies framed on more robust planning based on equality across citizens, public support, and the intrinsic cultural heritages of each country, as well as the new social issues imposed by economic growth and higher longevity.

In sum, our contributions are diverse: i) we achieve a stable LTC typology, with some similarities with other previous typologies, and in some cases, novel results; ii) we apply different clustering algorithms and also we recognize the current fuzziness associated with the LTC policies; iii) we choose the best clustering partition solution produced by different methods, which is richer than just adopting one solution based on a restricted algorithm definition, iv) our clustering $K = 7$ is based on measures of the economic analysis domain (supply, demand, financing, and policy provision and regulation); v) our clustering solution is adjusted to the current scenario of population aging and reflects LTC policies oriented to the elderly and their dependence, vi) we provide a new typology of the LTC policies which could be an empirical tool for future policies analysis, and vii) our research is useful for several stakeholders, such as economic, social and civil organizations, public research entities, independent consultants, public centers of competencies, public decision-makers, and international policy organizations.

This study has limitations. The variables available and the sample of countries are still small, and data are often not up to date. We overcame some of those limitations by using and restricting our study to OECD countries, where data are more readily available. We also innovated by including countries that, until now, had not yet been studied in LTC policy clustering, such as Australia, Ireland, Portugal, and the USA, but the residual availability of comparable data prevents us from including low- and middle-income countries. These limitations open future research opportunities.

We recognize the impact of the selected variables/measures on our final typology. Based on Tables 3.10 and 3.12, we infer the variables' contributions and the main baseline measures behind our final cluster proposal. Under our robustness check, we concluded that changing algorithm parameters could alter our cluster composition but did not significantly change the number of clusters that group our sample. Our random sample selection robustness check also guarantees the number of partitions but highlights the impact of each country on the final typology proposed.

Our model did not include a direct variable about the informal care sphere as it is difficult to obtain comparable data across countries. We proxied it by including female labor market participation and household size. However, variables such as time spent on informal care activities, informal care activities as a percentage of formal care activities, and the number of hours of LTC provided via informal and formal markets would all be relevant. In future studies, it could be valuable to include measures that analyze the index of care poverty within the countries since it has been identified as an important feature to compare countries' LTC policies (Kröger, 2022). Furthermore, we recognize that cluster analysis is a robust statistical approach that could be complemented and enhanced with structured qualitative analysis and embodied under theoretical considerations.

Finally, studying LTC and supporting countries to define their internal policies on LTC are both crucial research topics. A sustainable and universal LTC system is a necessary policy embedded in the long-run countries' strategies for economic growth, labor market, welfare systems, and public healthcare service. The demographic change implies structured policies to define how people will get care, how they will pay for it, and which are the shared roles of the State, the individual, the family, and the market.

3.8 Appendix

3.8.1 Review of countries LTC clusters, criteria, and main methods

Table 3.18: Review of countries LTC clusters, criteria, and main methods

Paper	Cluster label attributed	Countries	Criteria	Main methods
Pacolet et al. (1998)	Beveridge oriented social protection/Long term care included in social protection	DK; FI; IE; NO; SE; UK	Orientation of the welfare state and LTC insurance	Description/discussion of institutional arrangements, organization, and social-economic context
	Bismarck oriented social protection/In between	BE		
	Bismarck oriented social protection/Ongoing or finalised debate for new insurance schemes	AT; FR; DE; GR; IT; LU; PT; ES; NL		
Kautto (2002)	Service approach	DK; FI; FR; DE; NO; SE; UK	Investment in benefits in kind (service effort) and in cash benefits (transfer effort)	Cluster analysis: performs boxplots. Apply hierarchical cluster analysis. Display hierarchical cluster on a dendrogram. Apply K-means to check previous interpretations.
	Third group	GR; IE; PT; ES		
	Transfer approach	AT; BE; IT; NL		
Bettio & Plantenga (2004)	Collective/State interference	NL; UK	Types of social support: time, money and service	Description/discussion of institutional arrangements, organization, and social-economic context, with indexes based on data
	Delegate care to the family	GR; IE; IT; PT; ES		
	Formal care strategies well developed	BE; FR		
	Publicly facilitated, private care model	AT; DE		
Timonen (2005)	Universalist approach with high public care provision	DK; FI; SE	Who finances and provides care	Description/discussion of institutional arrangements, organization, and social-economic context
	‘State pays, others provide’ paradigm	FR; DE		
	Familialist/individualist paradigm	ES; UK		
	Statist paradigm	SE		

Table 3.18: Review of countries LTC clusters, criteria, and main methods (cont.)

Paper	Cluster label attributed	Countries	Criteria	Main methods
Burau et al. (2007)	Type of cultural framework: Communitarian; Female part-time carer model of the male breadwinner family; Care regime: Subsidiarity model; Type of policy subsystem: Decentralised and cohesive	DE; JP	Home care governance characteristics	Description/discussion of institutional arrangements, organization, and social-economic context, including other typologies
	Type of cultural framework: Communitarian; Dual breadwinner/female carer model Care regime: Family care model; Type of policy subsystem: Strongly decentralised and cohesive	EE		
	Type of cultural framework: Communitarian; Female part-time carer model of the male breadwinner family; Care regime: Public service model; Subsidiarity model; Type of policy subsystem: Centralised and cohesive	NL		
	Type of cultural framework: Communitarian; Housewife model of the male breadwinner family (Southern Italy); Dual breadwinner/female carer model (Northern Italy); Care regime: Family care model; Type of policy subsystem: Highly decentralised and fragmented	IT		
	Type of cultural framework: Egalitarian; Dual breadwinner/ institutional care model; Care regime: Public service model; Type of policy subsystem: Strongly decentralised and cohesive	SE		
	Type of cultural framework: Egalitarian; Female part-time carer model of the male breadwinner family; Care regime: Means-tested model; Type of policy subsystem: Centralised and cohesive	NZ; UK		
	Type of cultural framework: Individualistic; Dual breadwinner/female carer model; Care regime: Means-tested model; Type of policy subsystem: Highly decentralised and fragmented	US		
Lamura et al. (2007)	Baltic	LV; LT	Health-related demand of care; Socio-economic needs; Informal provision of elder care; Formal provision of elder care	Cluster analysis: apply hierarchical cluster analysis, with Ward linkage and Square Euclidean Distances. Analyze results through dendrogram. Apply discriminant function analysis.
	Family based	GR; IE; PT; ES		
	Public-Nordic	DK; SE; NL		
	Standard care-mix	AT; BE; CZ; FI; FR; DE; IT; UK		
	Transition	HU; PL; SK; SI		
Camacho et al. (2008)	Beveridge model	FI; NO; SE	Financing; Provision	Description/discussion of institutional arrangements, organization, and social-economic context, with data description
	Bismarck model	DE; LU; NL		
	Mediterranean model	GR; IT; ES		

Table 3.18: Review of countries LTC clusters, criteria, and main methods (cont.)

Paper	Cluster label attributed	Countries	Criteria	Main methods
Simonazzi (2009)	Care regimes and employment models: Formal market and mixed workers	UK	Care regimes and employment model	Description/discussion of institutional arrangements, organization, and social-economic context, with data description
	Care regimes and employment models: Formal market and native workers	FR; SE		
	Care regimes and employment models: Informal market and immigrant workers	GR; IT; PT; ES		
	Care regimes and employment models: Mixed and mixed workers	AT		
	Care regimes and employment models: Mixed and native workers	DE		
da Roit & le Bihan (2010)	Highly regulated cash-for-care model	FR	Cash-for-care schemes	Description/discussion of institutional arrangements, organization, and social-economic context
	Little-regulated cash-for-care transfers model	AT; DE; IT		
	Social service model	SE; NL		
Kraus et al. (2010) Approach I	Cluster 1: profound organizational depth and high levels of financial generosity	BE; DK; FR; DE; SE; NL	Organisational depth; Financing generosity	Cluster analysis: create an index: variables coded from 1 to 3 and countries classified accordingly. Apply K-means.
	Cluster 2: medium organizational depth and medium financial generosity	AT; FI; IT; LV; SI; ES; UK		
	Cluster 3: profound organisational depth and low levels of financial generosity	BG; CZ; EE; SK		
	Cluster 4: low organisational depth and levels of financial generosity	HU; LT; PL; RO		
Kraus et al. (2010) Approach II	Cluster 1: medium financing and high informal care and support with low private expenditure	BE; CZ; DE; SK	Formal and Informal care use; Financing of care	Cluster analysis: run factor analysis and use four principal components. Apply K-means.
	Cluster 2: highly developed and generous LTC system with low private expenditure	DK; SE; NL		
	Cluster 3: low spending, high informal care use and support, and low private expenditure	AT; FI; FR; ES; UK		
	Cluster 4: low public expenditure, high informal care and high private financing	HU; IT; PL		
Saraceno & Keck (2010)	High degree de-familism and high minimum non-contributory pension	AT; BE; DK; FR; IE; LU; MT; SE; NL	People in institutional care as a share of the population 65+; Minimum non-contributory pension as a share of average net income	Cluster analysis: apply variants of cluster analysis (not clarified which were used). Based on fuzzy set theory apply qualitative comparative analysis (QCA)
	High degree de-familism and low minimum non-contributory pension	FI; DE; UK		
	Low degree de-familism and high minimum non-contributory pension	CZ; GR; LV; PT; SK; SI		
	Low degree de-familism and low minimum non-contributory pension	BG; EE; HU; IT; LT; PL; ES		

Table 3.18: Review of countries LTC clusters, criteria, and main methods (cont.)

Paper	Cluster label attributed	Countries	Criteria	Main methods
Colombo et al. (2011) and Colombo, F. in Costa-Font & Courbage (2012)	Means-tested arrangements for personal care	UK; US	Universal or means-tested entitlement; Coverage through single or multiple programs	Description/discussion of institutional arrangements, organization, and social-economic context, with data description
	Means-tested programme: No integral system for long-term care	SI;		
	Mixed system - Income related universal benefits or subsidy	AU; AT; FR; IE		
	Mixed system - Mix of universal and means tested (or no) benefits	CA; GR; NZ; ES; CH		
	Mixed system - Parallel universal schemes	CZ; IT; PL		
	Mixed system	HU; PT		
	Mixed/sub-national	MX;		
	Universal coverage within a single system - personal care through the health system	BE;		
	Universal coverage within a single system - public LTC insurance model	DE; JP; LU; KR; NL		
	Universal coverage within a single system - tax based model	DK; FI; NO; SE		
Damiani et al. (2011)	Group 1 - High alignment between old age related expenditure and elderly needs and low formal care	AT; DK; FI; FR; DE; IE; IT; LU; UK	Formal care: LTC beds and home recipients; Alignment between old age related expenditure and elderly needs	Cluster analysis: run Multiple Factor Analysis which performed separated principal component analysis (PCA) for each year. Construct a factorial space with PC's were represented by axes.
	Group 2 - Low alignment between old age related expenditure and elderly needs and low formal care	CZ; GR; PL; ES		
	Group 3 - High alignment between old age related expenditure and elderly needs and high formal care	BE; IS; NO; SE; NL		
	Group 4 - Low alignment between old age related expenditure and elderly needs and high formal care	BG; CY; EE; HU; LV; LT; MT; PT; RO; SK; SI		
Bettio & Vrashchagina (2012)	Cost type 1: comprehensive care but rationalized 'face time'	DK; FI; IS; SE; NL	Organizational setting/costs for home care	Description/discussion of institutional arrangements, organization, and social-economic context, with data description
	Cost type 2: migrants-in-the-family	AT; CY; GR; IT; PT; ES; TR		
	Cost type 3: service vouchers	BE; FR		
	Cost type 4: minimal reliance on care outsourcing	HU; PL; SI		
Applebaum et al. (2013)	Group 1: Universal Coverage	DE; JP; KR; NL	Public insurance funding; Definition of disability; Supply of LTC services; Access	Description/discussion of institutional arrangements, organization, and social-economic context
	Group 2: Mixed Funding	AU; FR; IE; ES; CH		
	Group 3: No Public Insurance	EE; IT; PL; RO; US		
	Group 4: Few Public Funds, Private Providers Developing	AR; BR; CN; EG; IN; MX; ZA; TH		
	Group 5: Few Services, No Funding	BD; GH; KE; NP		
European Commission (2013)	Cluster A - FC oriented provision, generous, accessible and affordable	DK; SE; NL	Organisation depth; Financing generosity; Use; Financing of care	Description/discussion of institutional arrangements, organization, and social-economic context, including other typologies
	Cluster B - FC of medium accessibility Some IC orientation	BE; CZ; DE; LU; SK		
	Cluster C - FC of medium to low accessibility Medium IC orientation	AT; FI; FR; IE; ES; UK		
	Cluster D - Low FC accessibility Strong IC orientation	GR; HU; IT; PL; PT; SI		
	Cluster E - Rather low FC accessibility Almost exclusive IC orientation in LTC approach	BG; CY; EE; LV; LT; MT; RO		

Table 3.18: Review of countries LTC clusters, criteria, and main methods (cont.)

Paper	Cluster label attributed	Countries	Criteria	Main methods
Ranci & Pavolini (2013)	Residual	AT; CZ; FR; DE; IT; ES	Level of coverage; Level of integration with other social and healthcare services	Description/discussion of institutional arrangements, organization, and social-economic context, including data and other typologies
	Semi-universalistic	UK		
	Universalistic	DK; SE; NL		
Leone et al. (2014)	Cluster 1 - Professionalism-based regulatory system	AT; DE; JP; CH	Regulatory approach	Description/discussion of institutional arrangements, organization, and social-economic context
	Cluster 2 - Inspection-based regulatory system	AU; ES; NL; UK		
	Cluster 3 - Data measurement and public reporting regulatory system	CA; FI; NZ; US		
	Cluster 4 - Developing regulatory systems	CN; KR		
Rodrigues (2015)	Private insurance (residual)	FR	Financing approaches to LTC	Description/discussion of institutional arrangements, organization, and social-economic context, including data and other typologies
	Social insurance	BE; DE; LU; NL		
	Tax-based system (universal)	AT; CZ; DK; SE		
Ilinca et al. (2015) and Leichsenring & Schulmann (2016)	Family based	GR; IE; IT; PT; ES	Demand for care; Provision of informal and formal care	Description/discussion of institutional arrangements, organization, and social-economic context, including other typologies
	Standard-care mix	AT; FR; DE; UK		
	Transition/Central & Eastern European (CEE)	BG; CZ; EE; HU; LV; LT; PL; RO; SK		
	Universal-Nordic	DK; FI; SE; NL		
Scheil-Adlung (2015)	Mix of schemes and systems	FR; ZA; UK	Organizational and financial approaches	Description/discussion of institutional arrangements, organization, and social-economic context, including other typologies
	Social-Assistance	SE;		
	Specific LTC scheme or system	DE; JP; KR		
Greve (2017)	Central European model	DE;	Classical analysis of welfare state clusterings	Description/discussion of institutional arrangements, organization, and social-economic context
	Eastern Europe	HU; LT; PL		
	Liberal model	UK;		
	Nordic welfare state model	DK; FI		
	Southern Europe	GR; IT; PT		

Table 3.18: Review of countries LTC clusters, criteria, and main methods (cont.)

Paper	Cluster label attributed	Countries	Criteria	Main methods
Halásková et al. (2017)	Cluster 1 - lowest total LTC expenditures as a percentage of GDP; highest LTC expenditures on institutions as a percentage of total LTC expenditures, and highest LTC recipients	AU; KR	LTC expenditures; LTC recipients	Cluster analysis: run PCA. Apply K-means and hierarchical cluster analysis with Euclidean distance, Akaike information criterion, Shapiro-Wilk test. Analyze Silhouette measure.
	Cluster 2 - lower total LTC expenditures as a percentage of GDP and the highest LTC expenditures on institutions as a percentage of total LTC expends; lowest values in the total number of LTC recipients aged 65+ as percentage of total LTC recipients, among the clusters	CZ; EE; HU		
	Cluster 3 - highest total LTC expenditures as a percentage of GDP; higher total number of LTC recipients aged 65+ as percentage of total LTC recipients	DK; FI; DE; LU; NO; SE; CH; NL		
Joshua (2017)	Hybrid System and Approach	FR;	Financing scheme; Provision	Description/discussion of institutional arrangements, organization, and social-economic context
	Means Tested Systems	UK; US		
	Social Insurance Model	DE; JP; KR; NL		
	Universal Model	DK; FI; SE		
Feng & Glinskaya (2019)	Mean tested financed through safety-net approaches	UK; US	LTC financing scheme	Description/discussion of institutional arrangements, organization, and social-economic context
	Mixture of financing methods	AU; AT; CA; FR; GR; IE; IT; NZ; PL; ES; CH		
	Universal coverage financed through public social insurance	DE; JP; LU; KR; NL		
	Universal coverage financed through taxation	DK; FI; NO; SE		
Bartha & Zentai (2020)	Countries close to double earner, supported carer ideal type	AT; BE; DK; FI; SE; NL	Generosity of LTC expenditures; Unmet care needs; Quality of home care regulation; Full-time equivalent employment gap	Fuzzy-set ideal type analysis (FSITA)
	Countries close to double earner, unsupported carer ideal type	BG; CY; GR; IT; LV; PT; RO		
	Countries loosely fitting the double earner, supported carer ideal type	CZ; EE; FR; DE; IE; LU; SI; UK		
	Countries loosely fitting the double earner, unsupported carer ideal type	HR; HU; LT; PL; SK; ES		
Fuino et al. (2020)	Family Care (the family as a major actor)	CZ; EE; GR; IT; SI; ES	Major actors involved	Description/discussion of institutional arrangements, organization, and social-economic context, including other typologies
	None (no proper scheme LTC system developed)	CH;		
	State responsibility (government plays a central role)	AT; DK; SE		
	Subsidiary (trade-off between State responsibility and family care models)	BE; FR; DE		
Ariaans et al. (2021)	Evolving private need-based system	EE; FR; IL; NZ; ES; UK; US	Supply; Public-private mix; Access regulation; Performance	Cluster analysis: apply K-means and hierarchical with z- and range standardized variables, Gower and squared Euclidean distance, average and Ward's linkage methods. Apply stopping rules CH, Duda-Hart, Dendrograms. Calculate the connection between countries.
	Evolving public supply system	JP; KR		
	Need-based supply system	AU; BE; LU; SK; SI; CH; NL		
	Private supply system	DE; FI		
	Public supply system	DK; IE; NO; SE		
	Residual public system	CZ; LV; PL		

Table 3.18: Review of countries LTC clusters, criteria, and main methods (cont.)

Paper	Cluster label attributed	Countries	Criteria	Main methods
Barber et al. (2021)	Emerging Private Sector in Middle-Income Settings	AR; BR; CN; EG; IN; MX; ZA; TH	Public funding; Eligibility	Description/discussion of institutional arrangements, organization, and social-economic context, including data and other typologies
	Informal Care in Low-Income Settings	BD; GH; KE; NP		
	Means-tested safety net scheme	IL; UK; US		
	Mixed system	AU; AT; CZ; FR; GR; IE; NZ; CH		
	Single universal coverage LTC systems	FI; JP; NO; KR; SE; NL		
Leichsenring (2021)	Emerging (-market) LTC regime	BR; CN; CZ; GR; IN; IR; KZ; PL; RS; ZA; KR; TH; TR	Family ethics; Gender work division; Recurse to family help; Political economy of care; Acknowledgment of LTC as social risk	Description/discussion of institutional arrangements, organization, and social-economic context, including other typologies
	Rights-oriented LTC regime	DK; NO; SE; NL		
	Rudimentary LTC regime	CL; EG; ID; ML; NE; OM; PA; VE		
	Subsidiary LTC regime	AU; AT; CA; FR; DE; IL; IT; JP; ES; CH; UK; US		
Angrisani et al. (2022)	Higher affordability	AT; BE; FR; DE; LU; SE; NL	LTC affordability index (sufficient resources to afford LTC costs)	T-test of equality using panel data
	Lower affordability	HR; CZ; EE; IT; SI; ES; US		
Karagiannidou & Wittenberg (2022)	Mixed system	AU; AT; CA; FR; GR; IE; IT; ES	Eligibility criteria; Funding system	Description/discussion of institutional arrangements, organization, and social-economic context, including data and other typologies
	Safety net tax-funded system	UK; US		
	Social insurance system	DE; JP		
	Universal coverage tax-funded system	DK; FI; NO; SE		
Pavolini (2022)	A limited State intervention model	BG; HR; CY; EE; GR; HU; LV; PT; RO	Public spending on long-term care as a share of GDP; Public spending on long-term care cash benefits as a share of total long-term care public spending	Description/discussion of institutional arrangements, organization, and social-economic context, including data and other typologies
	A mild State intervention through cash benefits model	LT; PL; SK; SI; ES		
	A mild State intervention through services model	IE; LU; MT		
	A strong State intervention through cash benefits model	AT; CZ; DE; IT		
	A strong State intervention through services model	BE; FI; FR		
	A very strong State intervention through services model	DK; SE; NL		

Note: Countries codes are from www.nationsonline.org: AR - Argentina; AT - Austria; AU - Australia; BD - Bangladesh; BE - Belgium; BG - Bulgaria; BR - Brazil; CA - Canada; CH - Switzerland; CL - Chile; CN - China; CY - Cyprus; CZ - Czech Republic; DE - Germany; DK - Denmark; EE - Estonia; EG - Egypt; ES - Spain; FI - Finland; FR - France; GH - Ghana; GR - Greece; HR - Croatia; HU - Hungary; ID - Indonesia; IE - Ireland; IL - Israel; IN - India; IR - Iran; IS - Iceland; IT - Italy; JP - Japan; KE - Kenya; KR - South Korea; KZ - Kazakhstan; LV - Latvia; LT - Lithuania; LU - Luxembourg; ML - Mali; MT - Malta; MX - Mexico; NL - Netherlands; NO - Norway; NP - Nepal; NZ - New Zealand; OM - Oman; PA - Panama; PL - Poland; PT - Portugal; RO - Romania; RS - Serbia; SE - Sweden; SI - Slovenia; SK - Slovakia; TH - Thailand; TR - Turkey; UK - United Kingdom; US - USA; VE - Venezuela; ZA - South Africa. Formal Care (FC). Informal Care (IC). Caliński-Harabasz (CH)

3.8.2 FCM algorithm

The FCM algorithm is based on Cebeci et al. (2022), and the steps involved are the following:

Step 1:

Given the data points and the number of clusters defined, randomly initialize the membership matrix $\mathbf{U}$, which expresses the membership probability of each element belonging to a specific cluster prototype. In our case, the number of rows equals the number of countries, and the number of columns is similar to the number of clusters. The constraints must be satisfied: the sum of the importance of each column cannot exceed 1, and each country must belong to a cluster with a total membership of 1.

Step 2:

To minimize the objective function according to the defined constraints, it's calculated the centroid v_j , performing a $V^j = [v_j]$, using a predetermined measure of fuzziness and based on the formula:

$$v_j = \frac{\sum_{i=1}^n u_{ij}^m x_i}{\sum_{i=1}^n u_{ij}^m} \quad (3.12)$$

Step 3:

Calculate the dissimilarity between each data point x_i and each centroid v_j , using the squared Euclidean distance:

$$d_{(ij)}^2 = \|x_i - v_j\|^2 \quad (3.13)$$

Step 4:

Update the membership values, i.e., the previous version of u_{ij} by using the distances of each point towards each cluster prototype through the formula:

$$u_{ij} = \frac{1}{\sum_{j=1}^k (d_{(ij)}/d_{(il)})^{2/(m-1)}} \quad (3.14)$$

such that, $1 \leq l \leq k$ and l are the other centroids prototypes.

Step 5:

Repeat steps 2 to 4 (i.e., compare $\mathbf{U}^{t+1}$ with $\mathbf{U}^t$, where t is the iteration number) until constant values for the membership values are reached or the difference value is less than the tolerance value of 0,0001 (Wierzchoń & Kłopotek, 2018). Otherwise, the algorithm returns iteratively to updating the cluster centers and the membership grades for the data point.

3.8.3 SOM algorithm

The batch version of the SOM algorithm used follows the description from Kohonen (2001), Kohonen (2005), and also Kohonen (2013):

A - Competitive phase:

Step 1:

Using random initial values, initialize the weight vectors w_k , where k are nodes (i.e., clusters).

Step 2:

Compute the Euclidean distance $d_k(t)$ between the input vector and each weight vector using the equation:

$$d_k(t) = ||\mathbf{x}(t) - \mathbf{w}_i(t_0)||^2 \quad (3.15)$$

where $\mathbf{x}(t)$ are input vectors, $\mathbf{w}_i(t_0)$ are the weight vectors computed at the end of the previous iteration.

Step 3:

Compute the winning node, i.e., the weight vector closest to the input data through the $d_k(t)$ minimization:

$$d_c(t) \equiv \min_k d_k(t) \quad (3.16)$$

such that, c denotes the winning node.

B - Cooperative phase:

Step 4:

Weight value of each neuron updated through the equation:

$$\mathbf{w}_i(t_f) = \frac{\sum_{t=t_0}^{t=t_f} h_{ci} \bar{x}(t)}{\sum_{t=t_0}^{t=t_f} h_{ci}} \quad (3.17)$$

where t_0 and t_f denote respectively the start and finish of the present epoch/iteration, $\mathbf{w}_i(t_f)$ are the weight vectors computed at the end of the present epoch, h_{ci} are the standard Gaussian neighborhood functions around the winner, and $\bar{x}(t)$ is the mean of the inputs x that are able to update vector. It's concluded one updating cycle/iteration.

Step 5:

Repeated steps 2 to 3 until the maximum number of iterations is reached.

3.8.4 PAM algorithm

We follow the algorithm PAM developed by the Leonard & Rousseeuw (1990) and explained in the edition of Leonard & Rousseeuw (2005) and it runs as follows:

Step 1:

Initialize: define the number of clusters, K .

Step 2:

Arbitrarily choose representative data points x in the dataset as the initial medoids.

Step 3:

Based on a dissimilarity matrix, for each non-representative point p in the dataset, calculate the total cost, which is the distance between medoids and data points.

By minimizing the following objective function, find which medoid is closest to p :

$$Cost = \sum_{i=1}^N \min_{1 \leq j \leq K} D(x_i, m_j) \quad (3.18)$$

where x_i are data points to be clustered with $X = x_1, \dots, x_N$, m_j are the medoids such that $M \subset X$, K is the number of clusters, D is the distance metric from each object x_i to its nearest medoid m_j .

Step 4:

Randomly select a non-representative point p_{rand} and recalculate the cost.

Step 5:

Compute the overall cost C of swapping p_{rand} (current) to x (previous) .

Step 6:

If $C < 0$, swap x to p_{rand} (i.e., replacement is allowed) to form a new set of representative points x_{new} and return at Step 3.

Step 7:

If $\min C > 0$, the cost value cannot be decreased, and the algorithm stops because all values of C are positive, which is precisely the algorithm's stopping condition.

3.8.5 R software packages

Table 3.19: R software packages

Algorithm / Procedure	R package	Arguments
Pearson Correlation matrix	"stats" by Team & contributors worldwide (2023) and "ggcorrplot" by Kassambara (2023)	Data unscaled. Binary variable not included.
Hopkins Test	"hopkins" by Wright (2023)	Data scaled
PCA	"PCAmixdata" by Chavent et al. (2022)	Continuous variables are scaled. Numerical variables use standard PCA algorithm. Discrete variable uses multiple correspondence analysis algorithm.
FCM	"ppclust" by Cebeci et al. (2022)	Squared Euclidean distance Fuzziness exponent m : 2 (by default) Number of cluster centers: 2 to 9 Number for the convergence value between the iterations: by default 1e-09 Standardized data: by default was FALSE
SOM	"multisom" by Chair et al. (2016)	Euclidean distance Grid size: K=2:2x1; K=3:3x1; K=4:2x2; K=5:5x1; K=6:3x2; K=7:7x1; K=8:4x2; K=9:3x3 Batch version minimum neighbourhood radius: 0,5 maximum neighbourhood radius: 1,0 maximum number of iterations: 1000 method used to initialize the prototypes: "linear" which uses the linear grids upon the first two principle components direction radius.type: gaussian neighborhood function Topology type: hexagonal
PAM	"cluster" by Maechler (2022)	Euclidean distance data: is a dissimilarity matrix cluster.only: true and we obtain a vector specifying the clustering keep.diss: false, and dissimilarities are not kept in the result and save time
Internal criteria: CH, DB, and DI	"clusterCrit" by Desgraupes (2017)	Input: Data are 5 PC's
Silhouette Width	"cluster" by Maechler (2022)	Euclidean distance Dissimilarity matrix
External criteria: RI, ARI, JI	"clues" by Chang et al. (2019)	Cluster proposals from FCM, SOM, PAM, and our clustering $K = 7$
Pearson's χ^2 independence test	"gmodels" by Warnes et al. (2022)	chisq: true, the results of a chi-square test are computed
Multiple Comparisons of Mean - continuous variable	"stats" by Team & contributors worldwide (2023)	Fit an Analysis of Variance Model (aov); pairwise comparisons using Tukey HSD Test
Multiple Comparisons of Mean - binary variable	glm function from "stats" by Team & contributors worldwide (2023); ANOVA by Fox (2023); "emmeans" by Lenth (2024)	Logistic regression; least square means for pairwise comparisons; Tukey HSD Test

3.8.6 Clustering ensemble modeling

Our clustering ensemble modeling applies the consensus function through the analysis of the voting approach. It involves the following steps:

First - An appropriate number of clusters K should be defined:

Based on Table 3.18, the number of the LTC typologies ranges from two to nine proposals. We define the partitions of our model from two to nine to account for such cluster proposals.

Second - Run the FCM, SOM, and PAM algorithms:

To initialize the algorithms, we set a seed. Appendix 3.8.5 describes the R packages used and the arguments included.

Third - Apply internal criteria evaluation to each partition ($K=2, \dots, K=9$): By algorithm we calculate the internal criteria: the Average Silhouette width, percentage of observations with $ASW > 0,5$, percentage of observations with $ASW < 0$, Calinski-Harabazs index, Davies-Bouldin index, and Dunn index, to base the selection procedure of the optimal number of clusters.

Fourth - Select the optimal cluster partitioning ($K=2, \dots, K=9$):

For each partitioning and method (FCM, SOM, PAM), we get a value of each internal criterion. Hence, we identify if each partitioning is the first and the second best around all partitioning ($K=2, \dots, K=9$). First best is by partition the best value of Average Silhouette width (maximum), the percentage of observations with $ASW > 0,5$ (maximum), the percentage of observations with $ASW < 0$ (minimum), the Calinski-Harabaz index (maximum), the Davies-Bouldin index (minimum), and the Dunn index (maximum). After that, using the same method, we found the second best. We count the times (or votes) each partitioning is classified as first and second best. We define the partition with a higher sum of first and second best as the optimal number of clusters proposed by each algorithm. If there is a consensus on one partition (from algorithm votes), we accept and assign this partition as our optimal. If a tie occurs or if each algorithm votes on a different partition solution, we decide the optimal number of cluster K based on the partitioning with the highest Average Silhouette width²⁹. At this point, we also monitored the existence of non-empty clusters, i.e., clusters that no country is assigned to them and are empty. If we get empty clusters, we ignore this cluster partition and set $K = K - 1$, and we repeat the procedure.

Fifth - Make the correspondence between the assigned clusters attributed to each country to get a unique ensemble classification:

Taking the optimal K partitioning selected in the previous step, we analyze, by country, the cluster assignment proposed by the FCM, SOM, and PAM. We have "groups" of countries belonging to the same partitioning. We perform an analysis based on the frequency of how each country is grouped with others. We analyze these frequencies, and we redefined the cluster label attributed to each country, i.e., we make the correspondence between the labels attributed from the base assignment and a new label attributed.

Sixth - Using the new label of clustering, apply the majority voting rule:

Using the assignment of the new label, we count how often each country is grouped into one of the clustering K partitions. If one country gets majority proposals from FCM, SOM, and PAM to belong to a specific partition, we assign this country to such proposal. If the country is classified as having a tie between partitions, we use the Average Silhouette width to decide. The partition with the highest value is the "winner," i.e., the country belongs to that partition.

²⁹Rousseeuw (1987) describes the advantages of this criteria, highlighting that silhouette shows which objects are within clusters, and which are merely somewhere in between clusters. Silhouette reveals good properties on the identification of the 'natural' value of K and also when it's applied to the comparison of outputs of different clustering algorithms.

We get our Clustering Ensemble K partition at this point, which means we get a clustering proposal solution for each country.

Seventh - Apply external criteria evaluation:

We compare, by algorithm, the Clustering Ensemble proposal and the clustering proposal of each algorithm. The similarity between each pair of partitioning is analyzed using four external criteria: Simple Matching, Rand Index, adjusted Rand Index, and Jaccard index. After that, we test Pearson's chi-square to evaluate the significance independence for each cross-check.

Eighth - Test significant differences across the clusters of the Clustering Ensemble modeling:

We validated our proposal by testing whether each original variable of our model is significantly different across the clusters obtained by the clustering ensemble. We analyze this by computing Tukey's 'Honest Significant Difference' method (HSD) for differences in the mean values of each variable and by pair clusters. We test the significance differences at $p\text{-value} \leq 0,05$ for each variable across the clusters.

3.8.7 Clustering ensemble modeling application

The Ariaans et al. (2021) dataset use six quantitative measures from the OECD health data and five institutional variables computed by the authors for twenty-five countries between 2014 and 2016. The variables are grouped into four dimensions: supply, public-private mix, access regulation, and performance³⁰.

Hierarchical agglomerative and K-means partitioning cluster analyses were applied. For the agglomerative method, the first and second-best results determined by the Caliński-Harabasz and Duda-Hart stopping rules were used to determine the number of clusters. Both stopping rules require the researcher to choose the number that maximizes the criteria since larger values indicate more distinct clustering (Mooi et al., 2018; StataCorp, 2023c). To complement both methods, the authors also analyzed the dendrograms.

In the case of the K-means partitioning method, the authors followed Makles (2012). They searched for a kink in the curve generated from within the sum of squares (WSS) or its logarithm [$\log(\text{WSS})$] for all considered cluster solutions, the η^2 coefficient, similar to the R^2 , and the proportional reduction of error (PRE) coefficient. The Caliński-Harabasz stopping rule is also accounted for.

Based on the 24 separate cluster proposals (16 from hierarchical and 8 from K-means), the authors calculated how often each country was in the same cluster with every other country. To classify as full membership, two countries had to be in the same cluster more than $\geq 66\%$ of the times and needed to have such strong ties with at least half of all countries in the cluster. Then, the cluster solutions were mapped using the UCINET/Netdraw package for social network analysis, yielding the network graph of OECD LTC systems.

From this replication process, some issues arise:

1. Selecting the optimal number of clusters based on the Caliński-Harabasz and the Duda-Hart indexes is a complex task that often leads to contradictory conclusions, requiring subjective decisions. According to Mooi et al. (2018), one should combine the Caliński-Harabasz and the Duda-Hart indices by selecting the number of clusters that yield a large Caliński-Harabasz and a large Duda-Hart index. However, often this means that these values are not at their maximum for both or even for any of the indexes. Consequently, a bargaining process between these two rules is usually required.
2. A matching process was not applied on Ariaans et al. (2021) 24 cluster analyses to make the correspondence between the labels of the 24 clusters before the calculation of the full membership classification. This is an essential step because the cluster labels are attributed arbitrarily, and they should be set in such a way that the best agreement can be achieved between the cluster labels.
3. The dendrogram analysis is a visual decision method. Even with expert support, the selection methodology is prone to mistakes. It is a very subjective and complex task to make decisions based on twenty-five data points (number of countries). Applying any rule of thumb to cut a dendrogram tree with a horizontal line is beneficial to the clustering decisions.
4. Ariaans et al. (2021) performed all hierarchical and partitioning methods' calculations with K between 2 and 15. The selection of the K span is a crucial decision since the Caliński-Harabasz rule depends on that K definition, and the Duda-Hart indexes include the number of observations in each cluster. StataCorp (2023a) highlighted that these two stopping rules become less informative as the number of group elements becomes small. Since there was a higher number of clusters K (groups), each cluster gets a very reduced number of observations (countries).

³⁰Please see Ariaans et al. (2021) for further details.

5. Alongside the Ariaans et al. (2021) categorical variables, such as availability of cash benefits, choice index, and mean-testing for any benefit, were computed on agglomerative algorithms and K-means as if they were continuous variables, either transformed on range-standardized or z-scores.
6. Internal criteria to evaluate the goodness of the clustering in terms of compactness, connectedness, and separation of the cluster partitions (e.g., silhouette analysis measures, Dunn index, ...) were not considered on the Ariaans et al. (2021).

Applying our Clustering ensemble modeling to the Ariaans et al. (2021) data implied using the R software. Based on the Principal Component Analysis, we retained six principal components, explaining 80,99% of the variation. We ran the model from $K=2$ to $K=9$ cluster partitions. The optimal number of clusters for each algorithm was selected by examining the Average Silhouette width ASW , the percentage of observations with $ASW > 0,5$ and with $ASW < 0$, the Calinski-Harabaz index, the Davies-Bouldin index, and the Dunn index. Based on the count of the number of times each partition is identified as first and second best³¹, we got a tie (we could not apply the majority voting rule) between partitions $K=2$, $K=6$, and $K=8$. Given the defined procedure, we follow the partition with the highest Average Silhouette width. $K = 8$ is the partition with higher ASW , however it has empty clusters. The $K = 6$ partition collects the following highest ASW . Taking this cluster partition, we got the following clusters: Cluster 1 - Australia, Belgium, Czech Republic, Finland, Germany, and Slovakia. Cluster 2 - Denmark, Ireland, Japan, South Korea, Latvia, and Sweden. Cluster 3 - Norway, Spain, and the USA. Cluster 4 - France, Israel, New Zealand, Slovenia, Switzerland, and UK. Cluster 5 - Luxembourg and Netherlands. Cluster 6: Estonia, Poland.

The composition of each cluster was tested using the Tukey honestly significant difference (HSD) test. We tested the significance differences at $p\text{-value} \leq 0,05$ for each variable across the clusters. In general, the ensemble significantly differentiates between the LTC clusters. The number of beds is significantly different between Clusters 5 and 2, and Clusters 5 and 6. The availability of cash benefits differs between Clusters 1 and 2, and Clusters 4 and 2. The choice index collects the most significant pairwise differences between Clusters 1 and 2, 3, and Clusters 5 and 2, 3. The mean-testing measure also reveals significance between Clusters 2 and 4, 5³².

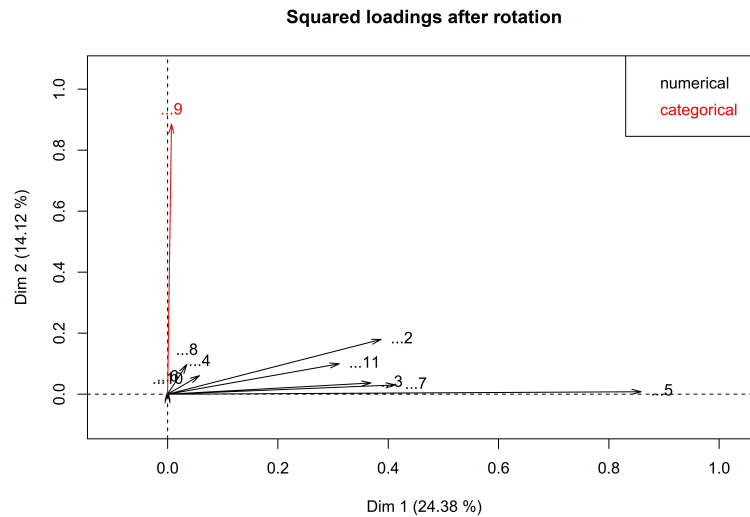
³¹First best is by partition the best value of Average Silhouette width (maximum), the Calinski-Harabaz index (maximum), the Davies-Bouldin index (minimum), and the Dunn index (maximum). After that, using the same method, we found the second best.

³²For comparing means from continuous data, analysis of variance (ANOVA) is the most frequently used statistical approach. For binary data, the assumption of normality is apparently violated, and it is unreliable to use classical ANOVA to compare means of binary or count data. Furthermore, for the mean-testing binary variable, we perform a logistic regression and then calculate the least square means, and by the Tukey HSD Test, we generate contrasts for all pairwise comparisons among estimated marginal mean (Yujiao & Zhiyong, 2017).

3.8.8 PCA squared loadings

From both Figures, we observe higher factor loading of female employment rate and government LTC spending for the rotated PC1 and the mean-tested qualitative measure for the rotated PC2. Higher distances from the origin indicate a higher contribution to the factor map, and it is important for overall variation in the entire input data.

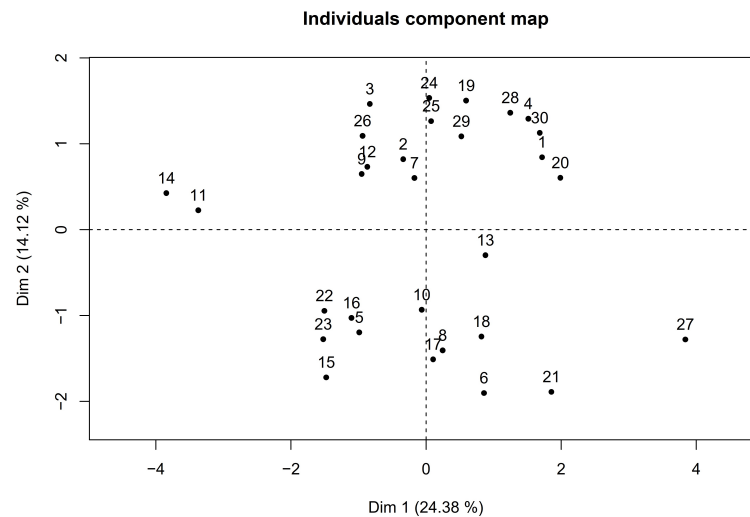
Figure 3.9: Squared loadings, by variable, after rotation



Notes: Data sources are described in Table 3.2. Data covered the period 2016-2019 (N=30). Continuous data standardized. The numbers identify the variables of our model: 2-LTC beds; 3-Health and social workers; 4-Household size; 5-Female employment rate; 6-Life expectancy at birth; 7- Government LTC spending; 8-Private LTC spending; 9-Mean testing for benefits; 10-Elderly income inequality; 11-Elderly self-health status.

In Figure 3.10, we can observe the countries that are more similarly grouped based on the two dimensions:

Figure 3.10: Squared loadings, by country, after rotation



Data sources are described in Table 3.2. Data covered the period 2016-2019 (N=30). Continuous data standardized. The numbers identify the countries of our sample: 1-Australia; 2-Austria; 3-Belgium; 4-Canada; 5-Czech Republic; 6-Denmark; 7-Estonia; 8-Finland; 9-France; 10-Germany; 11-Greece; 12-Hungary; 13-Ireland; 14-Italy; 15-Japan; 16-South Korea; 17-Latvia; 18-Lithuania; 19-Luxembourg; 20-Netherlands; 21-Norway; 22-Poland; 23- Portugal; 24-Slovak Republic; 25-Slovenia; 26-Spain; 27-Sweden; 28-Switzerland; 29-United Kingdom; 30-United States.

3.8.9 Plot countries by variables and clusters

Figure 3.11: LTC beds

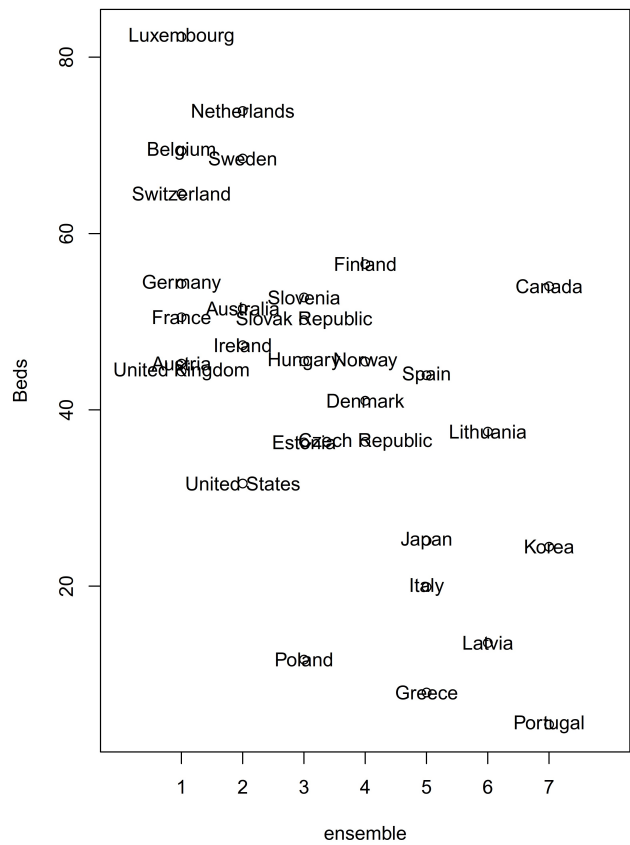


Figure 3.12: LTC workers

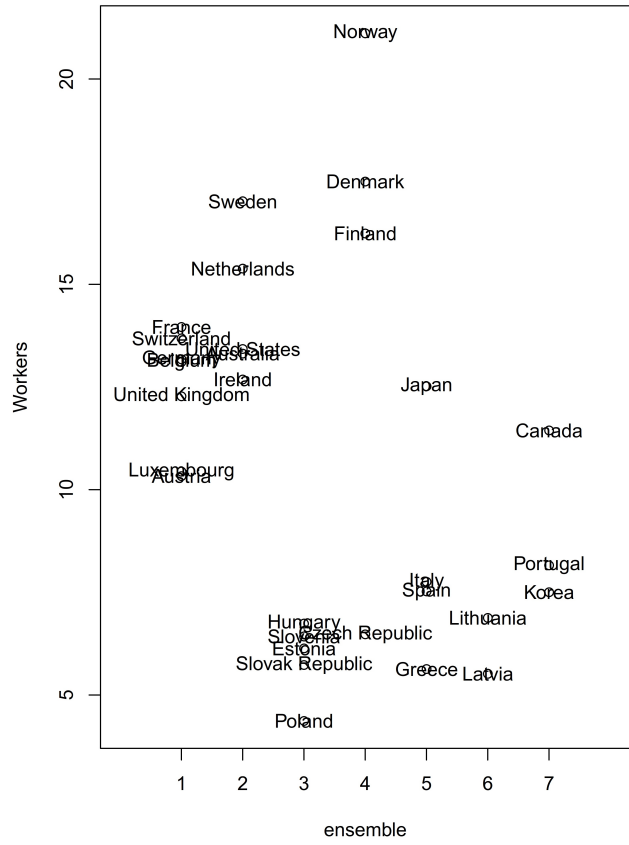


Figure 3.13: Household size

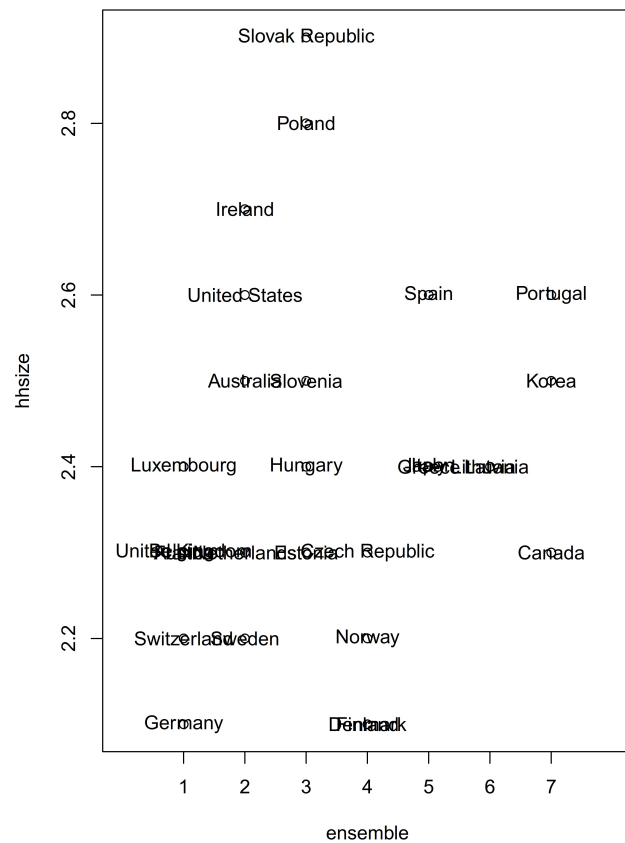


Figure 3.14: Female employment rate

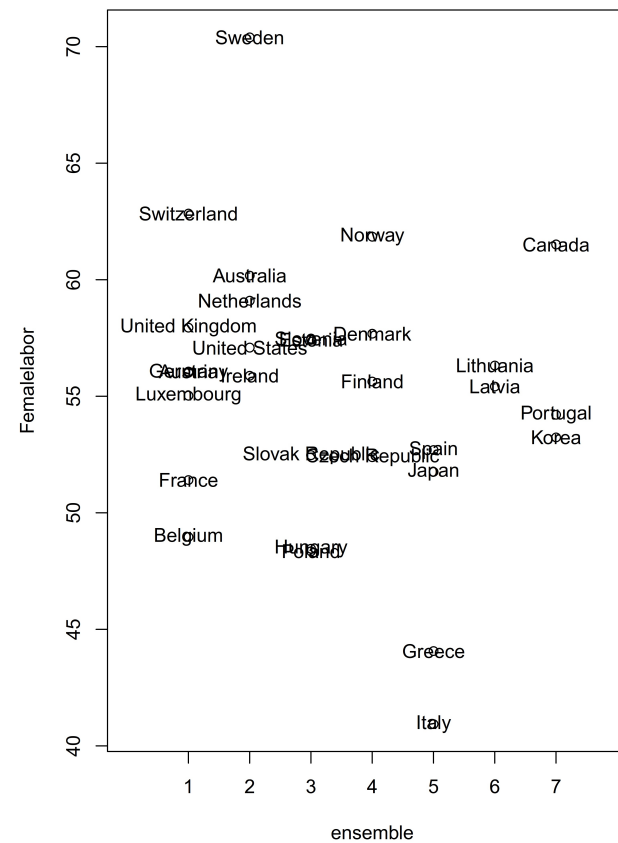


Figure 3.15: Life Expectancy at birth

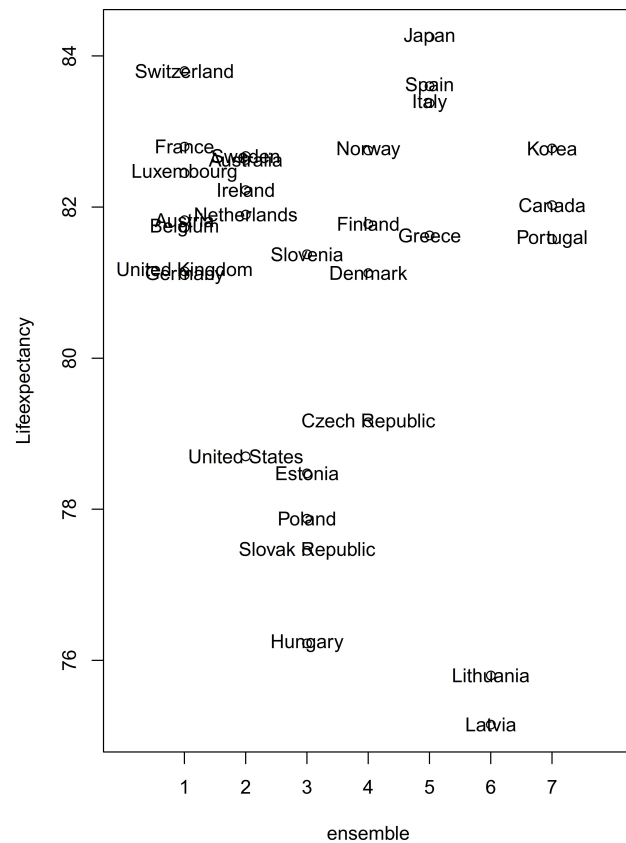


Figure 3.16: Public LTC spending

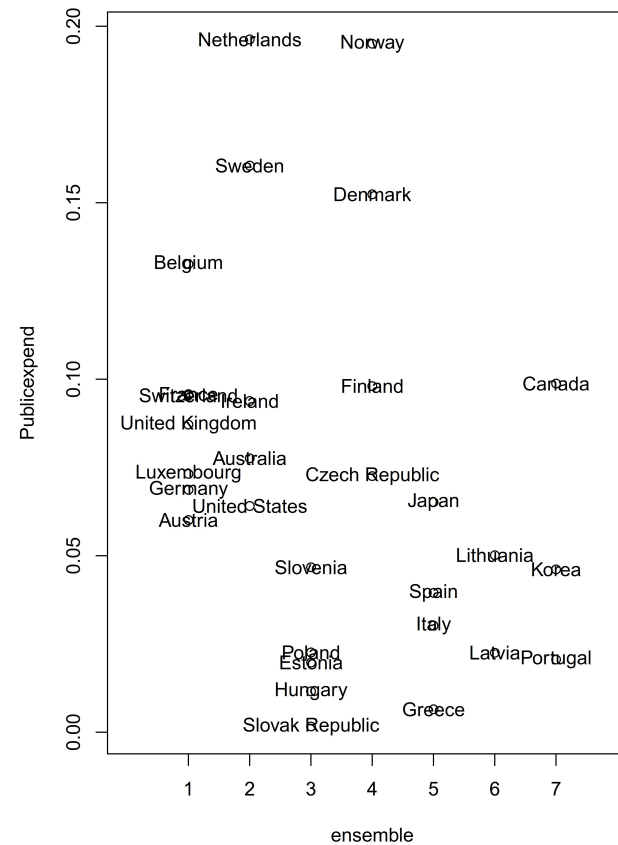


Figure 3.17: Private LTC spending

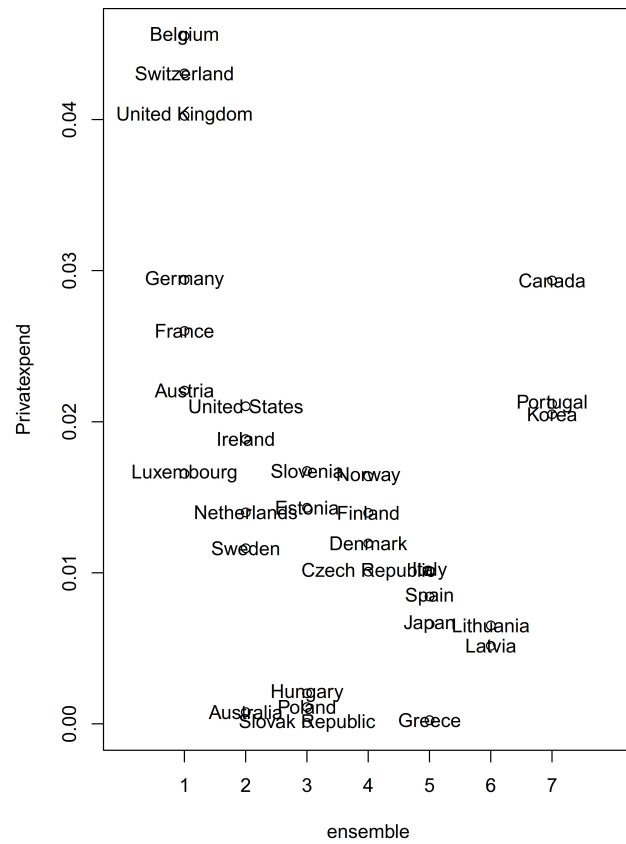


Figure 3.18: Mean-testing benefits

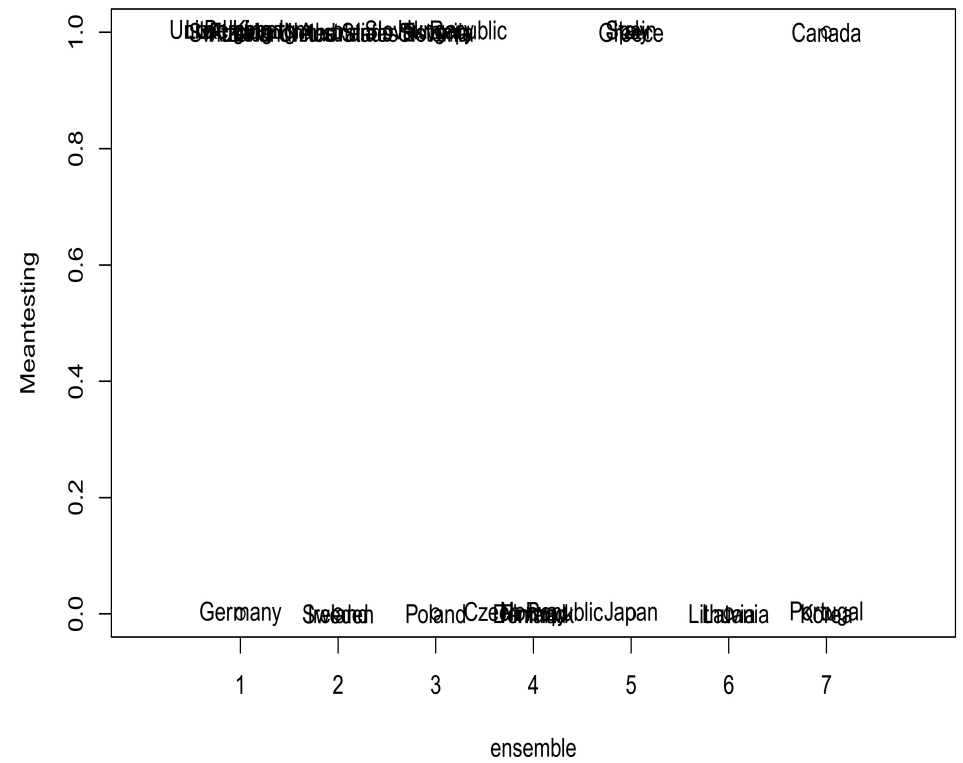


Figure 3.19: Gini Coeficient

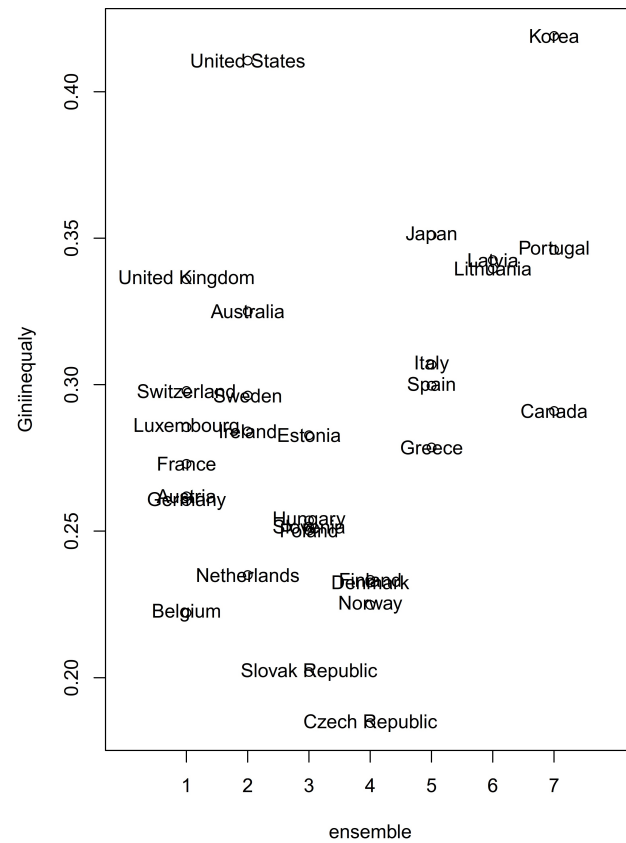
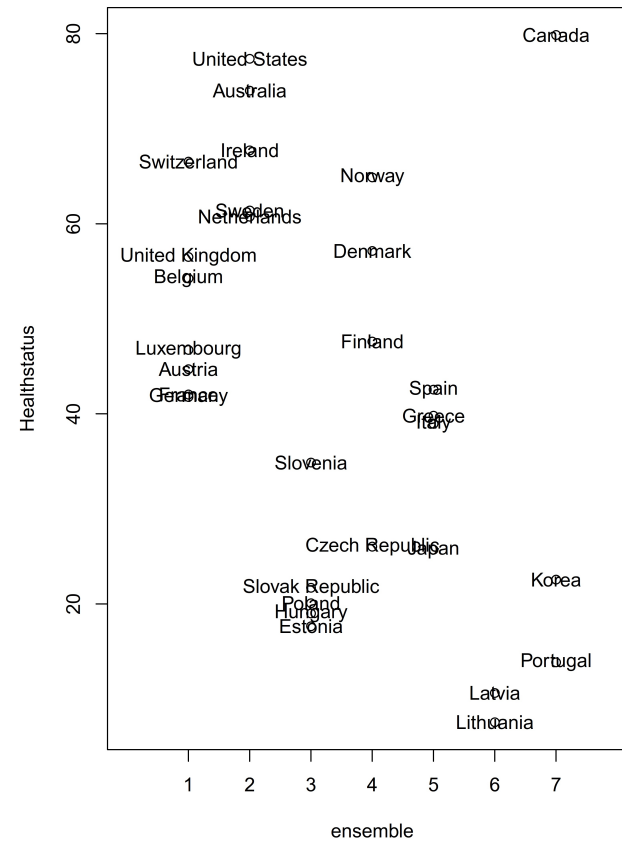


Figure 3.20: Self-rated health



Notes: Data sources are described in Table 3.2. Data covered the period 2016-2019 (N=30) and included the original dataset. "ensemble" respects to the $K = 7$ clustering proposal.

3.8.10 COVID-19 descriptive statistics, by country

Table 3.20: COVID-19 descriptive statistics, by country

Country	Stringency Index	Total confirmed cases of COVID-19 per 1000000 people	Total deaths attributed to COVID-19 per 1000000 people	Total tests for COVID-19 per 1000 people	Total number of people who received at least one vaccine dose per 100 people	Hospital beds per 1000 people	Death rate from cardiovascular disease in 2017	Diabetes prevalence (% of population aged 20 to 79) in 2017	Excess deaths associated with COVID-19 from all-causes by people 65+ years, per million	Excess deaths associated with COVID-19 from all-causes by people 85+ years, per million
Australia	47,28	170277,15	320,74	1038,05	47,81	3,84	107,79	5,07	43,50	27,43
Austria	49,23	305484,25	1606,09	6939,66	63,78	7,37	145,18	6,35	866,12	500,22
Belgium	39,12	215912,84	2185,15	1233,85	66,73	5,64	114,90	4,29	902,32	409,81
Canada	50,40	63695,20	828,72	758,48	65,23	2,50	105,60	7,37	188,62	70,15
Czech Republic	39,70	253773,96	2793,78	2435,72	55,07	6,63	227,48	6,82	1831,15	644,76
Denmark	35,38	286356,40	766,05	4694,46	66,42	2,50	114,77	6,41	212,15	219,07
Estonia	32,08	241131,56	1278,16	1034,46	54,72	4,69	255,57	4,02	1097,84	618,45
Finland	32,58	119758,62	739,37	857,02	65,68	3,28	153,51	5,76	311,99	185,67
France	42,35	277120,32	1765,38	1609,17	66,08	5,98	86,06	4,77	685,09	392,05
Germany	44,12	196589,85	1223,57	673,51	62,47	8,00	156,14	8,31	561,23	244,55
Greece	52,74	226664,59	1951,19	1446,38	63,57	4,21	175,70	4,55	1180,15	776,19
Hungary	36,61	125527,72	3169,70	388,73	47,67	7,02	278,30	7,55	1593,05	405,81
Ireland	42,62	180318,91	1156,31	1064,55	67,57	2,96	126,46	3,28	391,73	98,58
Italy	52,43	201631,65	2179,97	1259,56	71,86	3,18	113,15	4,78	1422,64	700,64
Japan	40,43	90022,90	240,02	124,45	68,41	13,05	79,37	5,72	-41,23	-275,94
South Korea	40,83	228546,96	281,67	465,45	69,44	12,27	86,00	6,80	100,16	62,39
Latvia	35,55	260717,86	2295,65	1490,26	44,77	5,57	350,06	4,91	1646,37	614,93
Lithuania	36,09	255103,40	2191,95	1316,18	58,51	6,56	342,99	3,67	2425,36	863,00
Luxembourg	37,75	282021,91	970,26	3616,48	59,65	4,51	128,43	4,42	178,72	24,09
Netherlands	42,98	259464,70	997,09	798,19	60,99	3,32	109,36	5,29	849,10	504,19
Norway	35,70	137147,98	452,75	984,84	59,18	3,60	114,32	5,31	181,08	205,85
Poland	39,87	97747,42	1972,14	409,32	48,99	6,62	227,33	5,91	1884,51	799,77
Portugal	43,78	269775,94	1726,72	1360,80	78,60	3,39	127,84	9,85	1074,49	626,99
Slovak Republic	39,05	178961,18	2411,39	4593,03	34,66	5,82	287,96	7,29	2009,01	598,24
Slovenia	40,66	315399,37	2682,31	717,15	41,93	4,50	153,49	7,25	505,76	396,15
Spain	45,04	159197,05	1801,13	879,14	57,72	2,97	99,40	7,17	1027,67	695,81
Sweden	36,76	147544,49	1504,10	919,35	59,24	2,22	133,98	4,79	564,49	276,89
Switzerland	36,42	252709,78	1161,11	986,47	56,50	4,53	99,74	5,59	690,01	383,32
United Kingdom	43,15	195008,10	2320,05	2758,65	66,09	2,54	122,14	4,28	938,15	446,22
United States	48,49	166637,70	2161,29	1217,77	64,46	2,77	151,09	10,79	953,33	378,92
Mean	41,31	205341,66	1571,13	1602,37	59,79	5,07	159,14	5,95	875,82	396,47
SD	5,50	66416,88	782,33	1486,30	9,44	2,60	74,26	1,72	637,99	268,83

Notes: Data sources and period are described in Table 3.16. N=30. Data are unstandardized. Standard deviation (SD).

Chapter 4

Older couples and long-term care coverage - a theoretical approach*

4.1 Introduction

Recent estimates suggest that approximately 70% of individuals aged 65 and older in the United States require assistance with basic daily activities (Mommaerts & Truskinovsky, 2020). The uncertainty around long-term care (LTC) needs and costs represents a significant source of financial and personal risk for the elderly (Bueren, 2023; Coe et al., 2025). LTC financing and provision typically rely on three pillars: public programs offering in-kind and cash benefits (e.g., Medicaid), private insurance policies purchased in the marketplace, and informal care provided by family and friends (Cremer et al., 2012; Mommaerts & Truskinovsky, 2020). Care for older adults is generally delivered through two primary sources: formal care, which involves paid services from social and medical professionals or trained individuals (Oh et al., 2024), and informal care, which remains the most common form of support and is defined by Costa-Font & Vilaplana-Prieto (2025) as non-professional assistance with basic and instrumental activities of daily living.

Pauly (1990) conceptualized LTC decisions within a traditional family structure, where elderly parents prefer to age at home and rely extensively on their children for informal care provision. However, demographic and social shifts, such as declining fertility rates, increased geographic mobility, and rising female labor force participation, have reduced the availability of informal care from adult children (Zweifel, 2021; Oh et al., 2024). These changes necessitate a reevaluation of LTC planning, provision, and financing.

While formal LTC services like nursing homes and professional in-home care are essential, informal care remains critical for supporting older adults at home. Oh et al. (2024) report that informal care was the most common source of home care in the United States between 2004 and 2016, accounting for nearly three-quarters of care received in 2016. Many older adults prefer informal care and community-based services, viewing institutional care as a last resort (Mommaerts, 2018). Informal caregiving offers a potentially more sustainable and cost-effective alternative to formal care (de Zwart et al., 2017). In the absence of informal caregiving, individuals face greater financial risks associated with LTC needs. Limited informal support correlates with increased formal care consumption, 2.5 times more on average, and a 30% higher likelihood of nursing home entry (Bueren, 2023).

Among married individuals, spousal care is a key source of informal LTC. The presence of a spouse strongly predicts informal care provision (Barczyk & Kredler, 2017). OECD data show that the proportion of informal caregivers providing care to spouses (31.6%) is comparable to that of individuals caring for parents (36.1%), with some countries reporting higher

*We thank Professor José Manuel Peres Jorge for his supervision on the model setup.

spousal caregiving rates (Colombo et al., 2011; Klimaviciute, 2019). Marital status is a strong determinant of access to informal care, as married people are more likely to receive care from their spouses (Mellor, 2001; Mommaerts & Truskinovsky, 2020). Empirical results show that LTC planning is often undertaken jointly by spouses (Caro et al., 2010; Klimaviciute, 2019; Coe et al., 2025), and spousal caregiving serves as a key informal insurance mechanism (Tennyson et al., 2022).

Despite its importance, the spousal caregiving relationship has received limited attention in theoretical models compared to parent-child dynamics. Modeling LTC decision-making at the couple level introduces complexity, requiring consideration of individual and joint probabilities of disability and care needs (Coe et al., 2025). A central concern for elderly couples is the financial well-being of the surviving spouse, underscoring the interdependent nature of LTC choices (Pauly, 1990). Informal caregiving entails substantial opportunity costs, including adverse effects on caregivers' health, increased healthcare expenditures, reduced labor force participation, and absenteeism. These consequences may be long-lasting and not easily offset by financial compensation (de Zwart et al., 2017). Nicholas & Baum (2020) show that the death of a dependent spouse often results in significant financial and health shocks for the surviving partner. In the United States, widowed individuals, especially women, frequently experience poverty despite not being poor during marriage. Future dependency further exacerbates financial vulnerability, as surviving spouses cannot rely on spousal support and may have depleted resources due to prior LTC expenditures (Klimaviciute, 2019).

Given the declining role of children in LTC provision and the limited theoretical focus on couple-level decision-making, this paper models older couples as the primary decision-making unit. We relax the common assumption that children provide informal care and instead focus on LTC coverage within the couple. Our research question is: How do older couples make decisions about covering uncertain future LTC needs? To address this, we extend the principal-agent model proposed by Zweifel & Strüwe (1996), originally applied to parent-child interactions. In our extension, the principal-agent relationship is internal to the couple: the older spouse, more likely to require LTC, acts as the principal and designs an optimal contract for the younger caregiver spouse.

This paper proceeds as follows. The next section introduces the model and presents the principal, the agent, and the maximization problem. Section 4.3 presents comparative statics, examining how exogenous shocks affect choice variables. Section 4.4 concludes. Proofs are provided in the appendix (Section 4.5).

4.2 The model

Our model builds on Zweifel & Strüwe (1996) to address the problem of how an older couple covers LTC needs. We consider three participants: the principal (the oldest spouse), the agent (the youngest spouse), and the private insurance company. We consider the oldest spouse as the principal since he may suffer firstly from disabilities and health conditions that require the provision of a range of LTC services and assistance. The other spouse is younger and will be hired by the principal to carry out informal care activities that help tackle his dependency level. The gross cost of covering the principal's LTC needs $\theta > 0$ is stochastic and normally distributed, such that $\theta \sim N(\mu, \sigma^2)$, and the assistance in facing LTC needs imply providing both health and social care. To guarantee this coverage, the principal may engage three different sources: private LTC insurance benefits i , informal care provided by their spouse (the agent) a , and public LTC insurance benefits g .

The private insurance benefit i originates from a contract established between the principal and the private insurance company. The principal can purchase insurance that pays him $i\theta$ dollars if he needs LTC. The amount of money he pays for $i\theta$ dollars of LTC insurance coverage is the insurance premium r_p . The principal pays an insurance premium equal to $r_p = b_1 + (b_2 + i)\mu\theta$,

with $r_p > 0$, $b_1 \neq 0$ is a parameter of market imperfection since we assume imperfect competition on LTC insurance market, $b_2\mu_\theta$ is the insurance company risk, and $i\mu_\theta$ is the insurance benefit that the principal expects to receive, giving that $E[\theta] = \mu_\theta$. The insurance company collects the LTC insurance premium r_p , and, if the principal has LTC needs, the insurance company transfers a cash benefit to the principal equal to a fraction $i \in (0, 1]$ of the realized LTC cost θ , i.e., a benefit of $i\theta$. The principal will use $i\theta$ transfer to purchase services to cover his LTC needs. If the principal does not have LTC needs $\theta = 0$, or he did not pay an insurance premium $r_p = 0$, he receives no transfer from the insurance company $i\theta = 0$.

The contract establishes a relationship between the principal and the agent regarding the provision of LTC. The principal designs the contract and offers it to the agent by requiring the agent to exert an informal care effort. The agent must decide whether or not to accept the contract. If the agent accepts the contract, he provides the level of informal care. The informal care provided is a continuous variable $a = \gamma\theta$, where $\gamma \geq 0$ represents the care effort provision, so that a can take any non-negative value. If the agent refuses the contract and does not provide informal care effort $\gamma = 0$, the principal must guarantee his LTC coverage using both the private insurance and the public LTC benefit.

The public LTC benefit $g\theta$ is a monetary transfer from the government to the principal when LTC needs arise. This public transfer is a universal, in-cash benefit that depends on the principal's LTC needs θ . The coverage rate g , representing the share of LTC costs covered by the government, is guaranteed regardless of the principal's prior contributions to the welfare state and is constrained to lie in the interval $(0, 1]$.

Formally, the timeline of the model begins with the principal, the older spouse, anticipating future LTC needs, designing and offering a contract to the agent. Since effort is observable and contractible, the principal directly defines the level of effort to be exerted by the agent γ and the payment to cover a share of the principal's future LTC costs $q + \gamma\mu_\theta$. The agent observes the contract and decides whether to accept it. Acceptance occurs if the expected utility from the contract is at least as high as the agent's reservation utility $\bar{v}$. If accepted, the agent exerts the effort level γ as written in the contract, and the principal pays the compensation $q + \gamma\mu_\theta$. If the agent rejects, the informal caregiving tasks are not provided by the agent and the principal must to guarantee their LTC needs coverage through public and private insurance benefits.

4.2.1 The principal's problem

The principal consumable wealth x at the date he has LTC needs is given by:

$$x = s - \tau + g\theta - (b_1 + (b_2 + i)\mu_\theta) - \theta + i\theta + \gamma\theta - (q + \gamma\mu_\theta) \quad (4.1)$$

with $s > 0$ being the stock of savings accumulated through life, $\tau \in [0, 1]$ is the State mandatory general taxes paid by the principal, θ are the principal's gross LTC costs, $g\theta$ is the public transfer from the State to the principal when he has LTC needs, $b_1 + (b_2 + i)\mu_\theta$ is the insurance premium paid by the principal to the insurance company, $i\theta$ is the private insurance in-cash benefit transferred from the insurer company to the principal, $\gamma\theta$ is the agent informal care provided to the principal to overcome their LTC needs, and $q + \gamma\mu_\theta$ is the principal transfer to the agent, which includes a fixed payment q and a variable payment $\gamma\mu_\theta$ related with the expected LTC cost and informal care provided by the agent.

Assuming an exponential utility function, the principal's utility is given by:

$$u(x) = -e^{-\alpha_P[s - \tau + g\theta - (b_1 + (b_2 + i)\mu_\theta) - \theta + i\theta + \gamma\theta - (q + \gamma\mu_\theta)]} \quad (4.2)$$

where $\alpha_P > 0$ is the principal coefficient of constant absolute risk aversion (CARA).

Since $u(x) = -e^{-\alpha x}$ and given the monotonicity of the exponential function, maximizing the function is equivalent to maximizing the exponent. The expected utility of the principal is given by:

$$Eu(x) = s - \tau + g\mu_\theta - b_1 - b_2\mu_\theta - \mu_\theta - q - \frac{\alpha_P}{2}(g - 1 + i + \gamma)^2\sigma_\theta^2 \quad (4.3)$$

where μ_θ is the expected value or mean of LTC gross costs θ , and σ_θ^2 is the variance.

Proof: See Appendix 4.5.1

4.2.2 The agent's problem

The agent's wealth y when the principal has LTC needs is given by:

$$y = q + \gamma\mu_\theta - \frac{1}{2}c(\gamma\theta)^2 \quad (4.4)$$

where $q + \gamma\mu_\theta$ is the principal transfer to the agent, composed of a fixed component q and a variable component $\gamma\mu_\theta$ related to the stochastic characteristic of the LTC costs θ . The agent incurs disutility from the effort necessary to provide informal care to the principal. The disutility is determined by the level of informal care provided by the agent, and this cost of effort is given by the quadratic function $\psi(\gamma\theta) = \frac{1}{2}c(\gamma\theta)^2$.

The agent is risk averse, and his utility function takes the general separable form composed by a benefit $q + \gamma\mu_\theta$ and an effort $\frac{1}{2}c(\gamma\theta)^2$:

$$v(y) = -e^{-\alpha_A[q + \gamma\mu_\theta - \frac{1}{2}c(\gamma\theta)^2]} \quad (4.5)$$

with $\alpha_A > 0$ is the agent CARA coefficient, and the expected utility of the agent is given by:

$$Ev(y) = q + \gamma\mu_\theta - \frac{1}{2}c\gamma^2(\sigma_\theta^2 + \mu_\theta^2) - \frac{\alpha_A}{4}c^2\gamma^4\sigma_\theta^2(\sigma_\theta^2 + 2\mu_\theta^2) \quad (4.6)$$

Proof: See Appendix 4.5.2

4.2.3 The maximization problem of the principal

The principal's problem is designing a contract that elicits the agent's informal care effort γ and maximizes the agent expected utility:

$$\gamma = \frac{\mu_\theta}{c(\sigma_\theta^2 + \mu_\theta^2)} \left[1 - \alpha_A \frac{c^2\sigma_\theta^2(\sigma_\theta^2 + 2\mu_\theta^2)\mu_\theta^2}{(\sigma_\theta^2 + \mu_\theta^2)^3} \right] \quad (4.7)$$

The agent decides whether to accept the contract proposed by the principal. This decision is given by:

$$q + \gamma\mu_\theta - \frac{1}{2}c\gamma^2(\sigma_\theta^2 + \mu_\theta^2) - \frac{\alpha_A}{4}c^2\gamma^4\sigma_\theta^2(\sigma_\theta^2 + 2\mu_\theta^2) \geq \bar{v} \quad (4.8)$$

Equation (4.8) is the participation constraint (PC) of the agent and states that the agent will not sign a contract that gives him a lower expected utility than the alternative market opportunities $\bar{v}$.

From the maximization problem, the principal designs the contract and defines the agent's optimal effort γ that maximizes the agent expected utility, the amount of private LTC insurance cash-benefit demanded i , and the fixed payment q to the agent, such that:

$$\begin{aligned} \max_{\gamma, i, q} \quad & s - \tau + g\mu_\theta - b_1 - b_2\mu_\theta - \mu_\theta - q - \frac{\alpha_p}{2}(g - 1 + i + \gamma)^2\sigma_\theta^2 \\ \text{s.t.} \quad & q + \gamma\mu_\theta - \frac{1}{2}c\gamma^2(\sigma_\theta^2 + \mu_\theta^2) - \frac{\alpha_A}{4}c^2\gamma^4\sigma_\theta^2(\sigma_\theta^2 + 2\mu_\theta^2) \geq \bar{v} \end{aligned} \quad (4.9a)$$

$$\gamma = \frac{\mu_\theta}{c(\sigma_\theta^2 + \mu_\theta^2)} \left[1 - \alpha_A \frac{c^2\sigma_\theta^2(\sigma_\theta^2 + 2\mu_\theta^2)\mu_\theta^2}{(\sigma_\theta^2 + \mu_\theta^2)^3} \right] \quad (4.9b)$$

$$g + i + \gamma = 1 \quad (4.9c)$$

Proofs: See Appendix 4.5.3 to verify proofs of the maximization problem

The intuition behind this maximization problem is that the principal requires effort from the agent, and the latter decides whether to accept the contract proposed by the principal through the participation constraint (Equation 4.9a). Theoretically, the limit for participation in the contract is that his expected utility is not less than the reservation utility $\bar{v}$, i.e., the expected utility that external opportunities offer to the agent. From Equation (4.9b), we get the imposed level of effort γ that maximizes agent objective function. The problem is also subject to a budget constraint (Equation 4.9c) such that the total LTC costs θ should be entirely covered even by the public transfer g , the insurance cash-benefit i , and the agent care γ , and no debts occur.

From the first-order conditions (FOCs) of the choice variables optimization (γ, i, q) , we get the Lagrangian multipliers associated with each constraint.

Proofs: See Appendix 4.5.4.

The multiplier for the participation constraint λ_1 derives the optimal fixed payment q from principal to agent:

$$\frac{\partial \mathcal{L}}{\partial \lambda_1} = 0 \Leftrightarrow q = \bar{v} - \gamma\mu_\theta + \frac{1}{2}c\gamma^2(\sigma_\theta^2 + \mu_\theta^2) + \frac{\alpha_A}{4}c^2\gamma^4\sigma_\theta^2(\sigma_\theta^2 + 2\mu_\theta^2) \quad (4.10)$$

The optimal amount of q is defined by taking the agent reservation utility from the participation constraint, the expected LTC costs, the agent cost of effort, and risk aversion.

The FOC with respect to the multiplier λ_2 reveals the optimal informal care γ that the principal requests to the agent on the principal-agent contract:

$$\frac{\partial \mathcal{L}}{\partial \lambda_2} = 0 \Leftrightarrow \gamma = \frac{\mu_\theta}{c(\sigma_\theta^2 + \mu_\theta^2)} \left[1 - \alpha_A \frac{c^2\sigma_\theta^2(\sigma_\theta^2 + 2\mu_\theta^2)\mu_\theta^2}{(\sigma_\theta^2 + \mu_\theta^2)^3} \right] \quad (4.11)$$

Finally, the optimal choice of the private insurance i is derived from the first order condition with respect to the budget constraint multiplier λ_3 . Based on the budget restriction, the optimal private insurance i depends on the informal care γ and on the government benefit transfer g :

$$\frac{\partial \mathcal{L}}{\partial \lambda_3} = 0 \Leftrightarrow i = 1 - g - \left[\frac{\mu_\theta}{c(\sigma_\theta^2 + \mu_\theta^2)} \left[1 - \alpha_A \frac{c^2\sigma_\theta^2(\sigma_\theta^2 + 2\mu_\theta^2)\mu_\theta^2}{(\sigma_\theta^2 + \mu_\theta^2)^3} \right] \right] \quad (4.12)$$

4.3 Comparative statics

Until now, our model does not account for shocks that could impact the principal-agent contract. We will try to capture it by deriving how exogenous shocks induce shifts in the choice variables. We evaluate the following shocks: in mean of the LTC costs μ_θ , the variance and associated risk of the LTC costs σ_θ^2 , the amount of the LTC public insurance benefit g , and

the agent coefficient of absolute risk aversion α_A . These exogenous shocks of μ_θ , σ_θ^2 , g , and α_A could occur due to the randomness of the LTC needs, unpredictable changes in public policies concerning the public support, and changes in individuals' willingness to take risks.

We consider these shocks as we are interested in studying how a change in the LTC costs and their variance, which expresses in our model the risk and the uncertainty associated with the LTC costs, could change the amount of private insurance purchased i , the informal care effort exerted by the agent γ , and the fixed transfer from the principal to the agent q . We also study how the public LTC benefit and the agent's willingness to take risks on their end-of-life would affect the incentives of the principal to purchase LTC insurance i , the fixed q transfer, and the agent effort to provide informal care γ ¹.

4.3.1 The private insurance coverage i purchased by the principal

Proposition 1. If $\mu_\theta < \sigma_\theta^2$ and the agent has low to moderate degree of risk aversion α_A , an exogenous change in LTC mean costs μ_θ leads to a decrease in the private insurance benefit i demanded by the principal²:

$$\frac{\partial i}{\partial \mu_\theta} = \frac{\mu_\theta^2 - \sigma_\theta^2}{c(\sigma_\theta^2 + \mu_\theta^2)^2} + \frac{3\alpha_A c \sigma_\theta^2 \mu_\theta^2}{(\sigma_\theta^2 + \mu_\theta^2)^5} (\sigma_\theta^4 + \sigma_\theta^2 \mu_\theta^2 - 2\mu_\theta^4) \quad (< 0) \quad (4.13)$$

Proof. Derivative of the Equation (4.12) with respect to μ_θ on Appendix 4.5.5

We assume that the stochastic mean LTC costs μ_θ is closely related to the principal needs and health status. When $\mu_\theta < \sigma_\theta^2$ and the agent exhibits a low to moderate degree of risk aversion α_A , an exogenous change in the mean of the LTC costs μ_θ decreases the demand for private insurance benefits i . Supporting this, Mellor (2001) found that poor self-reported health status (as a measure of uncertain need costs) decreases the likelihood of LTC insurance coverage by 0.8 percentage points. Also Tennyson et al. (2022) found that past health status, measured by the number of chronic health conditions ever diagnosed, significantly decreased the husband's probability of being covered by LTC insurance, while the wife's increase but is insignificant.

Conversely, under the same condition $\mu_\theta < \sigma_\theta^2$ but if the agent has highest levels of risk aversion α_A , an exogenous change in the mean of the LTC costs μ_θ leads to an increase in the private insurance benefit i demanded, avoiding highest negative impacts on the agent physical and mental health.

Proposition 2. If $\mu_\theta < \sigma_\theta^2$ and the agent has low to moderate degree of risk aversion α_A , an increase in the LTC costs variance σ_θ^2 increases the insurance demand i :

$$\frac{\partial i}{\partial \sigma_\theta^2} = \frac{\mu_\theta}{c(\sigma_\theta^2 + \mu_\theta^2)^2} - \frac{2\alpha_A c \mu_\theta^3}{(\sigma_\theta^2 + \mu_\theta^2)^5} (\sigma_\theta^4 + 2\sigma_\theta^2 \mu_\theta^2 - \mu_\theta^4) \quad (> 0) \quad (4.14)$$

Proof. Derivative of the Equation (4.12) with respect to σ_θ^2 on Appendix 4.5.5

LTC costs could vary according to the care settings where it is provided (e.g., in-home care, community services, or in a nursing home), the level of care required, and the duration of such needs. Higher LTC cost variance captures the uncertainty around these costs, specifically, those

¹The derivative proofs are identified in each subsection.

²We assume that $\mu_\theta < \sigma_\theta^2$ because according to Genworth Cost of Care Survey (2023) in the USA the LTC costs vary widely based on care setting, geographic location of care, level of care required, person and country heterogeneity. Based on OECD (2021) we also assume $\mu_\theta^2 < \sigma_\theta^2$, implying that the LTC cost volatility is large relative to its squared average.

provided in formal care settings instead of those from the informal networks. Equation (4.14) behind the LTC mean costs μ_θ also depends on their variance σ_θ^2 and the agent cost of effort c and risk aversion α_A coefficients. This result is aligned with Sloan & Norton (1997) who found that when an increased probability of one or both spouses entering a nursing home occurs, with the corresponding rise in costs variance, it significantly increases the probability of purchasing private LTC insurance. From empirical results of Caro et al. (2010), among the USA older couples, when the perceived risk of nursing home use is 50% or higher of both spouses, it is associated with possession of a LTC insurance policy. However, none of other need variables used by Caro et al. (2010) to evaluate the spouses health status and limitations were associated with insurance coverage. Eling et al. (2021) show that higher body mass index levels (as it could indicate lower health status) and higher subjective life expectancy are both positive and significant to LTC insurance holding. However, when $\mu_\theta < \sigma_\theta^2$ and if the agent has highest levels of risk aversion α_A , an increase in the LTC costs variance σ_θ^2 , decreases the principal private insurance benefit demand i .

Proposition 3. An increase in the government benefit g decreases the principal LTC insurance demand i :

$$\frac{\partial i}{\partial g} = -1 \quad (< 0) \quad (4.15)$$

Proof. Derivative of the Equation (4.12) with respect to g on Appendix 4.5.5

This effect is well recognized in the literature, specifically in the context of the USA: an increase in public in-cash benefit used to cover LTC needs g diminishes the decision to purchase private insurance i . Several empirical studies have found similar effects. Brown et al. (2007) estimated that more generous Medicaid³ is associated with less private long-term care insurance coverage. Sloan & Norton (1997) found evidence that Medicaid "crowds out" demand for private long-term care insurance coverage for the oldest-old persons, as it becomes a substitute for private long-term care insurance. Finally, using data from the USA to calibrate the model, Brown & Finkelstein (2008) highlighted a key finding related to "even if we eliminate all potential market failures and make fully comprehensive insurance policies available at actuarially fair prices" individuals were still unwilling to pay for LTC private insurance policies in the presence of Medicaid. Under the European context characterized by a diversity of welfare states and universalism of public LTC policies, Costa-Font & Courbage (2015) did not conclude that public support diminished private insurance expectations.

Proposition 4. An increase in the agent degree of risk aversion α_A , increases the insurance demand i :

$$\frac{\partial i}{\partial \alpha_A} = \frac{c\mu_\theta^3\sigma_\theta^2(\sigma_\theta^2 + 2\mu_\theta^2)}{(\sigma_\theta^2 + \mu_\theta^2)^4} \quad (> 0) \quad (4.16)$$

Proof. Derivative of the Equation (4.12) with respect to α_A on Appendix 4.5.5

Risk-aversion is relevant in principal-agent models since it is the source of incentives-insurance trade-off that commonly arises in such models (O'Donoghue & Somerville, 2018). In our model, when the agent exhibits a high level of risk aversion α_A , it seems to increase the insurance demand i , which suggests that increased agent risk aversion leads the principal to rely more heavily on private insurance, thereby increasing the value of the insurance benefit i .

³The Medicaid program provides public long-term care insurance in the USA with applied eligibility rules based on individuals mean-testing.

This is aligned with the economic rationale that "people dislike risks", and when people have risk aversion, their demand for insurance is higher (O'Donoghue & Somerville, 2018).

Providing informal care involves effort and uncertain costs, such as time, health impacts, and opportunity costs that are influenced by the random gross cost of covering the principal's LTC needs $\theta > 0$. Equation (4.16) captures this relationship, as it depends on the agent's cost of effort c , the mean μ_θ , and the variance σ_θ of LTC costs. Since the agent has low to moderate degree of risk aversion α_A , our result follows the theories around risk aversion and the purchase of insurance, as well the empirical findings from Eling et al. (2021) who found that average willingness to take financial risks is positively and significantly associated with LTC insurance holding, compared with no willingness to take those risks. Similarly, de Bresser et al. (2022) showed that more risk-averse people are more willing to pay for home care insurance with domestic, personal, and social care coverage rather than for the annuity and the lump sum.

However, from LTC insurance related literature we also denote opposite results. Fuino et al. (2022) verified that the individuals with higher risk aversion did not show a higher share of interest in LTC insurance compared to those who were more risk seekers, and explain it to under the hypothesis of LTC cost and financing are a long-run risk decision. Sloan & Norton (1997) found that a moderate level of risk aversion diminished the probability of purchasing private LTC insurance, while "very risk averse" individuals increased its purchase, but with insignificant effect, highlighting that measuring the degree of risk aversion "is no simple matter".

4.3.2 The fixed transfer q from the principal to the agent

Generally, transfers and bequests are studied under the relationship established between parents and their children (Albertini et al., 2007; Groneck, 2016; Kusa, 2019). Other research branches have studied their effect on the decision to demand LTC insurance policies (Sloan & Norton, 1997; Lockwood, 2018).

Our model studies the contract established between the two members of the couple, and through comparative statics, we analyze how exogenous shocks could influence fixed transfers q . According to Maichanou et al. (2022), private intra-household transfers could be through bequests, inheritance, grants, or donations. Their results showed that the percentage of transfers from husband or wife is lower than those to children. However, the amount of spouse transfers is higher than that to children.

Proposition 5. A shock in the mean costs of LTC μ_θ has a negative effect on the amount of the fixed transfer q from the principal to the agent:

$$\frac{\partial q}{\partial \mu_\theta} = -\gamma + \mu_\theta(c\gamma^2 + \alpha_A c^2 \gamma^4 \sigma_\theta^2) \quad (< 0) \quad (4.17)$$

Proof. Derivative of the Equation (4.10) with respect to μ_θ on Appendix 4.5.5

This result reveals that a higher mean LTC cost μ_θ negatively affects the fixed transfers q from the principal to the agent. Nicholas & Baum (2020) highlighted that LTC costs are generally very high, particularly in the last year of people's lives, and how it can impose significant financial constraints on spouses. Pozo-Rubio et al. (2020) identified the financial risks and impoverishment effects associated with LTC expenditures. Their findings suggest that LTC payments vary according to the individual's level of dependence, with those at the highest levels requiring higher care effort from the agent at associated increased financial risk. Our model assumes moderate effort levels, but when effort γ increases, the fixed transfer q from the principal to their spouse increases, since the optimal q depends on care effort γ .

Proposition 6. The effect of higher LTC costs variance σ_θ^2 on the fixed transfers q , is positive:

$$\frac{\partial q}{\partial \sigma_\theta^2} = \frac{1}{2} c \gamma^2 (1 + \alpha_A c \gamma^2 (\sigma_\theta^2 + \mu_\theta^2)) \quad (> 0) \quad (4.18)$$

Proof. Derivative of the Equation (4.10) with respect to σ_θ^2 on Appendix 4.5.5

A shock on the LTC cost variance has a positive effect on the amount of fixed payment transferred from the principal to the agent. The spread-out nature of LTC costs captured by their variance could affect the principal's transfer to the agent when the former needs LTC. The care provision among married people could be motivated by altruistic reasons or "imposed" by social norms and traditional cultural ideologies. Based on a more altruistic vision, Pauly (1990) highlighted that "impoverishing a spouse" is a huge problem for older married people and is a more complex concern than the relationship established between parents and children. The final year of life for older adults is often marked by intensive health care utilization and increased expenditures on medical care, home modifications, and other health-related goods and services (Nicholas & Baum, 2020). Regarding the couple's contract, the higher variance of LTC costs σ_θ^2 could signal the principal's highest needs, imposing on the agent higher disutility with increased health and financial costs associated, which needs to be compensated with higher transfers from the principal.

Proposition 7. The public insurance g is independent of the fixed transfers q :

$$\frac{\partial q}{\partial g} = 0 \quad (4.19)$$

Proof. Derivative of the Equation (4.10) with respect to g on Appendix 4.5.5

From Equation 4.10, the fixed payment q is independent of the public insurance g . Our model assumes that the public benefit transfer g is a universal and in-cash benefit only determined by the principal LTC needs θ and independent from the principal's choice. Nikolov & Bonci (2020) identified the behavioral response of private transfers to public program benefits in the context of developing countries. Introducing social protection could diminish existing informal mechanisms for risk protection and private transfers. Furthermore, private transfers, compared to benefits offered by public social protection, have a significant impact on the enhancement of living conditions, reduction of income inequalities, and capital accumulation (Maichanou et al., 2022).

Proposition 8. Higher agent's risk aversion α_A increases the fixed payment q from the principal to the agent:

$$\frac{\partial q}{\partial \alpha_A} = \frac{1}{4} c^2 \gamma^4 \sigma_\theta^2 (\sigma_\theta^2 + 2\mu_\theta^2) \quad (> 0) \quad (4.20)$$

Proof. Derivative of the Equation (4.10) with respect to α_A on Appendix 4.5.5

Equation 4.20 depends on the disutility c from informal care effort γ and the mean μ_θ and variance of the LTC costs σ_θ^2 . In this context, higher risk aversion on the part of the agent appears to increase the fixed transfer q from the principal, suggesting that more risk-averse agents demand increased fixed payment.

4.3.3 The informal care effort γ provided by the agent

Informal care is currently the primary source of LTC care provision. In the USA, the prevalence of adult people who provide informal care is nearly 17%, while among people older than 50 years old this prevalence broke down to 7%. In Europe, there is an opposite scenario as the prevalence of informal caregivers increases with age: on adults, the prevalence is 17%, but across people over 50 years, the prevalence ranges between 13,5 and 25,6% (Tur-Sinai et al., 2020).

Informal care is mainly studied within the relationship between parents and their children. Barczyk & Kredler (2017) estimated a linear probability model for the informal care choice and found that the presence of a spouse/partner is a crucial predictor of informal care. Our model assumes that informal care is one source for overcoming LTC needs and is also defined under the contract established between the two spouses.

Proposition 9. If $\mu_\theta < \sigma_\theta^2$ and the agent has low to moderate degree of risk aversion α_A , a shock in the mean of LTC costs μ_θ increases the informal care effort γ provided by the agent:

$$\frac{\partial \gamma}{\partial \mu_\theta} = \frac{\sigma_\theta^2 - \mu_\theta^2}{c(\sigma_\theta^2 + \mu_\theta^2)^2} - \frac{\alpha_A c \sigma_\theta^2 \mu_\theta^2}{(\sigma_\theta^2 + \mu_\theta^2)^5} (3\sigma_\theta^4 + 5\sigma_\theta^2 \mu_\theta^2 - 6\mu_\theta^4) \quad (> 0) \quad (4.21)$$

Proof. Derivative of the Equation (4.11) with respect to μ_θ on Appendix 4.5.5

An increase in the LTC mean costs induces higher informal care effort. Higher expected LTC expenditures μ_θ could be associated with higher care needs, and under low to moderate risk-aversion level, the agent has increased willingness to provide care. Maia et al. (2022) compared data from Portugal and Denmark using measures from the Survey of Health, Ageing and Retirement in Europe (SHARE) and found that the likelihood of older people's receiving informal care from household caregivers was positively related with depressive symptoms and with health limitations.

Equations 4.13 and 4.17 reveal that when a shock on the LTC mean costs occurs, it decreases the insurance uptake and the amount of the fixed transfers, but Equation 4.21 indicates an increase of the informal care effort. These results suggest the potential substitution effect of informal care γ and private insurance i , enhancing that relying on a spouse may serve as a substitute for private insurance. However, this substitution effect needs to be better studied. From Haag (2020) being married is more likely to complement rather than substitute for long-term care insurance. Additionally, when $\mu_\theta < \sigma_\theta^2$ and the agent exhibits a high degree of risk aversion α_A , a shock to the mean of LTC costs μ_θ decreases the informal care γ provided by the agent.

Proposition 10. If $\mu_\theta < \sigma_\theta^2$ and the agent has low to moderate degree of risk aversion α_A , a shock in the variance of LTC costs σ_θ^2 decreases the informal care γ provided by the agent:

$$\frac{\partial \gamma}{\partial \sigma_\theta^2} = -\frac{\mu_\theta}{c(\sigma_\theta^2 + \mu_\theta^2)^2} + \frac{\alpha_A c \mu_\theta^3}{(\sigma_\theta^2 + \mu_\theta^2)^5} (2\sigma_\theta^4 + 4\mu_\theta^2 \sigma_\theta^2 - 2\mu_\theta^4) \quad (< 0) \quad (4.22)$$

Proof. Derivative of the Equation (4.11) with respect to σ_θ^2 on Appendix 4.5.5

A shock in the LTC cost variance decreases informal care effort when the agent exhibits low to moderate degree of risk aversion α_A . When the LTC cost variance increases, the associated health, social, and financial constraints likely increase, and the agent decreases their effort on

the informal care task. However, when $\mu_\theta < \sigma_\theta^2$ and the agent exhibits a high degree of risk aversion α_A , a shock in the variance of LTC costs σ_θ^2 increases the informal care γ provided by the agent.

Proposition 11. The optimal informal care γ is independent of the public benefit g :

$$\frac{\partial \gamma}{\partial g} = 0 \quad (4.23)$$

Proof. Derivative of the Equation (4.11) with respect to g on Appendix 4.5.5

Our model assumes that the public benefit transfer g is a universal and in-cash benefit independent from the family and informal care provision. From Equation 4.11, we observe that the informal care effort by the agent γ is not a function of the public insurance g . The result indicates that spouse informal care effort γ is independent of the level of public benefits g , meaning that changes in public benefit provision don't affect the optimal allocation decisions of effort.

However, on the related literature we find different results on the effect of LTC public programs on the behavior of informal caregivers. On one side, the influence of public LTC insurance on informal care was empirically studied by Ettner (1994), Pezzin et al. (1996), and Stabile et al. (2006), who, for the USA and Canada, found that the public LTC support increased the use of formal home care, but decreased informal care. Recognizing the existence of a "substitution" hypothesis due to more generous welfare state services in support of older people that "crowd out" family help, Motel-Klingebiel et al. (2005) studied five European countries. The findings pointed to higher informal care provided in countries with lower development of welfare regimes; however, when personal and household attributes of older people (partnership status, health status, the number of children, and normative beliefs) were controlled for, the country differences in family help became insignificant. Liu & Zai (2022) studied the effect of the USA Medicaid aging waiver (MAW) programs⁴, concluding that an increase in MAW expenditures increased the likelihood that an adult child became an informal caregiver. In complement, Courbage et al. (2020) pointed out that countries' public LTC financing typologies may impact informal care differently. Their findings showed a positive relationship between public coverage and informal care in Italy, while in Spain, LTC public support decreased the receipt of informal care⁵, highlighting the importance of controlling public policies to support LTC and their impact on family dynamics.

Proposition 12. The agent decreases informal care effort γ when their risk aversion α_A increases:

$$\frac{\partial \gamma}{\partial \alpha_A} = -\frac{c\mu_\theta^3\sigma_\theta^2(\sigma_\theta^2 + 2\mu_\theta^2)}{(\sigma_\theta^2 + \mu_\theta^2)^4} \quad (< 0) \quad (4.24)$$

Proof. Derivative of the Equation (4.11) with respect to α_A on Appendix 4.5.5

When agents become more risk-averse, they are less willing to exert effort related to provide LTC to their spouse, who acts as the principal. This aligns with economic theory and, more specifically, with principal-agent models: higher risk aversion leads to lower incentivized effort

⁴MAW programs subsidize professional providers for in-home formal care besides offering home or community-based services.

⁵In Italy, the primary public support is through cash benefits, and in Spain, it is mainly through in-kind support.

unless the agent is compensated with contracts offering greater certainty. Since the agent is risk averse, our intuition confirmed by Equation 4.24, is that their effort in providing care decreases. This equation shows that effort depends on the mean μ_θ and variance σ_θ^2 of LTC costs for the principal, as well as the cost of effort c for the agent. This suggests that the agent risk aversion α_A becomes a parameter that reduces the value of informal care provision γ , implying the agent adjusts their effort downward to account for the additional perceived risk.

4.4 Conclusion

This paper employs a principal-agent framework to examine LTC decision-making within couples, modeling one spouse as the principal and the other as the agent. Drawing inspiration from Pauly (1990) and extending the model of Zweifel & Strüwe (1996), we adapt the framework to reflect intra-couple dynamics, wherein caregiving responsibilities are typically assumed by the younger or healthier spouse. Specifically, the older spouse (the principal) offers a contract to the younger spouse (the agent) to provide informal care.

By assuming that caregiving effort is observable and contractible, the model abstracts from informational asymmetries and focuses on optimal contract design to internalize LTC risk. The principal accounts for the agent’s disutility from caregiving, including exposure to financial and health risks, while the agent accepts the contract if it maximizes expected utility, conditional on compensation and risk preferences. Although the principal-agent framework is not conventionally applied to spousal interactions, our results demonstrate its utility in capturing intra-couple coordination under LTC uncertainty.

Our comparative statics results indicate that our model findings are aligned with empirical research. Shocks on the mean LTC associated costs lead to a decrease in the purchase of LTC insurance and in transfers, while increases the agent’s effort to provide care. However, shocks on the LTC cost variance yield the opposite decisions concerning the three choice variables. The results show that an agent with higher risk aversion increases the principal purchase of private insurance and the amount of fixed transfers from the principal to the agent, while the agent exerts less informal care effort. Since spouses are one primary source of LTC provision, but the duration and costs associated with LTC are uncertain, this reflects the agent’s sensitivity to caregiving related risk and their preference for financial compensation over caregiving effort. Our model highlights a critical trade-off, since when the LTC cost variance increases, informal care becomes less attractive relative to formal arrangements. In this setting, the principal offsets the agent’s reduced caregiving effort by increasing insurance purchases and monetary transfers, highlighting how intra-couple risk-sharing can be adjusted in response to changing LTC risk profiles.

We analyze a reference case under the strong assumption that informal care effort is defined on the contract, observable and contractible. Following Barczyk & Kredler (2017), this assumption is supported by empirical evidence showing that care arrangements are closely linked to marital status. Data indicate that providing care for a spouse or partner often is a role which arises naturally, as the presence of a spouse is a strong predictor of informal care provision, rather than the use of formal care services. However, we still recognize that this baseline model and assumptions could be extended by incorporating the unpredictability of LTC costs and considering cases where informal care effort is unobserved. This would introduce asymmetric information, as the agent’s behavior becomes a non-verifiable variable from the principal’s perspective, leading to a moral hazard problem. Future research could also estimate the model using couple-level data, allowing for the identification of unobserved risk preferences and how couples behave when purchasing private LTC insurance in the marketplace.

Our findings carry important implications for LTC policy design. First, they highlight the role of intra-couple risk aversion in shaping preferences for informal care versus private insurance. As demographic aging continues and the availability of informal care from extended

family members declines, this essay contributes to informing how couples decide to cover LTC needs. Second, from our results, we denoted that informal care and insurance purchase are both possible sources of overcoming needs and financing issues related to LTC. Third, we emphasize intra-couple transfers as a tool for safeguarding the financial well-being of caregiving spouses, particularly in later life.

4.5 Appendix

4.5.1 Proofs of the principal's problem

$$x = s - \tau + g\theta - (b_1 + (b_2 + i)\mu_\theta) - \theta + i\theta + \gamma\theta - (q + \gamma\mu_\theta)$$

Given that $\theta \sim N(\mu, \sigma^2)$, then $E[\theta] = \mu_\theta$, and we get:

$$\begin{aligned}\mu_x &= s - \tau + g\mu_\theta - (b_1 + (b_2 + i)\mu_\theta) - \mu_\theta + i\mu_\theta + \gamma\mu_\theta - (q + \gamma\mu_\theta) \\ &= s - \tau + g\mu_\theta - b_1 - b_2\mu_\theta - i\mu_\theta - \mu_\theta + i\mu_\theta + \gamma\mu_\theta - q - \gamma\mu_\theta \\ &= s - \tau + g\mu_\theta - b_1 - b_2\mu_\theta - \mu_\theta - q\end{aligned}$$

Given that $\sigma_x^2 = E[(x - E(x))^2]$, i.e., the variance is the expected difference between the variable's value and its mean (squared), we get:

$$\begin{aligned}\sigma_x^2 &= g\theta - \theta + i\theta + \gamma\theta \\ &= (g - 1 + i + \gamma)^2 \sigma_\theta^2\end{aligned}$$

We modeled the risk and uncertainty, using the exponential utility function to maximize the expected utility. Formally, the exponential utility is given by:

$$u(x) = -e^{-\alpha_P f(x)}, \alpha > 0$$

Under exponential utility, the expected utility can be calculated by:

$$E(u(x)) = E[-e^{-\alpha_P f(x)}] = -E[e^{-\alpha_P f(x)}] = -e^{-\alpha_P E[f(x)] + \frac{1}{2}\alpha_P^2 \sigma^2[f(x)]}$$

The expected utility is maximized under the following:

$$\begin{aligned}\max \quad E[-e^{-\alpha_P f(x)}] &= \max \quad -e^{-\alpha_P E[f(x)] + \frac{1}{2}\alpha_P^2 \sigma^2[f(x)]} \\ &= \max \quad E[f(x)] - \frac{\alpha_P}{2} \sigma^2[f(x)]\end{aligned}$$

Applying it to our case and using Equations above of x , μ_x , and σ_x^2 , we have :

$$\begin{aligned}Eu(x) &= -E[e^{-\alpha_P [s - \tau + g\theta - (b_1 + (b_2 + i)\mu_\theta) - \theta + i\theta + \gamma\theta - (q + \gamma\mu_\theta)]}] \\ &= -E[e^{-\alpha_P [s - \tau - (b_1 + (b_2 + i)\mu_\theta) - (q + \gamma\mu_\theta)]} e^{-\alpha_P [g\theta - \theta + i\theta + \gamma\theta]}] \\ &= -e^{-\alpha_P [s - \tau + g\mu_\theta - b_1 - b_2\mu_\theta - \mu_\theta - q + \frac{1}{2}\alpha_P (g - 1 + i + \gamma)^2 \sigma_\theta^2]}\end{aligned}$$

The principal's expected utility maximization is given by:

$$\max \quad Eu(x) = \max \quad [s - \tau + g\mu_\theta - b_1 - b_2\mu_\theta - \mu_\theta - q] - \frac{\alpha_P}{2} (g - 1 + i + \gamma)^2 \sigma_\theta^2$$

4.5.2 Proofs of the agent's problem

Following Bolton & Dewatripont (2005), we assume that the agent's cost of effort is a quadratic function:

$$\psi(\gamma\theta) = \frac{1}{2}c(\gamma\theta)^2$$

where ψ is the cost of informal care provided, $\gamma\theta$ is the informal care output, and c is the cost coefficient. From derivatives we get $\psi'(\gamma\theta) > 0$ and $\psi''(\gamma\theta) > 0$.

The agent's consumable wealth includes the transfer from the principal to the agent and the cost of effort:

$$\begin{aligned} y &= q + \gamma\mu_\theta - \frac{1}{2}c(\gamma\theta)^2 \\ \mu_y &= q + \gamma\mu_\theta - \frac{1}{2}c\gamma^2(\sigma_\theta^2 + \mu_\theta^2) \\ \sigma_y^2 &= \frac{1}{2}c^2\gamma^4\sigma_\theta^2(\sigma_\theta^2 + 2\mu_\theta^2) \end{aligned}$$

Following the assumptions presented in the proofs of the principal's problem and applying them to the agent's problem, from Equations above of y , μ_y , and σ_y^2 , we get:

$$\begin{aligned} Ev(y) &= -E[e^{-\alpha_A[q + \gamma\mu_\theta - \frac{1}{2}c(\gamma\theta)^2]}] \\ &= -E[e^{-\alpha_A[q + \gamma\mu_\theta - \frac{1}{2}c\gamma^2(\sigma_\theta^2 + \mu_\theta^2)]}e^{-\alpha_A[\frac{1}{2}c^2\gamma^4\sigma_\theta^2(\sigma_\theta^2 + 2\mu_\theta^2)]}] \\ &= -e^{-\alpha_A[q + \gamma\mu_\theta - \frac{1}{2}c\gamma^2(\sigma_\theta^2 + \mu_\theta^2) + \frac{1}{2}\alpha_A c^2\gamma^4\sigma_\theta^2(\sigma_\theta^2 + 2\mu_\theta^2)]} \end{aligned}$$

The agent's expected utility maximization is given by:

$$\begin{aligned} \max \quad Ev(y) &= \max \quad [q + \gamma\mu_\theta - \frac{1}{2}c\gamma^2(\sigma_\theta^2 + \mu_\theta^2)] - \frac{\alpha_A}{2} \frac{1}{2}c^2\gamma^4\sigma_\theta^2(\sigma_\theta^2 + 2\mu_\theta^2) \\ &= \max \quad [q + \gamma\mu_\theta - \frac{1}{2}c\gamma^2(\sigma_\theta^2 + \mu_\theta^2)] - \frac{\alpha_A}{4}c^2\gamma^4\sigma_\theta^2(\sigma_\theta^2 + 2\mu_\theta^2) \end{aligned}$$

4.5.3 Proofs of maximization problem of the principal

In the first stage, the principal designs the contract including the agent's effort. Since effort is observable, the principal directly chooses the level of effort γ . To ensure that the contract is efficient, the principal selects the effort level that would maximize the agent's expected utility, subject to the agent's participation constraint. This is given by:

$$\max_{\{\gamma\}} \quad q + \gamma\mu_\theta - \frac{1}{2}c\gamma^2(\sigma_\theta^2 + \mu_\theta^2) - \frac{\alpha_A}{4}c^2\gamma^4\sigma_\theta^2(\sigma_\theta^2 + 2\mu_\theta^2)$$

Applying the FOC with respect to γ to the agent's maximization problem yields:

$$\begin{aligned} \frac{\partial E[v(y)]}{\partial \gamma} &= 0 \Leftrightarrow \mu_\theta - \frac{1}{2}c2\gamma(\sigma_\theta^2 + \mu_\theta^2) - \frac{\alpha_A}{4}c^24\gamma^3\sigma_\theta^2(\sigma_\theta^2 + 2\mu_\theta^2) = 0 \\ &\Leftrightarrow \mu_\theta - c\gamma(\sigma_\theta^2 + \mu_\theta^2) - \alpha_A c^2\gamma^3\sigma_\theta^2(\sigma_\theta^2 + 2\mu_\theta^2) = 0 \\ &\Leftrightarrow \mu_\theta = c\gamma(\sigma_\theta^2 + \mu_\theta^2) + \alpha_A c^2\gamma^3\sigma_\theta^2(\sigma_\theta^2 + 2\mu_\theta^2) \end{aligned}$$

This is a cubic equation in γ , and even if we factorize, the equation remains implicit in γ , and hence we can use Cardano's formula. For simplicity we define:

$$\begin{aligned}
A &= \alpha_A c^2 \sigma_\theta^2 (\sigma_\theta^2 + 2\mu_\theta^2) \\
B &= c(\sigma_\theta^2 + \mu_\theta^2) \\
D &= -\mu_\theta
\end{aligned}$$

This is in the form $A\gamma^3 + B\gamma + D = 0$. Since we do not have γ^2 term, we have a "depressed cubic". We convert our equation to standard depressed cubic form, by dividing the equation by A to get:

$$\frac{A\gamma^3}{A} + \frac{B}{A}\gamma + \frac{D}{A} = 0$$

where:

$$\begin{aligned}
P &= \frac{B}{A} = \frac{c(\sigma_\theta^2 + \mu_\theta^2)}{\alpha_A c^2 \sigma_\theta^2 (\sigma_\theta^2 + 2\mu_\theta^2)} = \frac{\sigma_\theta^2 + \mu_\theta^2}{\alpha_A c \sigma_\theta^2 (\sigma_\theta^2 + 2\mu_\theta^2)} \\
Q &= \frac{D}{A} = \frac{-\mu_\theta}{\alpha_A c^2 \sigma_\theta^2 (\sigma_\theta^2 + 2\mu_\theta^2)}
\end{aligned}$$

By substituting, we get:

$$\gamma^3 + P\gamma + Q = 0$$

For the depressed cubic $\gamma^3 + P\gamma + Q = 0$, the discriminant is:

$$\Delta = -4P^3 - 27Q^2$$

Substituting our values:

$$\begin{aligned}
\Delta &= -4 \left(\frac{\sigma_\theta^2 + \mu_\theta^2}{\alpha_A c \sigma_\theta^2 (\sigma_\theta^2 + 2\mu_\theta^2)} \right)^3 - 27 \left(\frac{-\mu_\theta}{\alpha_A c^2 \sigma_\theta^2 (\sigma_\theta^2 + 2\mu_\theta^2)} \right)^2 \\
&= -\frac{4(\sigma_\theta^2 + \mu_\theta^2)^3}{\alpha_A^3 c^3 \sigma_\theta^6 (\sigma_\theta^2 + 2\mu_\theta^2)^3} - \frac{27\mu_\theta^2}{\alpha_A^2 c^4 \sigma_\theta^4 (\sigma_\theta^2 + 2\mu_\theta^2)^2}
\end{aligned}$$

Therefore $\Delta < 0$ for all parameter values where α_A , c , μ_θ and σ_θ are all > 0 . In that case there is one real root and two complex conjugate roots. We focus on the unique positive root as negative informal care effort is not economically meaningful in our model context. By applying it to our model, it means that we have a unique real optimal solution for γ , which is the economically meaningful under our model assumptions.

At this point, we apply the Cardano's formula in our case:

$$\gamma = \sqrt[3]{-\frac{Q}{2} + \sqrt{\frac{Q^2}{4} + \frac{P^3}{27}}} + \sqrt[3]{-\frac{Q}{2} - \sqrt{\frac{Q^2}{4} + \frac{P^3}{27}}}$$

The solution for γ is:

$$\begin{aligned}
\gamma &= \sqrt[3]{\frac{\mu_\theta}{2\alpha_A c^2 \sigma_\theta^2 (\sigma_\theta^2 + 2\mu_\theta^2)} + \sqrt{\frac{\mu_\theta^2}{4\alpha_A^2 c^4 \sigma_\theta^4 (\sigma_\theta^2 + 2\mu_\theta^2)^2} + \frac{(\sigma_\theta^2 + \mu_\theta^2)^3}{27\alpha_A^3 c^3 \sigma_\theta^6 (\sigma_\theta^2 + 2\mu_\theta^2)^3}}} \\
&\quad + \sqrt[3]{\frac{\mu_\theta}{2\alpha_A c^2 \sigma_\theta^2 (\sigma_\theta^2 + 2\mu_\theta^2)} - \sqrt{\frac{\mu_\theta^2}{4\alpha_A^2 c^4 \sigma_\theta^4 (\sigma_\theta^2 + 2\mu_\theta^2)^2} + \frac{(\sigma_\theta^2 + \mu_\theta^2)^3}{27\alpha_A^3 c^3 \sigma_\theta^6 (\sigma_\theta^2 + 2\mu_\theta^2)^3}}}
\end{aligned}$$

Given the complexity of the exact cubic solution, we employ a perturbation expansion approach to obtain a tractable approximation. Under the assumption that α_A is small but positive, we expand the optimal effort level as:

$$\gamma = \sum_{n=0}^{+\infty} \alpha_A^n \gamma_n \approx \gamma_0 + \alpha_A \gamma_1$$

Hence solving order by order we get the tractable approximation FOC equation:

$$\gamma = \frac{\mu_\theta}{c(\sigma_\theta^2 + \mu_\theta^2)} \left[1 - \alpha_A \frac{c^2 \sigma_\theta^2 (\sigma_\theta^2 + 2\mu_\theta^2) \mu_\theta^2}{(\sigma_\theta^2 + \mu_\theta^2)^3} \right] \quad (4.24)$$

By using the approximate γ , we proceed analytically by retaining the economic intuition about how γ depends on μ_θ , c , σ_θ^2 and α_A . The first-order expansion in Equation (4.24) provides a close approximation to the exact solution from the cubic equation when α_A is sufficiently small.

Formally, the optimal contract is the solution to the following maximization problem:

$$\begin{aligned} \max_{\gamma, i, q} \quad & s - \tau + g\mu_\theta - b_1 - b_2\mu_\theta - \mu_\theta - q - \frac{\alpha_p}{2}(g - 1 + i + \gamma)^2 \sigma_\theta^2 \\ \text{s.t.} \quad & q + \gamma\mu_\theta - \frac{1}{2}c\gamma^2(\sigma_\theta^2 + \mu_\theta^2) - \frac{\alpha_A}{4}c^2\gamma^4\sigma_\theta^2(\sigma_\theta^2 + 2\mu_\theta^2) \geq \bar{v} \end{aligned} \quad (4.25a)$$

$$\gamma = \frac{\mu_\theta}{c(\sigma_\theta^2 + \mu_\theta^2)} \left[1 - \alpha_A \frac{c^2 \sigma_\theta^2 (\sigma_\theta^2 + 2\mu_\theta^2) \mu_\theta^2}{(\sigma_\theta^2 + \mu_\theta^2)^3} \right] \quad (4.25b)$$

$$g + i + \gamma = 1 \quad (4.25c)$$

The first restriction (Equation 4.25a) is the agent participation constraint. The second restriction of the maximization problem (Equation 4.25b) is the agent's optimal effort γ derived from the agent's utility maximization and the principal adopts it in the contract restrictions. Equation (4.25c) of the maximization problem is the budget constraint (BC) that guarantees all the LTC costs covered using, if necessary, the three sources: LTC insurance public transfer g , private LTC insurance i , and informal care γ .

4.5.4 Proofs of first order conditions (FOC's)

$$\begin{aligned} \max_{\gamma, i, q} \quad & s - \tau + g\mu_\theta - b_1 - b_2\mu_\theta - \mu_\theta - q - \frac{\alpha_p}{2}(g - 1 + i + \gamma)^2 \sigma_\theta^2 \\ \text{s.t.} \quad & q + \gamma\mu_\theta - \frac{1}{2}c\gamma^2(\sigma_\theta^2 + \mu_\theta^2) - \frac{\alpha_A}{4}c^2\gamma^4\sigma_\theta^2(\sigma_\theta^2 + 2\mu_\theta^2) \geq \bar{v} \end{aligned} \quad (4.26a)$$

$$\gamma = \frac{\mu_\theta}{c(\sigma_\theta^2 + \mu_\theta^2)} \left[1 - \alpha_A \frac{c^2 \sigma_\theta^2 (\sigma_\theta^2 + 2\mu_\theta^2) \mu_\theta^2}{(\sigma_\theta^2 + \mu_\theta^2)^3} \right] \quad (4.26b)$$

$$g + i + \gamma = 1 \quad (4.26c)$$

Therefore, formally, this maximization problem⁶ gives the following Lagrangian:

⁶We use the first-order approximation of the agent's optimal effort under small α_A , and we assume this holds for the principal's design problem.

$$\begin{aligned}
\mathcal{L} = & s - \tau + g\mu_\theta - b_1 - b_2\mu_\theta - \mu_\theta - q - \frac{\alpha_p}{2}(g - 1 + i + \gamma)^2\sigma_\theta^2 \\
& + \lambda_1[q + \gamma\mu_\theta - \frac{1}{2}c\gamma^2(\sigma_\theta^2 + \mu_\theta^2) - \frac{\alpha_A}{4}c^2\gamma^4\sigma_\theta^2(\sigma_\theta^2 + 2\mu_\theta^2) - \bar{v}] \\
& + \lambda_2[\frac{\mu_\theta}{c(\sigma_\theta^2 + \mu_\theta^2)}[1 - \alpha_A\frac{c^2\sigma_\theta^2(\sigma_\theta^2 + 2\mu_\theta^2)\mu_\theta^2}{(\sigma_\theta^2 + \mu_\theta^2)^3}] - \gamma] \\
& + \lambda_3[1 - g - i - \gamma]
\end{aligned}$$

where λ_1 is the multiplier for the participation constraint, the λ_2 is that of the optimal effort level and, λ_3 that of the budget restriction.

From the Lagrangian, we can derive the FOC's with respect to the choice variables: q , i , and γ .

Taking the FOC with respect to the fixed transfer q , we get the multiplier for the participation constraint equal to a constant, such that:

$$\begin{aligned}
\frac{\partial \mathcal{L}}{\partial q} = 0 & \Leftrightarrow -1 + \lambda_1 = 0 \\
& \Leftrightarrow \lambda_1 = 1
\end{aligned}$$

From FOC with respect to the level of insurance benefit i , we get the budget constraint multiplier λ_3 , which depends on the principal risk aversion, on the arguments within budget constraint g, i, γ , and the variance of the θ :

$$\begin{aligned}
\frac{\partial \mathcal{L}}{\partial i} = 0 & \Leftrightarrow 2(-\frac{\alpha_p}{2})(g - 1 + i + \gamma)\sigma_\theta^2 + \lambda_3(-1) = 0 \\
& \Leftrightarrow \lambda_3 = -\alpha_p(g - 1 + i + \gamma)\sigma_\theta^2
\end{aligned}$$

The optimal γ denotes the multiplier for the optimal effort level λ_2 . It depends on the mean, the cost of effort due to performing informal care activities, their individual CARA coefficient, and the variance of the θ :

$$\begin{aligned}
\frac{\partial \mathcal{L}}{\partial \gamma} = 0 & \Leftrightarrow 2(-\frac{\alpha_p}{2})(g - 1 + i + \gamma)\sigma_\theta^2 + \lambda_1[\mu_\theta - 2\frac{1}{2}c\gamma(\sigma_\theta^2 + \mu_\theta^2) \\
& - 4\frac{\alpha_A}{4}c^2\gamma^3\sigma_\theta^2(\sigma_\theta^2 + 2\mu_\theta^2)] + \lambda_2[-1] + \lambda_3[-1] = 0 \\
& \Leftrightarrow -\alpha_p(g - 1 + i + \gamma)\sigma_\theta^2 + \lambda_1[\mu_\theta - c\gamma(\sigma_\theta^2 + \mu_\theta^2) - \alpha_Ac^2\gamma^3\sigma_\theta^2(\sigma_\theta^2 + 2\mu_\theta^2)] - \lambda_2 - \lambda_3 = 0
\end{aligned}$$

replacing with Equations obtained from $\frac{\partial \mathcal{L}}{\partial q}$ and $\frac{\partial \mathcal{L}}{\partial i}$, and solving to λ_2 , we have:

$$\begin{aligned}
-\alpha_p(g - 1 + i + \gamma)\sigma_\theta^2 + [\mu_\theta - c\gamma(\sigma_\theta^2 + \mu_\theta^2) - \alpha_Ac^2\gamma^3\sigma_\theta^2(\sigma_\theta^2 + 2\mu_\theta^2)] - \lambda_2 - (-\alpha_p(g - 1 + i + \gamma)\sigma_\theta^2) &= 0 \\
-\lambda_2 = \alpha_p(g - 1 + i + \gamma)\sigma_\theta^2 - [\mu_\theta - c\gamma(\sigma_\theta^2 + \mu_\theta^2) - \alpha_Ac^2\gamma^3\sigma_\theta^2(\sigma_\theta^2 + 2\mu_\theta^2)] - \alpha_p(g - 1 + i + \gamma)\sigma_\theta^2 & \\
-\lambda_2 = -[\mu_\theta - c\gamma(\sigma_\theta^2 + \mu_\theta^2) - \alpha_Ac^2\gamma^3\sigma_\theta^2(\sigma_\theta^2 + 2\mu_\theta^2)] & \\
\lambda_2 = \mu_\theta - c\gamma(\sigma_\theta^2 + \mu_\theta^2) - \alpha_Ac^2\gamma^3\sigma_\theta^2(\sigma_\theta^2 + 2\mu_\theta^2) &
\end{aligned}$$

The multiplier for the participation constraint λ_1 derives the optimal fixed payment q from principal to agent:

$$\begin{aligned}
\frac{\partial \mathcal{L}}{\partial \lambda_1} = 0 & \Leftrightarrow [q + \gamma\mu_\theta - \frac{1}{2}c\gamma^2(\sigma_\theta^2 + \mu_\theta^2) - \frac{\alpha_A}{4}c^2\gamma^4\sigma_\theta^2(\sigma_\theta^2 + 2\mu_\theta^2) - \bar{v}] = 0 \\
q &= \bar{v} - \gamma\mu_\theta + \frac{1}{2}c\gamma^2(\sigma_\theta^2 + \mu_\theta^2) + \frac{\alpha_A}{4}c^2\gamma^4\sigma_\theta^2(\sigma_\theta^2 + 2\mu_\theta^2)
\end{aligned}$$

The FOC with respect to the λ_2 reveals the optimal informal care effort γ used by the principal in the principal-agent contract:

$$\frac{\partial \mathcal{L}}{\partial \lambda_2} = 0 \Leftrightarrow \gamma = \frac{\mu_\theta}{c(\sigma_\theta^2 + \mu_\theta^2)} \left[1 - \alpha_A \frac{c^2 \sigma_\theta^2 (\sigma_\theta^2 + 2\mu_\theta^2) \mu_\theta^2}{(\sigma_\theta^2 + \mu_\theta^2)^3} \right]$$

The optimal choice of the private insurance i is derived from the first order condition with respect to the budget constraint multiplier λ_3 :

$$\begin{aligned} \frac{\partial \mathcal{L}}{\partial \lambda_3} &= 0 \Leftrightarrow 1 - g - i - \gamma = 0 \\ &\Leftrightarrow -i = -1 + g + \gamma \\ &\Leftrightarrow i = 1 - g - \gamma \end{aligned}$$

replacing with Equation $\gamma = \frac{\mu_\theta}{c(\sigma_\theta^2 + \mu_\theta^2)} \left[1 - \alpha_A \frac{c^2 \sigma_\theta^2 (\sigma_\theta^2 + 2\mu_\theta^2) \mu_\theta^2}{(\sigma_\theta^2 + \mu_\theta^2)^3} \right]$ and solving to i :

$$i = 1 - g - \left[\frac{\mu_\theta}{c(\sigma_\theta^2 + \mu_\theta^2)} \left[1 - \alpha_A \frac{c^2 \sigma_\theta^2 (\sigma_\theta^2 + 2\mu_\theta^2) \mu_\theta^2}{(\sigma_\theta^2 + \mu_\theta^2)^3} \right] \right]$$

4.5.5 Proofs of Comparative Statics

The optimal insurance i

$$\begin{aligned} i &= 1 - g - \left[\frac{\mu_\theta}{c(\sigma_\theta^2 + \mu_\theta^2)} \left[1 - \alpha_A \frac{c^2 \sigma_\theta^2 (\sigma_\theta^2 + 2\mu_\theta^2) \mu_\theta^2}{(\sigma_\theta^2 + \mu_\theta^2)^3} \right] \right] \\ \frac{\partial i}{\partial \mu_\theta} &= - \left[\frac{c(\sigma_\theta^2 + \mu_\theta^2) - \mu_\theta c(2\mu_\theta)}{[c(\sigma_\theta^2 + \mu_\theta^2)]^2} \left[1 - \alpha_A \frac{c^2 \sigma_\theta^2 (\sigma_\theta^2 + 2\mu_\theta^2) \mu_\theta^2}{(\sigma_\theta^2 + \mu_\theta^2)^3} \right] \right. \\ &\quad + \frac{\mu_\theta}{c(\sigma_\theta^2 + \mu_\theta^2)} \left[-\alpha_A \left(\frac{(c^2 \sigma_\theta^2 (4\mu_\theta) \mu_\theta^2 + c^2 \sigma_\theta^2 (\sigma_\theta^2 + 2\mu_\theta^2) 2\mu_\theta) (\sigma_\theta^2 + \mu_\theta^2)^3}{[(\sigma_\theta^2 + \mu_\theta^2)^3]^2} \right. \right. \\ &\quad \left. \left. - \frac{c^2 \sigma_\theta^2 (\sigma_\theta^2 + 2\mu_\theta^2) \mu_\theta^2 3(\sigma_\theta^2 + \mu_\theta^2)^2 2\mu_\theta}{[(\sigma_\theta^2 + \mu_\theta^2)^3]^2} \right) \right] \left. \right] \\ &= - \left[\frac{\sigma_\theta^2 - \mu_\theta^2}{c(\sigma_\theta^2 + \mu_\theta^2)^2} \left[1 - \alpha_A \frac{c^2 \sigma_\theta^2 (\sigma_\theta^2 + 2\mu_\theta^2) \mu_\theta^2}{(\sigma_\theta^2 + \mu_\theta^2)^3} \right] \right. \\ &\quad + \frac{\mu_\theta}{c(\sigma_\theta^2 + \mu_\theta^2)} \left[-\alpha_A \frac{2c^2 \sigma_\theta^2 \mu_\theta (\sigma_\theta^2 + 4\mu_\theta^2) (\sigma_\theta^2 + \mu_\theta^2)^3}{(\sigma_\theta^2 + \mu_\theta^2)^6} \right. \\ &\quad \left. \left. - \frac{c^2 \sigma_\theta^2 (\sigma_\theta^2 + 2\mu_\theta^2) \mu_\theta^2 \cdot 6\mu_\theta (\sigma_\theta^2 + \mu_\theta^2)^2}{(\sigma_\theta^2 + \mu_\theta^2)^6} \right] \right] \\ &= - \left[\frac{\sigma_\theta^2 - \mu_\theta^2}{c(\sigma_\theta^2 + \mu_\theta^2)^2} \left[1 - \alpha_A \frac{c^2 \sigma_\theta^2 (\sigma_\theta^2 + 2\mu_\theta^2) \mu_\theta^2}{(\sigma_\theta^2 + \mu_\theta^2)^3} \right] \right. \\ &\quad \left. + \frac{\mu_\theta}{c(\sigma_\theta^2 + \mu_\theta^2)} \left[-\alpha_A \frac{c^2 \sigma_\theta^2 \mu_\theta}{(\sigma_\theta^2 + \mu_\theta^2)^4} \left(2\sigma_\theta^2 (\sigma_\theta^2 + 2\mu_\theta^2) - 4\mu_\theta^4 \right) \right] \right] \end{aligned}$$

$$\begin{aligned}
&= \left[\frac{\mu_\theta^2 - \sigma_\theta^2}{c(\sigma_\theta^2 + \mu_\theta^2)^2} \left[1 - \alpha_A \frac{c^2 \sigma_\theta^2 (\sigma_\theta^2 + 2\mu_\theta^2) \mu_\theta^2}{(\sigma_\theta^2 + \mu_\theta^2)^3} \right] \right. \\
&\quad \left. + \frac{\mu_\theta}{c(\sigma_\theta^2 + \mu_\theta^2)} \left[\alpha_A \frac{c^2 \sigma_\theta^2 \mu_\theta}{(\sigma_\theta^2 + \mu_\theta^2)^4} (2\sigma_\theta^2 (\sigma_\theta^2 + 2\mu_\theta^2) - 4\mu_\theta^4) \right] \right] \\
&= \frac{\mu_\theta^2 - \sigma_\theta^2}{c(\sigma_\theta^2 + \mu_\theta^2)^2} + \frac{3\alpha_A c \sigma_\theta^2 \mu_\theta^2}{(\sigma_\theta^2 + \mu_\theta^2)^5} (\sigma_\theta^4 + \sigma_\theta^2 \mu_\theta^2 - 2\mu_\theta^4)
\end{aligned}$$

$$\begin{aligned}
\frac{\partial i}{\partial \sigma_\theta^2} &= - \left[- \frac{\mu_\theta}{c(\sigma_\theta^2 + \mu_\theta^2)^2} \left[1 - \alpha_A \frac{c^2 \sigma_\theta^2 (\sigma_\theta^2 + 2\mu_\theta^2) \mu_\theta^2}{(\sigma_\theta^2 + \mu_\theta^2)^3} \right] + \frac{\mu_\theta}{c(\sigma_\theta^2 + \mu_\theta^2)} \left[- \alpha_A c^2 \mu_\theta^2 \frac{(-\sigma_\theta^4 - 2\sigma_\theta^2 \mu_\theta^2 + 2\mu_\theta^4)}{(\sigma_\theta^2 + \mu_\theta^2)^4} \right] \right] \\
&= \left[\frac{\mu_\theta}{c(\sigma_\theta^2 + \mu_\theta^2)^2} \left[1 - \alpha_A \frac{c^2 \sigma_\theta^2 (\sigma_\theta^2 + 2\mu_\theta^2) \mu_\theta^2}{(\sigma_\theta^2 + \mu_\theta^2)^3} \right] - \frac{\mu_\theta}{c(\sigma_\theta^2 + \mu_\theta^2)} \left[\alpha_A c^2 \mu_\theta^2 \frac{(\sigma_\theta^4 + 2\sigma_\theta^2 \mu_\theta^2 - 2\mu_\theta^4)}{(\sigma_\theta^2 + \mu_\theta^2)^4} \right] \right] \\
&= \frac{\mu_\theta}{c(\sigma_\theta^2 + \mu_\theta^2)^2} \left[1 - \alpha_A \frac{c^2 \sigma_\theta^2 (\sigma_\theta^2 + 2\mu_\theta^2) \mu_\theta^2}{(\sigma_\theta^2 + \mu_\theta^2)^3} \right] - \frac{\alpha_A c \mu_\theta^3 (\sigma_\theta^4 + 2\sigma_\theta^2 \mu_\theta^2 - 2\mu_\theta^4)}{(\sigma_\theta^2 + \mu_\theta^2)^5} \\
&= \frac{\mu_\theta}{c(\sigma_\theta^2 + \mu_\theta^2)^2} - \frac{2\alpha_A c \mu_\theta^3}{(\sigma_\theta^2 + \mu_\theta^2)^5} (\sigma_\theta^4 + 2\sigma_\theta^2 \mu_\theta^2 - \mu_\theta^4)
\end{aligned}$$

$$\frac{\partial i}{\partial g} = -1$$

$$\begin{aligned}
\frac{\partial i}{\partial \alpha_A} &= - \left[\frac{\mu_\theta}{c(\sigma_\theta^2 + \mu_\theta^2)} \left[\frac{-c^2 \sigma_\theta^2 (\sigma_\theta^2 + 2\mu_\theta^2) \mu_\theta^2}{(\sigma_\theta^2 + \mu_\theta^2)^3} \right] \right] \\
&= \frac{\mu_\theta}{c(\sigma_\theta^2 + \mu_\theta^2)} \left[\frac{c^2 \sigma_\theta^2 (\sigma_\theta^2 + 2\mu_\theta^2) \mu_\theta^2}{(\sigma_\theta^2 + \mu_\theta^2)^3} \right] \\
&= \frac{c \mu_\theta^3 \sigma_\theta^2 (\sigma_\theta^2 + 2\mu_\theta^2)}{(\sigma_\theta^2 + \mu_\theta^2)^4}
\end{aligned}$$

The optimal fixed transfer q

$$q = \bar{v} - \gamma \mu_\theta + \frac{1}{2} c \gamma^2 (\sigma_\theta^2 + \mu_\theta^2) + \frac{\alpha_A}{4} c^2 \gamma^4 \sigma_\theta^2 (\sigma_\theta^2 + 2\mu_\theta^2)$$

$$\begin{aligned}
\frac{\partial q}{\partial \mu_\theta} &= -\gamma + \frac{1}{2} c \gamma^2 2\mu_\theta + \frac{\alpha_A}{4} c^2 \gamma^4 \sigma_\theta^2 (4\mu_\theta) \\
&= -\gamma + c \gamma^2 \mu_\theta + \alpha_A c^2 \gamma^4 \sigma_\theta^2 \mu_\theta \\
&= -\gamma + \mu_\theta (c \gamma^2 + \alpha_A c^2 \gamma^4 \sigma_\theta^2)
\end{aligned}$$

$$\begin{aligned}
\frac{\partial q}{\partial \sigma_\theta^2} &= \frac{1}{2} c \gamma^2 + \frac{\alpha_A}{4} c^2 \gamma^4 [(\sigma_\theta^2 + 2\mu_\theta^2) + \sigma_\theta^2] \\
&= \frac{1}{2} c \gamma^2 + \frac{\alpha_A}{4} c^2 \gamma^4 (2\sigma_\theta^2 + 2\mu_\theta^2) \\
&= \frac{1}{2} c \gamma^2 + \frac{\alpha_A}{2} c^2 \gamma^4 (\sigma_\theta^2 + \mu_\theta^2) \\
&= \frac{1}{2} c \gamma^2 (1 + \alpha_A c \gamma^2 (\sigma_\theta^2 + \mu_\theta^2))
\end{aligned}$$

$$\frac{\partial q}{\partial g} = 0$$

$$\begin{aligned}\frac{\partial q}{\partial \alpha_A} &= \frac{1 \cdot 4}{4^2} c^2 \gamma^4 \sigma_\theta^2 (\sigma_\theta^2 + 2\mu_\theta^2) \\ &= \frac{1}{4} c^2 \gamma^4 \sigma_\theta^2 (\sigma_\theta^2 + 2\mu_\theta^2)\end{aligned}$$

The optimal informal care γ

$$\gamma = \frac{\mu_\theta}{c(\sigma_\theta^2 + \mu_\theta^2)} \left[1 - \alpha_A \frac{c^2 \sigma_\theta^2 (\sigma_\theta^2 + 2\mu_\theta^2) \mu_\theta^2}{(\sigma_\theta^2 + \mu_\theta^2)^3} \right]$$

$$\begin{aligned}\frac{\partial \gamma}{\partial \mu_\theta} &= \frac{c(\sigma_\theta^2 + \mu_\theta^2) - \mu_\theta c(2\mu_\theta)}{[c(\sigma_\theta^2 + \mu_\theta^2)]^2} \left[1 - \alpha_A \frac{c^2 \sigma_\theta^2 (\sigma_\theta^2 + 2\mu_\theta^2) \mu_\theta^2}{(\sigma_\theta^2 + \mu_\theta^2)^3} \right] \\ &\quad + \frac{\mu_\theta}{c(\sigma_\theta^2 + \mu_\theta^2)} \left[-\alpha_A \frac{2c^2 \sigma_\theta^2 \mu_\theta (\sigma_\theta^2 + 4\mu_\theta^2) (\sigma_\theta^2 + \mu_\theta^2)^3 - c^2 \sigma_\theta^2 (\sigma_\theta^2 + 2\mu_\theta^2) \mu_\theta^2 6\mu_\theta (\sigma_\theta^2 + \mu_\theta^2)^2}{(\sigma_\theta^2 + \mu_\theta^2)^6} \right] \\ &= \frac{\sigma_\theta^2 - \mu_\theta^2}{c(\sigma_\theta^2 + \mu_\theta^2)^2} \left[1 - \alpha_A \frac{c^2 \sigma_\theta^2 (\sigma_\theta^2 + 2\mu_\theta^2) \mu_\theta^2}{(\sigma_\theta^2 + \mu_\theta^2)^3} \right] \\ &\quad + \frac{\mu_\theta}{c(\sigma_\theta^2 + \mu_\theta^2)} \left[-\alpha_A \frac{c^2 \sigma_\theta^2 \mu_\theta [2\sigma_\theta^4 + 4\mu_\theta^2 \sigma_\theta^2 - 4\mu_\theta^4]}{(\sigma_\theta^2 + \mu_\theta^2)^4} \right] \\ &= \frac{\sigma_\theta^2 - \mu_\theta^2}{c(\sigma_\theta^2 + \mu_\theta^2)^2} \left[1 - \alpha_A \frac{c^2 \sigma_\theta^2 (\sigma_\theta^2 + 2\mu_\theta^2) \mu_\theta^2}{(\sigma_\theta^2 + \mu_\theta^2)^3} \right] - \frac{\alpha_A c \sigma_\theta^2 \mu_\theta^2 [2\sigma_\theta^4 + 4\mu_\theta^2 \sigma_\theta^2 - 4\mu_\theta^4]}{(\sigma_\theta^2 + \mu_\theta^2)^5} \\ &= \frac{\sigma_\theta^2 - \mu_\theta^2}{c(\sigma_\theta^2 + \mu_\theta^2)^2} - \frac{\alpha_A (\sigma_\theta^2 - \mu_\theta^2) c^2 \sigma_\theta^2 (\sigma_\theta^2 + 2\mu_\theta^2) \mu_\theta^2}{c(\sigma_\theta^2 + \mu_\theta^2)^2 (\sigma_\theta^2 + \mu_\theta^2)^3} - \frac{\alpha_A c \sigma_\theta^2 \mu_\theta^2 [2\sigma_\theta^4 + 4\mu_\theta^2 \sigma_\theta^2 - 4\mu_\theta^4]}{(\sigma_\theta^2 + \mu_\theta^2)^5} \\ &= \frac{\sigma_\theta^2 - \mu_\theta^2}{c(\sigma_\theta^2 + \mu_\theta^2)^2} - \frac{\alpha_A c \sigma_\theta^2 \mu_\theta^2}{(\sigma_\theta^2 + \mu_\theta^2)^5} (3\sigma_\theta^4 + 5\sigma_\theta^2 \mu_\theta^2 - 6\mu_\theta^4)\end{aligned}$$

$$\begin{aligned}\frac{\partial \gamma}{\partial \sigma_\theta^2} &= -\frac{\mu_\theta c}{[c(\sigma_\theta^2 + \mu_\theta^2)]^2} \left[1 - \alpha_A \frac{c^2 \sigma_\theta^2 (\sigma_\theta^2 + 2\mu_\theta^2) \mu_\theta^2}{(\sigma_\theta^2 + \mu_\theta^2)^3} \right] \\ &\quad + \frac{\mu_\theta}{c(\sigma_\theta^2 + \mu_\theta^2)} \left[-\alpha_A \frac{2c^2 \mu_\theta^2 (\sigma_\theta^2 + \mu_\theta^2) (\sigma_\theta^2 + \mu_\theta^2)^3 - c^2 \sigma_\theta^2 (\sigma_\theta^2 + 2\mu_\theta^2) \mu_\theta^2 3(\sigma_\theta^2 + \mu_\theta^2)^2}{[(\sigma_\theta^2 + \mu_\theta^2)^3]^2} \right] \\ &= -\frac{\mu_\theta}{c(\sigma_\theta^2 + \mu_\theta^2)^2} \left[1 - \alpha_A \frac{c^2 \sigma_\theta^2 (\sigma_\theta^2 + 2\mu_\theta^2) \mu_\theta^2}{(\sigma_\theta^2 + \mu_\theta^2)^3} \right] \\ &\quad + \frac{\mu_\theta}{c(\sigma_\theta^2 + \mu_\theta^2)} \left[-\alpha_A \frac{c^2 \mu_\theta^2 [2(\sigma_\theta^2 + \mu_\theta^2)^2 - 3\sigma_\theta^2 (\sigma_\theta^2 + 2\mu_\theta^2)]}{(\sigma_\theta^2 + \mu_\theta^2)^4} \right]\end{aligned}$$

$$\begin{aligned}
&= -\frac{\mu_\theta}{c(\sigma_\theta^2 + \mu_\theta^2)^2} \left[1 - \alpha_A \frac{c^2 \sigma_\theta^2 (\sigma_\theta^2 + 2\mu_\theta^2) \mu_\theta^2}{(\sigma_\theta^2 + \mu_\theta^2)^3} \right] + \frac{\mu_\theta}{c(\sigma_\theta^2 + \mu_\theta^2)} \left[\frac{\alpha_A c^2 \mu_\theta^2}{(\sigma_\theta^2 + \mu_\theta^2)^4} \right] (\sigma_\theta^4 + 2\mu_\theta^2 \sigma_\theta^2 - 2\mu_\theta^4) \\
&= -\frac{\mu_\theta}{c(\sigma_\theta^2 + \mu_\theta^2)^2} + \frac{\mu_\theta \alpha_A c^2 \sigma_\theta^2 (\sigma_\theta^2 + 2\mu_\theta^2) \mu_\theta^2}{c(\sigma_\theta^2 + \mu_\theta^2)^2 (\sigma_\theta^2 + \mu_\theta^2)^3} + \frac{\mu_\theta}{c(\sigma_\theta^2 + \mu_\theta^2)} \left[\frac{\alpha_A c^2 \mu_\theta^2}{(\sigma_\theta^2 + \mu_\theta^2)^4} \right] (\sigma_\theta^4 + 2\mu_\theta^2 \sigma_\theta^2 - 2\mu_\theta^4) \\
&= -\frac{\mu_\theta}{c(\sigma_\theta^2 + \mu_\theta^2)^2} + \frac{\alpha_A c \mu_\theta^3}{(\sigma_\theta^2 + \mu_\theta^2)^5} (2\sigma_\theta^4 + 4\mu_\theta^2 \sigma_\theta^2 - 2\mu_\theta^4)
\end{aligned}$$

$$\frac{\partial \gamma}{\partial g} = 0$$

$$\begin{aligned}
\frac{\partial \gamma}{\partial \alpha_A} &= \frac{\mu_\theta}{c(\sigma_\theta^2 + \mu_\theta^2)} \left[\frac{-c^2 \sigma_\theta^2 (\sigma_\theta^2 + 2\mu_\theta^2) \mu_\theta^2}{(\sigma_\theta^2 + \mu_\theta^2)^3} \right] \\
&= -\frac{\mu_\theta c \sigma_\theta^2 (\sigma_\theta^2 + 2\mu_\theta^2) \mu_\theta^2}{(\sigma_\theta^2 + \mu_\theta^2)^4} \\
&= -\frac{c \mu_\theta^3 \sigma_\theta^2 (\sigma_\theta^2 + 2\mu_\theta^2)}{(\sigma_\theta^2 + \mu_\theta^2)^4}
\end{aligned}$$

Chapter 5

Mine and *my* spouse's preferences for risk-taking: how do older couples decide to insure their dependency costs?

5.1 Introduction

The economic theory postulates that people dislike risk. When presented with two lotteries, one offering a higher expected value but greater risk, individuals' choices depend on their level of risk aversion (O'Donoghue & Somerville, 2018). Risk aversion plays a crucial role in financial decisions particularly in evaluating the trade-off between risk and return. Insurance aims to align financial risk with the consequences of unpredictable shocks (Rieger-Fels, 2024). More risk-averse rational agents are, *ceteris paribus*, more likely to purchase insurance (Mossin, 1968).

Individual long-term care (LTC) expenditures represent a significant financial risk primarily borne by the elderly (Bueren, 2023; Coe et al., 2023). According to del Pozo-Rubio et al. (2019), in Spain, bearing LTC out-of-pocket payments increased the probability of impoverishment by 18,90%, an estimate that can be higher as people become more dependent. Amongst USA couples, longevity risks had the highest awareness level (33,4%), followed by health risks (28,5%). Greater longevity increases care needs, which may render income insufficient to cover associated expenses¹. In the absence of a robust public support system, LTC expenses can pose a significant threat to the welfare of the elderly (Hou, 2022).

Rational decision-making in the purchase of private long-term care insurance suggests that individuals who are averse to financial risk should be willing to pay a premium to mitigate the uncertainty associated with potential future wealth shocks arising from LTC expenditures. Long-term care insurance is particularly adequate for individuals who prefer to avoid the risk of significant and uncertain financial losses later in life and are willing to pay to mitigate that loss at younger ages (Curry et al., 2009).

Purchase of LTC private insurance policies has been feeble in all countries. France and the USA are the two most important markets for voluntary private long-term care insurance. Still, in the USA, in 2010, only about 11% of the population aged 55 and older was covered

¹According to Genworth Cost of Care Survey (2023), the monthly median cost of nursing home care in the United States is \$9733 for a private room, \$6292 for home health aide, and \$5720 for homemaker services, while community and assisted living through adult day health care costs \$2058. In 2022, older adults primary sources of income in the USA were Social Security payments (83%), assets (69%), pensions (30%), and earnings (23%) (Pension Rights Center, 2023b). On average, retirees receive around \$21,901 a year in Social Security benefits. These benefits raise to \$36,255 when they are received by both members of a couple. When one individual is a widow or widower, the median annual benefit is around \$20,463 (Pension Rights Center, 2023a).

by private LTC insurance, and only 16% of the households had at least one member with LTC insurance (Hirth et al., 2019). In France, only 15% of people aged 40 years held private insurance (Mosca et al., 2016). Researchers explain the scarce purchase of LTC insurance as the result of behavioral, psycho-social and economic factors. But the question remains: if higher longevity brings more uncertainty regarding high financial risk with LTC costs, why is the purchase of LTC insurance so limited?

We aim to contribute to a better understanding of this puzzling reality by focusing on couples' joint decision (married or not) to acquire LTC insurance. To analyze couples' decisions, we highlight the importance of the spouse identified as the financial respondent (FR). Our model studies the effect of the financial respondent's willingness to take financial risks on the couple's decision to purchase LTC private insurance. We hypothesize that the financial respondent's willingness to take financial risks shapes the couple's decision to buy private LTC insurance policies. We rely on multilevel mixed-effects logistic regressions to estimate this. Our dependent variable equals one if at least one couple member is insured with private LTC insurance and zero if none is. The main independent variable is a categorical variable measuring the financial respondent's willingness to take financial risks, and it varies between 0 if he/she is unwilling and 10 if she/he is fully prepared to take those risks. We include controls for demographic, economic, and health factors, as well as expectations about moving to nursing home. We focus on the USA context and use data from a national panel data aging survey, the HRS (Health and Retirement Study), between 2014 and 2020. Our final dataset contains 7296 older couples.

Our main finding is that the odds of purchasing private LTC insurance for at least one spouse are higher when the financial respondent exhibits a moderate to high willingness to take financial risks. This suggests that those willing to take more financial risks are also more concerned about guaranteeing that the surviving element of the couple is able to bear LTC costs. The finding that more risk aversion does not lead to higher insurance demand is aligned with previous studies. Fuino et al. (2022) claimed that individuals with higher risk aversion did not show more interest in LTC insurance than those who were more risk seekers. Costa-Font & Rovira-Forns (2008) estimated the willingness to pay for LTC coverage as a function of self-reported risk attitudes and found no statistical evidence of such a relationship. Some studies have found that risk-averse people are more willing to pay for insurance that covers LTC costs (de Bresser et al., 2022). Other studies have indicated that moderate levels of willingness to take risks were positively and significantly associated with LTC insurance holding (Eling et al., 2021), but Sloan & Norton (1997), using data from the HRS, showed that a moderate level of risk aversion diminished the probability of purchasing LTC insurance. In contrast, Stum (2008) and Gousia (2016) found that higher tolerance towards financial risks is associated with higher insurance demand, while Chatterjee and Lu (2017) concluded that risk seekers were less likely to have LTC coverage.

This essay is organized as follows. The following section reviews the literature about private LTC insurance for older couples and their willingness to take financial risks. Section 5.3 presents the methodology, data, sample selection criteria, used variables, and implemented econometric strategy. Sections 5.4 and 5.5 present the main empirical results and robustness checks. Finally, in sections 5.6 and 5.7, we discuss the results considering related literature and present some concluding remarks.

5.2 Older couple's willingness to take financial risks and private LTC insurance demand

Couples and people living alone face LTC risks differently. Single persons are solely exposed to their risks and only have their savings and resources to bear them. For couples, new issues arise from the addition of each partner's risk and the benefit of using joint savings and resources to face them (De Nardi et al., 2024). Unlike the study of individuals' decisions,

studying couples implies observing not only each individual but also the interaction between them (Klimaviciute, 2019). Agnew et al. (2003) studied asset allocation and highlighted that "marital status matters". Couples have higher diversification to face labor-income shocks, and being married positively affects income and wealth accumulation. Besides, for altruistic reasons, spouses need to plan even for after their death to safeguard the welfare of the spouse who lives longer. Pauly (1990) focused on the "elderly persons with a surviving spouse sharing the same household", describing it as a complex case within the long-term care insurance analysis because the risk of "impoverishing one's spouse, rather than one's children, seems to be the major fear of many married elderly".

Consequently, the relationship between married status and insurance demand is molded by two opposite forces (Wang et al., 2023b). On the one hand, marriage status triggers an increase in personal insurance since couples need to tackle more potential joint life event shocks and associated risks. In addition, couples who share their resources may increase insurance demand because they also share costs, having higher available income to invest in insurance while facing lower individual premia through risk pooling. On the other hand, marriage can reduce the demand for insurance because marriage acts as a form of self-risk protection mechanism, as individuals can rely on their partner to help cover risks.

The willingness to take risks affects insurance decisions and is a valid measure to assess risk preferences in large and longitudinal surveys and experimental risk data (Li et al., 2021). Private LTC insurance is more likely to be purchased by those who are more risk-averse, but other factors also affect this decision. For example, when people age, their willingness to take risks changes. Studies on older people's willingness to take financial risks and their decision to purchase private insurance to cover LTC costs have found mixed results, but Josef et al. (2016) and Dohmen et al. (2017) suggest that the willingness to take risks decreases with age. Research on the acquisition of private LTC insurance by couples has been scarce and based on different methods. Tennyson et al. (2022) suggest that a bargaining process between spouses is present, but Hirth et al. (2019) assume the financial decisions about LTC insurance purchase are likely to be made jointly by both spouses and study their intrinsic strategic incentives in this process. Several issues emerge in the study of the decision on how to cover LTC costs by couples: i) care provided by a spouse is available only to the spouse who becomes dependent first; ii) lower financial resources may be available to finance care for the second spouse after the first spouse becomes dependent; iii) the spouse who is the caregiver may suffer negative health effects as a result of the effort put into supporting the dependent spouse, iv) the surviving spouse is less likely to have family or informal care, and so will be more likely to demand formal services at higher costs (Klimaviciute, 2019), and v) married individuals make insurance coverage decisions jointly and studies found a 50-60% correlation between one spouse being covered by LTC insurance and the other also having LTC insurance (Caro et al., 2010; Hirth et al., 2019).

Cramer & Jensen (2006) hypothesized that being married can have two distinct effects on the decision to be insured to cover LTC costs: if a spouse relies on the other spouse's care, insurance purchase is lower, while if they want to avoid "impoverishing the spouse", the likelihood of insurance purchasing is higher. Using 2002 HRS data, they found that those who were married and had assets in the middle range of the wealth distribution were more likely to purchase LTC insurance. Haag (2020), using cross-section data from HRS 2016, showed that being married is a positive predictor of LTC insurance coverage and that marriage should be seen as a complement rather than a substitute for LTC insurance. Caro et al. (2010) used data from the HRS between 2002 and 2004 for older couples, distinguishing between primary (who answered the survey financial questions) and secondary respondents to conclude that the primary respondent's odds of buying LTC insurance were positive and significantly related to his own and his spouse's characteristics, such as nursing home expectation, the spouse's education level, and the couple's net worth and income. Tennyson et al. (2022) used HRS data from 1996

to 2014 and focused on who, within the couple, made the financial decisions. A lower likelihood of LTC insurance purchase was found in households where the husband had the final call. Fels (2015) modeled the insurance decision based on marital status and gender and predicted a lower usage rate when the insured was married and that, in the couple context, men were less likely to use LTC insurance than women due to their higher probability of needing LTC first and the fact that they could more likely rely on care provided by the spouse.

Previous research has been more focused on studying individuals' decisions to buy insurance and less on the couple's joint decision. The primary adopted methodological strategies have been to study both spouses' characteristics in isolation or to assume a more traditional organization of the couple's structure with pre-determined power and role for each spouse. In this case, the choice of "whom" is the respondent has driven the conclusions, which raises concerns (Rodrigues et al., 2024). We depart from this premise, by modeling the couple's decision to purchase private LTC insurance assuming an equal role for both spouses.

5.3 Methodology

The following sections provide an overview of the data, the adopted sample selection criteria and econometric strategy. We also describe the used variables and present descriptive statistics.

5.3.1 Data

We use data from the Health and Retirement Study (HRS) (Health and Retirement Study, 2023), complemented with data from the RAND HRS Longitudinal File (RAND HRS, 2024) and the HRS 2020 Tracker file².

The Health and Retirement Study is a longitudinal survey of individuals over 50 years old and their spouses (of any age). It has been implemented every two years since 1992 in the USA. The RAND HRS is a longitudinal user-friendly data produced by the RAND Center for the Study of Aging that is publicly available³. The HRS Tracker file facilitates using HRS data within and across waves. It contains one record for every person eligible to be interviewed in any wave and the respective weights. In the case of households with a married or partnered couple, both HRS responses are included in the survey (RAND HRS, 2024; Health and Retirement Study, 2024).

5.3.2 Sample selection procedure

Our dataset includes older individuals who are coupled or partnered across the four waves (wave 12 to wave 15) encompassing the years between 2014 and 2020. We include the answers from the "Respondent", who is the primary randomly selected respondent, and from the "Spouse", who is the secondary respondent, i.e., the spouse or partner of the primary respondent⁴.

²Data versions: HRS 2010 - 2022 Core Early, Version 1.0 (Partial Release: Panel Cases Only) February 2024 (Health and Retirement Study, 2023); RAND HRS Longitudinal File 2020 (V2) public use dataset (RAND HRS, 2024); HRS 2020 Tracker file (Version 1.0) January 2024.

³The HRS is sponsored by the National Institute on Aging (grant number NIA U01AG009740) and is conducted by the University of Michigan. The RAND HRS Longitudinal File is an easy-to-use dataset based on the HRS core data. The data file was developed at RAND with funding from the National Institute on Aging and the Social Security Administration (RAND HRS, 2024).

⁴According to Sonnega et al. (2014), to determine the eligibility to participate in the survey, "a brief household screening interview is conducted with each sampled housing unit. Adults (age 18+) in the household are listed according to their age and marital status. A primary respondent is randomly selected from all age-eligible household members and, if the selected person is coupled, their spouse or partner is also included in the sample, regardless of age". "In the HRS, an age-eligible individual is sampled. Then, this individual and their spouse or partner are interviewed, but no other household members are, even if they are age-eligible. Thus, in the HRS,

To build our dataset, we adopted the following criteria: i) we kept the households that were composed of only two individuals who responded to the survey and were married (this includes those who were married, but the spouse was absent when the interview occurred or who were partnered with another person) (194798 observations deleted); ii) we deleted couples that had more than one associated spouse over all waves or those who had different individual code identifier across waves (2918 observations deleted); and iii) we limited our analysis to the 2014-2020 period (12885 observations deleted). The final panel contains 7296 older couples observed 20214 times (the average number of waves per couple is 2,77).

Our dataset has strengths and limitations. First, HRS is a representative sample of the USA population over age 50, making the extrapolation of the findings robust. Second, until now, HRS has already fifteen waves, making it a very long panel. Third, studying the context of the USA and private LTC insurance is important since this country has one of the highest percentages of people who voluntarily purchase insurance policies to cover LTC costs. Fourth, the HRS encompasses various multidisciplinary domains related to the elderly, from economic and psychosocial factors to health and well-being determinants (Sonnega et al., 2014).

The main limitations are that, first, using the variable willingness to take financial risks diminishes our panel data period and size since it is only available between waves 12 and 15⁵. This variable belongs to Section LB: Psycho-Social (Participant Lifestyle Leave-Behind Questionnaire), which is only provided to a sub-sample of respondents, i.e., to each half-sample of respondents every two waves, resulting in a four-year interval for each respondent. Second, the willingness to take financial risks is a self-assessment question, which raises concerns about its reliability. Courbage et al. (2018a) and Dohmen et al. (2011) recognized the skepticism among economists to include self-assessment of risk attitudes variables, emphasizing that context matters for self-reported willingness to take risks. Sloan & Norton (1997) argued that measuring "the degree of risk aversion is no simple matter" and "is likely that respondents had difficulty dealing with a hypothetical question that does not appear relevant at this stage of their life cycle". Third, we include the answers from the "financial respondent", and following the HRS survey design, we assume that the financial respondent is "fully informed about the finances of the couple, and willing to report all measures" (Banks, 2002). However, potential issues may emerge when couples manage their finances separately or when there are significant differences regarding information and financial education between the two members (Banks, 2002; Sonnega et al., 2014). Fourth, the HRS has been reducing the sample size of new cohorts (Sonnega et al., 2014), and limits using new population cohorts and observations. Fifth, we do not include the respondents' residence and the indicators of urban or rural status, which could capture proximity to a nursing home or care facilities and the main differences amongst States (Cramer & Jensen, 2006). Sixth, our sample is composed of older people, with, on average, almost 65 years old. We do not discard that respondents and their spouses could exhibit cognitive limitations that limit their answers and decisions, besides being a potential source of lower risk-taking (Bonsang & Dohmen, 2015).

5.3.3 Variables

Private LTC insurance

Our dependent variable is current private LTC insurance coverage and is based on the following question: "Not including government programs, do you now have any insurance which specifically pays any part of long-term care, such as personal or medical care in the home or

there is usually no distinction between a "couple" and a "household". More precisely, "household" variables in the HRS (and the RAND HRS) are actually "couple variables" (Wang et al., 2023c).

⁵HRS has a categorical risk aversion variable based on the "income gamble" questions set, but it is only available for some waves until wave 8.

a nursing home?”. This question was answered by respondents and their spouses or partners in all HRS waves⁶. The variable indicates whether private long-term care insurance covers respondents, spouses, or partners (yes=1) or does not (no=0).

Since we aim to study private LTC insurance coverage of couples, we define our dependent variable as Hirth et al. (2019), being 1 if at least one couple member (respondent or spouse/partner) is covered by private long-term care insurance and 0 if neither is covered by private LTC insurance.

Tables 5.1 and 5.2 show the percentage of private LTC insurance coverage by year. Column 1 in Table 5.1 shows the percentage of coverage based on the respondents’ answers, while Column 2 measures the spouses’ answers. Table 5.2 presents the descriptive statistics of the categorical variable that equals 0 if “None is insured”, equals 1 if “One spouse is insured,” and equals 2 if “Both spouses are insured.”

Data reveal that respondents, on average, report a slightly lower average percentage of private insurance coverage than their spouses or partners. On average, 12,05% of older respondents and 12,19% of their spouses report being covered by LTC insurance, but the majority of couples are uninsured (83,07%). Approximately 17% of couples have at least one of the spouses insured, of whom 7,23% are cases in which both spouses are covered and 9,70% only one spouse within a couple has LTC insurance coverage. Our results are aligned with the percentages found by Caro et al. (2010) and Tennyson et al. (2022). Our final dataset using waves 12 to 15 presents a Pearson correlation coefficient between one spouse being insured and the other also having LTC insurance coverage of 0,52 (significance at 5% level), which is a positive and strong correlation and that follows the correlation found by Hirth et al. (2019). From the type of coverage purchased, amongst both respondents and spouses, we verify that almost 89% reveal that their LTC insurance policy covers costs from nursing homes and in-home services. The LTC insurance premium paid monthly (in nominal dollars) by the respondents is approximately 227 dollars (sd=353), while the spouses reported the payment of a slightly lower amount (201 dollars; sd=188)⁷.

Table 5.1: Private LTC insurance coverage by respondent and spouse

Year	Respondent (in %)	N	Spouse (in %)	N
2014	12,90	5400	12,68	5396
2016	11,52	5746	12,13	5747
2018	11,89	4583	11,90	4567
2020	11,89	4091	12,05	4100
Mean (in %)	12,05		12,19	

Notes: Data sources are the RAND HRS Longitudinal File (RAND HRS, 2024). Data based on 2014-2020. Weighted data using person-level (respondent and spouse) sampling weights for each wave (HRS Staff, 2019). N (Number of observations).

⁶Since wave 3 of HRS, long-term care insurance is treated separately from other health insurance, allowing respondents to consider private LTC insurance as a distinct insurance product.

⁷Weighted data using person-level (respondent) sampling weights for the year 2014.

Table 5.2: Private LTC insurance coverage among older couples

Year	None is insured (in %)	One spouse is insured (in %)	Both spouses are insured (in %)	N
2014	82,89	9,32	7,79	5478
2016	83,24	9,76	6,99	5856
2018	83,14	9,81	7,05	4655
2020	83,01	9,91	7,08	4189
Mean (in %)	83,07	9,70	7,23	

Notes: Data sources are the RAND HRS Longitudinal File (RAND HRS, 2024). Data based on 2014-2020. Weighted data using household-level sampling weights for each wave (HRS Staff, 2019). N (Number of observations).

Willingness to take financial risks

Our primary independent variable is the self-reported willingness to take financial risks. The HRS asked individuals to rate their willingness to take risks in financial matters: "People behave differently in different situations. We'd like to know how willing you are to take risks in the following areas: (...) How willing are you to take risks in financial matters?". Answers options range from 0 to 10, where 0 means "unwilling to take any risks" and the person is risk-averse, and 10 means "fully prepared to take risks," and the person is a risk seeker. This variable is only available after wave 12 (year 2014) through a self-completion questionnaire in the section "Leave behind questionnaire: Psycho-Social"⁸.

Descriptive statistics are shown in Table 5.3. Across the years, both the respondents and their spouses have chosen low levels of willingness to take financial risks as shown by the higher frequencies up to level 5. Level 5 is the most chosen level (in percentage) on the respondents' side, followed by level 0. In the spouses' case, the highest frequency is observed at level 0, followed by level 2.

Table 5.3: Self-reported willingness to take financial risks: respondents and spouses

WTFR [from 0-10]	Respondent (in %)					Spouse (in %)				
	2014	2016	2018	2020	Mean (in %)	2014	2016	2018	2020	Mean (in %)
0 (Unwilling)	16,46	13,66	14,56	14,94	14,91	18,06	16,17	15,31	14,48	16,01
1	10,58	11,64	9,56	10,58	10,59	12,97	10,58	12,47	12,32	12,09
2	13,53	14,88	14,34	12,06	13,70	16,10	14,14	13,86	14,95	14,76
3	13,79	14,28	12,49	12,81	13,34	12,78	14,11	14,57	14,02	13,87
4	7,64	8,08	8,49	8,72	8,23	9,26	8,51	7,87	8,26	8,48
5	16,06	14,10	15,96	16,63	15,69	12,65	14,92	14,08	14,27	13,98
6	6,30	7,71	7,48	8,89	7,60	5,68	6,14	7,63	6,25	6,43
7	7,67	7,64	7,52	7,64	7,62	6,90	7,76	7,25	6,15	7,02
8	4,88	5,57	5,66	4,70	5,20	2,71	3,62	4,32	6,03	4,17
9	1,68	1,09	2,26	1,67	1,68	0,95	1,91	1,20	1,13	1,30
10 (Fully prepared)	1,41	1,33	1,69	1,36	1,45	1,94	2,13	1,44	1,98	1,87
N	2722	2714	2309	1852		2767	2385	2045	1623	

Notes: Data sources are HRS (Health and Retirement Study, 2023). Data based on 2014-2020. Weighted data using person-level (respondent and spouse) sampling weights for the Leave-behind questionnaire and for each wave (HRS Staff, 2019). N (Number of observations). WTFR (Willingness to take financial risks).

⁸Leave behind questionnaire: since 2004, HRS collects data in the form of self-administered questionnaires that were left with respondents upon the completion of an in-person interview. "This psychosocial information is obtained in each biennial wave from a rotating (random) 50% of the core panel participants who complete the enhanced face-to-face interview (EFTF). Longitudinal data is available at four-year intervals: the 2010 wave provides the first longitudinal psychosocial data from the 2006 participants" (Smith et al., 2017).

The financial respondent

Previous studies that analyze couples' decisions adopted different frameworks to capture the two spouses' perspectives. Some identify a principal respondent, which could be the financial respondent, and assume the other spouse as the secondary respondent (Caro et al., 2010). Others divide their analysis by husbands and wives, presenting different estimates according to gender (Tennyson et al., 2022; Lim et al., 2021), while others calculate average values of both members and use it as the couple's data (Hirth et al., 2019). Rodrigues et al. (2024) used SHARE data from waves 6 (2015) and 8 (2019) to conclude that the choice of who is asked to report about informal care may yield different results on caring roles. We use the available information about who is the financial decision maker, independent of gender, age, or relative power within the couple.

The HRS started by asking who "in the couple" is the spouse with more knowledge about the family's financial issues, the denominated "financial respondent". The "financial respondent" ("Respondent" or "Spouse") is assumed to be fully informed about the household-level data such as housing, income, assets, and finance (RAND HRS, 2024). The "financial respondent" remains as such until, in any wave, any of the couple's members requests that to be changed. Our variables are built using the answers given by the nominated couples' financial respondent⁹. Our unit of analysis is the couple, and our approach allows us to: i) include information from both spouses because, across waves, any spouse could be identified as the "financial respondent"; ii) group and collect, at once, both spouses predictors and perspectives, because the couple could nominate as financial respondent the "Respondent" or the "Spouse"; iii) get a panel data with variables that reflect the couple as a whole, not distinguishing the estimates by "Respondent", "Husband", "Principal", "Spouse", "Wife", or "Secondary"; iv) avoid getting estimates biased by gender and socioeconomic characteristics because we do not separate the analysis and the estimates by each spouse, gender, or spouse with higher bargaining power, and v) avoid econometric issues related to the potential collinearity between variables measuring both spouses' characteristics (e.g., age of the primary respondent and the age of the secondary respondent).

Control variables

We include control variables identified in the literature as relevant determinants of an older couple's decision to purchase private LTC insurance coverage. We control for financial respondents sociodemographic characteristics (age, gender, race, education, retirement, number of children), health status, and probability of needing LTC (self-rated health, sum of diagnosed health conditions, probability of entering a nursing home in the next five years), and household financial measures (income and wealth). We also control for a time effect to capture the systematic differences in the year of the survey.

We use the financial respondent's age at the beginning of the interview. In Jiménez-Martín et al. (2016), age was not a significant predictor of the ownership of LTC insurance, but Courbage & Roudaut (2008) and Haag (2020) found a positive effect. In the case of older couples, Lim et al. (2021) found that the husband's age significantly decreased the odds of owning health insurance, while the wife's age had an insignificant influence.

The financial respondent's gender is included through a dummy variable that equals 1 if female and 0 if male. Researchers have found contradictory results about the impact of gender on LTC insurance holding. While Eling et al. (2021) and Caro et al. (2010) found no significant effect, Courbage & Roudaut (2008) concluded that being a female had a significant positive impact on owning LTC insurance.

⁹For example, the variable age refers to the age of the financial respondent, which means that it could include answers from the "Respondent" or "Spouse", from the husband or wife.

We also controlled for the financial respondent's race/ethnicity. It is coded as a dummy variable equal to 1 if white/caucasian and 0 if otherwise. Caro et al. (2010) controlled for race and found that Hispanics and non-Hispanic blacks were less likely to have LTC insurance policies than white people.

Education is an essential predictor of LTC insurance coverage (Cramer & Jensen, 2006). Caro et al. (2010) found a positive and significant effect of education on LTC insurance among couples. Tennyson et al. (2022) concluded that the respondent and the spouse's years of education both had positive and significant effects on the wife and husband's probability of owning LTC insurance. Eling et al. (2021) found that years of education had significantly positive average marginal effects for long-term care insurance holding.

We include the financial respondent's retirement status based on the revealed labor force status. Tennyson et al. (2022) found that when both the husband and the wife were retired, ownership of LTC insurance was significantly more likely, while Eling et al. (2021) did not find significance between being retired and LTC insurance coverage.

The number of children is considered because children's availability may be a potential source of LTC provision and decrease demand for LTC insurance. Our variable measures the couple's number of living and in-contact children¹⁰. Tennyson et al. (2022) found a negative effect of the couple's number of children on the wife and husband's probability of having LTC insurance coverage. Three or more living children were included as a control in Caro et al. (2010), with no significance found.

Our model also includes perceived health status and probability of needing LTC through three covariates: self-rated health, the sum of diagnosed health conditions, and the probability of entering a nursing home in the next five years. Health condition is measured through the self-reported general health status, coded on a range from "1" for Poor, "2" for Fair, "3" for Good, "4" for Very Good, and "5" for Excellent. Health status has been presented as a potential determinant of risk perception and security holdings (Bressan et al., 2014). Haag (2020) did not find that self-reported health status was a significant determinant of LTC insurance, while Courbage & Roudaut (2008) found that bad health compared with average health was positively related to having LTC insurance. The sum of diagnosed health conditions results from the sum of the diseases diagnosed by the doctor, among nine possible conditions¹¹ and controls for past health status affecting current LTC risk. Caro et al. (2010) included three or more chronic illnesses as a control variable and did not find significant results on the purchase of LTC insurance. However, Tennyson et al. (2022) and Eling et al. (2021) controlled for chronic health conditions and found a negative effect on LTC insurance holding. Finally, the probability of needing LTC is also measured by the probability of entering a nursing home in the next five years. Caro et al. (2010) concluded that the primary respondent's nursing home expectation was associated with possession of LTC insurance, but only when the perceived risk was high.

In the USA, people have the misperception that Medicare coverage will pay for LTC, but Medicare is not the main provider and financing source for LTC coverage. The primary public provider and financing source is Medicaid (Klimaviciute & Pestieau, 2022)¹². Following Hirth et al. (2019), we also include a measure related to the financial respondent's coverage of Medicaid as a control. It consists of a binary variable equal to 1 if Medicaid covers the financial respondent and 0 otherwise. Public support and financing of LTC via Medicaid may crowd out the market for private LTC (Brown et al., 2007; Kim, 2018), but the potential role that the eligibility for

¹⁰ All the "Respondents" and "Spouses" living children are included (RAND HRS, 2024).

¹¹ The health conditions are: 1) high blood pressure or hypertension; 2) diabetes or high blood sugar; 3) cancer or a malignant tumor of any kind except skin cancer; 4) chronic lung disease except asthma such as chronic bronchitis or emphysema; 5) heart attack, coronary heart disease, angina, congestive heart failure, or other heart problems; 6) stroke or transient ischemic attack 7) emotional, nervous, or psychiatric problems; 8) arthritis or rheumatism, 9) and Alzheimer (RAND HRS, 2024).

¹² Medicaid provides health care and long-term care services to those below a certain income and asset eligibility criteria. Please see www.medicare.gov for complementary information.

Medicaid support has in explaining low demand for private insurance to cover LTC costs has been debated.

Finally, we include controls for the couple’s economic resources through two measures: the logarithm of the couple’s total income (in nominal dollars) and the logarithm of the net value of their total wealth¹³. Tennyson et al. (2022) and Eling et al. (2021) found a positive effect of the log of income on the purchase of LTC insurance. Both studies found a significant effect of the wealth measure on the likelihood of purchasing LTC insurance, specifically for those in the highest net worth quartiles. However, Haag (2020) did not find that wealth significantly influenced having LTC insurance.

5.3.4 Econometric strategy

We use panel data composed of couples and the characteristics of each couple are derived from the financial respondents’ answers. Our panel data have repeated measurements of the financial respondent’s answers over time grouped through an identifier couple code. These data are a case of a nested structure where the multiple measurements are not independent of each other. Family members’ data tend to be correlated with one another, and Guo & Wang (2002) showed that mixed models were the adequate approach to handle these complex familiar structures. We assume that the financial respondent’s unobserved characteristics, such as preferences, may change over time but that they are somehow correlated and nested in the same cluster (couple ID) (Clark, 2013; Sommet & Morselli, 2017). Therefore, to account for those data characteristics and to produce nationally representative estimates by applying the recommended sampling weights defined by the HRS Staff (2019), we adopt a multilevel mixed-effects logistic model. This econometric framework relaxes the assumption of conditional independence among the financial respondent answers and includes a couple-specific random intercept. It applies both fixed and random effects and allows a wide variety of correlation patterns (or variance-covariance structures) to be explicitly modeled (Seltman, 2018; Rabe-Hesketh, 2022; StataCorp, 2023b). Fixed effects capture relationships assumed to be consistent across all couples, i.e., a fixed effect for one variable assumes that the impact of that variable is the same for all couples. Following StataCorp (2023c), random effects are useful for modeling intraclass correlation because observations in the same cluster are correlated and share common cluster-level random effects. By including a random intercept for couples, we account for variability across couples relative to the overall fixed effects, i.e., some couples may have higher or lower average scores than others (Rabe-Hesketh, 2022). To analyze the effects of the willingness to take financial risks on the private LTC insurance purchase decision, we consider the following equation of the multilevel mixed-effects logistic model, with random intercepts for couples:

$$\begin{aligned} \text{logit}\{\text{Pr}(LTCinsurance_{ik} = 1 | \mathbf{WTFR}_{ik}, \mathbf{x}_{ik}, \mathbf{w}_k, \mathbf{d}_i, \zeta_k)\} = & \beta_0 \\ & + \beta_1 WTFR_{ik} + \dots + \beta_{11} WTFR_{ik} \\ & + \beta_{z1} \mathbf{x}_{ik} + \beta_{z2} \mathbf{w}_k + \beta_{z3} \mathbf{d}_i \\ & + \zeta_k \end{aligned} \tag{5.1}$$

where the two-level structure includes the measurements at each wave i for a couple k . Our response variable is dichotomous $LTCinsurance_{ik}$, equals to 1 if at least one spouse has private

¹³The couple’s total income includes the income obtained in the last year through earnings, pensions and annuities, Disability and Social Security retirement, unemployment, workers’ compensation, other government transfers, household capital income, and other income (RAND HRS, 2024). The couple’s net value of total wealth (in nominal dollars) is the sum of all wealth components less all debt (RAND HRS, 2024). Both variables are divided into quartiles. When an income or wealth component is missing, it is imputed. Please see details on the imputation procedure on RAND HRS (2024), section “Income and Wealth Imputations.”

LTC insurance and 0 otherwise, β_0 is the intercept of the dependent variable, β_1 to β_{11} is a vector of parameters, $WTFR_{ik}$ are binary indicators for levels of willingness to take financial risks between 0 and 10 with the baseline reference being zero - not willing to take any financial risks; $\mathbf{x}_{ik}$ is a vector of covariates time-varying or individual characteristics; $\mathbf{w}_k$ is a vector of couple covariates; β_{z1} , β_{z2} , and β_{z3} are the regression coefficients; $\mathbf{d}_i$ is a vector of dummies for survey waves. We also include a random intercept at the couple level ζ_k to capture unobserved couple random effects. The random intercept $\zeta_k \sim N(0, \psi)$ measures how the couples vary on their insurance coverage choice. ζ_k is assumed to be independent and identically distributed across couples k and independent of the covariates at wave i . Given ζ_k and covariates, the responses $LTCinsurance_{ik}$ at different wave i are independently Bernoulli distributed (Rabe-Hesketh, 2022)¹⁴.

Using the latent-response formulation, the model can equivalently be written as:

$$\begin{aligned} LTCinsurance_{ik}^* = & \beta_0 + \beta_1 WTFR_{ik} + \dots + \beta_{11} WTFR_{ik} \\ & + \beta_{z1} \mathbf{x}_{ik} + \beta_{z2} \mathbf{w}_k + \beta_{z3} \mathbf{d}_i \\ & + \zeta_k + \epsilon_{ik} \end{aligned} \quad (5.2)$$

where ϵ_{ik} is a residual error term with standard logistic distributions. It's assumed to be independent across time, couples, ζ_k , and covariates (Rabe-Hesketh, 2022).

5.4 Results

5.4.1 Descriptive statistics

Table 5.4 provides descriptive statistics. Among older USA married couples, 18% of couples have at least one of the spouses owning private LTC insurance. On a range between 0 and 10, the financial respondent's willingness to take financial risks is, on average, 3,76 (sd=2,59), which reveals a low willingness to take financial risks. The financial respondent is the oldest spouse in 54% of the couples and is, on average, 67 years old (sd=8,78). The majority is male (62%), has 13,81 (sd=2,86) years of education, is white/caucasian, and 60% are retired. The couples have, on average, three children (sd=1,75). On average, the couples are close to the third quartile both on income and wealth, which indicates that financial resources are distributed unequally. Financial respondents self-rate their health as good and, on average, have almost two diseases diagnosed (among nine possible conditions). On average, 5% are covered by public support provided by Medicaid. In Appendix 5.8.1, we check multicollinearity through the analysis of the VIF (variance inflation factor), and we do not verify the existence of multicollinearity between these variables.

¹⁴We do not apply random slope at time/wave survey since the slope of the willingness to take financial risks is not expected to vary across time/wave survey.

Table 5.4: Descriptive statistics

Variable	Description and measurement	Time period	Mean or %	SD	N
Couple LTC insurance coverage (binary)	= 1 if at least one couple member is insured = 0 if neither couple member is insured	2014-2020	0,18	0,39	16876
FR willingness to take financial risks (category range 0-10)	= 0 if FR is unwilling to take financial risks = 10 if FR is fully prepared to take financial risks	2014-2020	3,76	2,59	5490
FR age	FR age (in years)	2014-2020	67,04	8,78	16886
FR aged (binary)	= 1 if FR is the oldest spouse = 0 otherwise	2014-2020	0,54	0,50	16898
FR gender (binary)	= 1 if FR is female = 0 otherwise	2014-2020	0,38	0,49	16886
FR education	FR education (in years)	2014-2020	13,81	2,86	16802
FR white race (binary)	= 1 if FR is white/caucasian = 0 if FR is other race	2014-2020	0,86	0,35	16900
FR is retired (binary)	= 1 if FR is retired or partially retired = 0 if otherwise	2014-2020	0,60	0,49	16886
Couple number of children	Couple number of living children (in number)	2014-2020	2,99	1,75	16596
Couple log income	Couple log income (in quartiles range 1-4)	2014-2020	2,71	1,09	16900
Couple log wealth	Couple log wealth (in quartiles range 1-4)	2014-2020	2,77	1,08	16900
FR probability of moving to NH	FR self-reported probability of moving to NH in next 5 years (in percent)	2014-2020	14,54	19,19	10030
FR chronic conditions	FR number of health chronic conditions diagnosed among 9 possible diseases	2014-2020	2,11	1,48	16878
FR self-reported general health status (category range 1-5)	= 1 if Poor; = 2 if Fair; = 3 if Good; = 4 if Very good; = 5 if Excellent	2014-2020	3,31	0,99	16880
FR covered by Medicaid	= 1 if FR is currently covered by Medicaid = 0 otherwise	2014-2020	0,05	0,22	16757

Notes: Data sources are from the RAND HRS Longitudinal File (RAND HRS, 2024), except financial respondent willingness to take financial risks variable is from HRS (Health and Retirement Study, 2023). Weighted data. Respondent-level sampling weights, except for variables of the number of children, income, and wealth that apply household-level sampling weights. Willingness to take financial risks uses respondent-level sampling weights from the leave-behind questionnaire. The base-year weight adopted is 2014 for all variables. Our weighting strategy followed HRS Staff (2019). Financial respondent (FR). Nursing home (NH). Standard deviation (SD). N (Number of observations).

5.4.2 Willingness to take financial risks and the couple's decision to purchase private LTC insurance

Table 5.5 reports the odds ratios (OR) obtained through multilevel mixed effects logistic regression models¹⁵. We ran three different models. The first is the Null model, which does not include covariates but only a random intercept at the couple level to model between-couple variation in the decision to purchase private LTC insurance. The Intermediate model is the unadjusted model that incorporates additional effects from the independent variable. It examines the association between the willingness to take financial risks and a couple's decision to purchase LTC insurance. The Full model studies this association while controlling for demographic, social, and economic features.

Across the three models, we calculate the intraclass correlation (ICC) at the couple level to measure the proportion of the model variability that is due to the clusters. We found on the Null Model a value of 0,97, which expresses that 97% of all the variability in our data is explained by couples (cluster) differences. Since the ICC approaches 1, it means that we have non-independent data, which reinforces the need for our econometric strategy of employing multilevel models to account for couples variance (Sommet & Morselli, 2017).

The Intermediate model aims to study the extent to which the effect of the financial respondent's willingness to take financial risks varies amongst couples (clusters). Our results indicate that, compared to financial respondents who are not willing to take any financial risks (risk level 0), those with risk tolerance levels of 2, 8, and 9 have significantly higher odds of having at least one spouse covered by private LTC insurance.

After controlling for demographic, social, and economic covariates and accounting for a random intercept at the couple level (Full model), in comparison with the financial respondents unwillingness to take financial risks, those at levels 1 through 9 of willingness to take financial risks have significantly higher odds of being covered by private LTC insurance. The highest statistically significant odds ratio is observed at level 6 (OR = 235,65, CI: 27,42;2024,92), indicating that financial respondents at a moderate level of risk tolerance are substantially more likely to hold LTC insurance compared to those in the unwillingness risk category.

We also estimate that, compared to financial respondents from other race, being white is associated with lower odds of at least one spouse being insured (OR: 0,68; CI: 0,44;1,05), and as the number of children increases the odds of being insured decrease (OR: 0,87; CI: 0,78;0,97). Couples in the third income quartile and those in the wealth quartiles 2 and 3 have higher odds of purchasing coverage for at least one spouse than those from the lowest quartiles. Further, as more diseases are diagnosed, the odds of couples purchasing LTC insurance coverage also increased (OR: 1,58; CI: 1,25;2,00).

The Wald χ^2 values test the significance of all our explanatory variables. We verify the variables are overall significant in both models, which is confirmed by the AIC information. The RE variance analyzes the variance of the intercept across the couples and exhibits higher values for the Full model, denoting that this model captures the highest difference across couples¹⁶.

5.4.3 Does age matter?

We also explore whether, within the couple, assuming that is the youngest member that decides leads to different conclusions. We compute our regressions using the youngest spouses'

¹⁵Statistical analyses were performed using Stata/SE 18.5. We run the Stata command *melogit* to fit multilevel mixed-effects models for binary dependent variables. OR "reports estimated fixed-effects coefficients transformed to odds ratios, that is, $\exp(\beta)$ rather than β . Standard errors and confidence intervals are similarly transformed. This option affects how results are displayed, not how they are estimated" (StataCorp, 2023c). Please see Appendix 5.8.2 to find more about the selected econometric model.

¹⁶The Wald test is used instead of the likelihood-ratio test because when we include sampling weight or clustering, we do not get true likelihood-ratio tests since the individual observations are no longer independent (StataCorp, 2024).

answers instead of the financial respondent's. From Table 5.8 available on Appendix 5.8.3, we verify that the youngest couple member has, on average, less 2,91 years than the financial respondent. We also observe that the youngest spouses are more unwilling to take financial risks than the financial respondents - their average willingness to take financial risks is 3,29, they are primarily female and have slightly lower education levels and better health conditions as measured by fewer diagnosed chronic diseases. Their self-rated probability of moving into a nursing home is slightly larger than the average percentage reported by the financial respondent.

The Intermediate model results¹⁷ suggest that, for the youngest couple member, almost all levels of willingness to take financial risks have a significant higher odds on the couple's decision to purchase LTC insurance comparing to the unwilling level. From the Full model, we observe that the youngest spouses seem to have significant higher odds to insure until level 7 but decrease their odd to purchase LTC insurance when they are fully prepared to take financial risks, compared to their unwillingness to take those risks. Being a woman increases the odds of owning insurance, but one more child decreases this probability. Compared to the lowest wealth quartile, those on the highest wealth quartile were less likely of buying insurance. When the youngest respondent has more diagnosed chronic conditions, the odds of being insured decreased (OR: 0,62; CI: 0,46;0,83), which is contrary to what was found for the financial respondent. Higher education increases the odds of being insured (OR: 1,23; CI: 1,09;1,39), as well as being retired (OR: 3,30; CI: 1,23; 8,86). At the same time, as the probability of entering a nursing home increases, the odds of be insured decreased (OR: 0,94; CI:0,91; 0,97). To capture if the age difference (in years) between both spouses has a significant effect on purchasing insurance, we include the variable age gap. However, this did not exhibit statistical significance.

The model evaluation follows the results from Table 5.5 and shows better criteria from the AIC, Wald test, and RE variance on the last model. It allows us to identify the Full model with the highest performance on estimates.

5.4.4 Wife has a higher education level than their husband: Does it impact the purchase of LTC insurance?

According to Scott & Gratton (2021), with the increased lifespan, new challenges have emerged, namely to the traditional family structure. The option to be married or partnered with someone, the way that people combine work and family time, and gender equality are mainstream topics discussed in more advanced economies and societies. We aim to capture some of these dynamics in our model. To achieve that goal, we restrict our sample to couples in which the women have more education than men, which could change the bargaining position of the spouses (7537 observations deleted).

As Table 5.10 available on Appendix 5.8.5 shows, in general, the sample in which the women have higher education levels has similar descriptive statistics to our primary sample (Table 5.4). In this subsample, the financial respondent has a slightly lower willingness to take risks, is almost one year younger, and the financial respondent role is more attributed to women.

Table 5.11 available in Appendix 5.8.6 presents the results of the regressions. As in Table 5.5, we find significantly higher odds of at least one spouse being insured across different levels of willingness to take financial risks, compared to the lowest willingness to take those risks. In general, regression odds ratio results on the Full model reveal higher odds values than those from Table 5.5. Previous literature pointed to women's higher risk aversion and higher awareness about future disability (Lim et al., 2021), which could theoretically support these odds ratios.

Our results also suggest that as years of education increased, the odds of insurance purchase increase (OR: 1,22; CI: 1,10;1,37). However, lower odds are observed when the age of the financial respondent increases (OR: 0,91; CI: 0,85; 0,97). Consistent with the results in Table 5.5, couples in which the women have more education than men, when the financial respondent

¹⁷Results are available on Table 5.9 available on Appendix 5.8.4.

Table 5.5: Multilevel mixed effects models for purchasing LTC insurance

Couple LTC insurance coverage (DV) = 1 if at least one couple member is insured;= 0 otherwise Estimated OR (95% CI)		
Null model	Intermediate Model	Full Model
WTFR (IV):		
0 (Unwilling)	(ref.)	(ref.)
1	1,57 (0,56;4,39)	21,50 (3,58;129,17)***
2	2,64 (0,97;7,24)*	22,98 (3,68;143,53)***
3	1,35 (0,37;4,86)	29,36 (4,69;183,72)***
4	1,76 (0,57;5,37)	21,51 (2,53;182,65)***
5	1,74 (0,61;4,99)	42,99 (6,04;306,03)***
6	2,58 (0,59;11,27)	235,65 (27,42;2024,92)***
7	1,40 (0,46;4,23)	17,87 (2,82;113,29)***
8	3,59 (0,97;13,26)*	8,01 (1,11;57,90)**
9	26,39 (7,23;96,33)***	43,23 (7,04;265,33)***
10 (Fully prepared)	4,84 (0,56;41,55)	6,01 (0,06;563,52)
Age		0,99 (0,96;1,03)
FR Oldest (=1 Yes)		1,30 (0,77;2,18)
Gender (=1 Female)		1,23 (0,71;2,12)
Education		0,99 (0,91;1,07)
White race (=1 Yes)		0,68 (0,44;1,05)*
Retired (=1 Yes)		1,38 (0,55;3,49)
Number of children		0,87 (0,78;0,97)**
Income quartile:		
Q1		(ref.)
Q2		0,91 (0,30;2,80)
Q3		2,57 (0,97;6,83)*
Q4		1,82 (0,50;6,60)
Wealth quartile:		
Q1		(ref.)
Q2		6,35 (1,33;30,24)**
Q3		4,84 (1,12;20,94)**
Q4		3,25 (0,75;14,07)
NH probability		1,00 (0,98;1,02)
Sum of diseases		1,58 (1,25;2,00)***
Health status (category):		
1.Poor		(ref.)
2.Fair		2,72 (0,20;36,23)
3.Good		2,35 (0,16;34,25)
4.Very good		5,34 (0,39;72,69)
5.Excellent		4,03 (0,24;68,71)
Medicaid (=1 Yes)		0,62 (0,07;5,29)
Time:		
2014		(ref.)
2016		1,19 (0,56;2,53)
2018		1,36 (0,48;3,84)
2020		0,75 (0,33;1,72)
Intercept	0,0002 (5,51e-06;0,005)***	3,52e-09 (1,12e-11;1,11e-06)***
RE variance	104,77 (52,24)	1922,96 (364,55)
AIC	5,66x10 ⁷	1,47x10 ⁷
ICC	0,97 (0,01)	0,99 (0,00)
Wald χ^2		
	34,52***	76,74***
Number of observations	16667	3700

Notes: Data sources are described in Table 5.4. Data from 2014 to 2020. We apply sampling weights at a couple's level (couple ID level) (HRS Staff, 2019), and it is recommended by the Health and Retirement Study (2024): "Since the HRS sample is a multi-stage area probability sample of the United States, with oversamples of Blacks and Hispanics, unbiased estimates of population parameters require the use of these sampling weights". Random intercept at couple level (couple ID level). Statistical significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Dependent variable (DV). Independent variable (IV). Willingness to take risks on financial matters (WTFR). Quartile (Q). Nursing home (NH). Akaike information criterion (AIC). Financial respondent (FR). Intraclass correlation coefficient (ICC). Standard deviation in parenthesis. RE variance is estimated random-effects variances. All variables are related to the financial respondent unless the number of children, couple log income quartiles, and couple log wealth quartiles are at the couple level. We declared to Stata a panel dataset with panel identifier (couple ID) and time variable (wave year). The Null model includes only the random intercept term. The Intermediate model includes only the willingness to take risks and the random intercept term. The Full model includes the willingness to take risks, covariates as fixed effects, and the random intercept term. Estimates are odds ratios (OR) and their 95% confidence intervals (CI).

has more diagnosed diseases and higher couple's wealth compared to the lowest quartile level, have increased odds of purchasing. When the probability of entering a nursing home increases, the odds of purchasing LTC insurance increase (OR: 1,04; CI: 1,01;1,06).

5.5 Robustness check

5.5.1 Private life insurance coverage

We also test how results change when life insurance is considered instead of private LTC insurance. LTC insurance and life insurance are both insurance policies that cover significant risks (Eling et al., 2021). Life insurance covers loss of income for the household due to early death, while LTC insurance protects against the high costs of LTC. The HRS private life insurance variable encompasses any life insurance, i.e., "whole life insurance policies, which are valid for an individual's entire life and include an investment component, as well as term life insurance policies, which are only valid for a predetermined period" (RAND HRS, 2024). Nam & Hanna (2018) found that risk aversion had significant but opposite effects on ownership of term and cash-value life insurance, respectively negative and positive.

Around 75% of our couples have at least one member insured with private life insurance, denoting a different scenario than the one observed for the LTC insurance coverage, which was low¹⁸. A positive, but small correlation is found between the couple's coverage with private LTC insurance and private life insurance measured by a Pearson correlation coefficient of 0,10 (significance at 5% level).

The regressions presented in Table 5.12 available on Appendix 5.8.7, show that, compared to the baseline category of willingness to take financial risks, financial respondents at levels 2 and 5 have higher odds of purchasing life insurance (OR: 2,18; CI: 0,98;4,83 and OR: 3,37; CI: 0,98;11,61) but lower odds at level 6 (OR: 0,45; CI: 0,22;0,90). The Full model presents lower odds ratio values of willingness to take financial risks than those shown in Table 5.5, for LTC insurance. The highest significant odds ratio of purchasing a life insurance product is observed at levels 5 (on the Intermediate model) and 9 (on the Full model). At levels 3 and 6 on the Full model the purchase is not significant and, respectively, 32% and 34% less likely compared to the unwilling level.

We observe that the financial respondents' age, being a woman, having higher education, being retired, and having Medicaid coverage are predictors of lower odds to purchasing of life insurance. When the financial respondent self-rated their health status as fair or good rather than poor, the odds that the couple will own life insurance coverage increase (OR: 2,37; CI: 1,26;4,46 and OR: 2,75; CI: 1,41;5,38), which may be related to access. Couple financial resources measured through the log income and wealth quartiles reveal that, when compared to those couples who are at the minimum quartiles, those at the medium and highest levels more likely purchase life insurance, which is aligned with our results from Table 5.5, and confirms that these are products that may have a positive income effect.

5.5.2 Private health insurance coverage

We also substitute the dependent variable for at least one couple member covered by private health insurance¹⁹, since we aim to observe, *ceteris paribus*, how results change when we analyze decisions about private health insurance rather than private LTC insurance. Based on our statistics, 72% of couples have at least one couple member insured with health insurance, revealing a higher coverage rate among married people than LTC insurance. A positive small

¹⁸Weighted data using respondent-level sampling weights and the base-year weight adopted is 2014.

¹⁹HRS private health insurance encompass "all plans purchased on the private market, including coverage purchased through an employer, the individual insurance marketplaces, a union, or a trade association" and does not include government health insurance programs (RAND HRS, 2024).

correlation exists between the couple's coverage with private LTC insurance and private health insurance since the Pearson correlation coefficient for this pair is 0,07 (significance at 5% level).

Our Full model presented in Table 5.13, available on Appendix 5.8.8 shows that, compared to an unwillingness to take financial risks, the financial respondent has lower odds on coverage with health insurance, with significant results observed for levels 2, 5, 7, and 10, but the odds are 161% higher at level 9. This is the first set of results that exhibit a negative relationship between willingness to take financial risks and insurance coverage, which may be a consequence of the specific regulatory and tax framework that affects health insurance, in particular the fact that it is intrinsically related to compensation packages. However, the Intermediate model shows significant positive effects across almost all levels of our independent variable. In terms of the model evaluation criteria, we denote lower RE variance and AIC score on the Full model but higher Wald χ^2 test value, which denotes that adding controls implies better performance to our estimation.

We also verify that as the financial respondents' age increase, being at retirement, and covered by Medicaid are variables that significantly decrease the odds of couples being covered with private health insurance. However, when the financial respondent is the older spouse, has more education, is white (compared to being from other races), and has the highest amounts of income and wealth (compared to having lower amounts) the acquisition of health insurance is more likely.

To complement our analysis, we estimate the effect of the financial respondent willingness to take risks on health matters on the likelihood of a couple being covered with health insurance. Appendix 5.8.9 shows those regressions estimates. The Intermediate model shows that, until level 9 of willingness to take health risks, there is more likely the purchase of the health insurance. When the financial respondent is fully willing to take health risks, he will significantly decrease the odds of demand for health insurance coverage by 79% (OR: 0,21; CI: 0,08;0,51). Results from the Full model, which includes covariate effects, show an opposite scenario. The willingness to take health risks decreases the odds of purchasing health insurance, with significant results at levels 6 and 10 (OR: 0,49; CI: 0,21;1,14 and OR: 0,21; CI: 0,07;0,58). Those results highlighted that, similar to a willingness to take financial risks, taking more health risks also seems to diminish the probability of purchasing private health insurance.

5.5.3 Willingness to take risks on health matters

Table 5.15, available on Appendix 5.8.10 presents results after re-estimation of our models, with the independent variable being the willingness to take health risks instead of financial risks²⁰. From the literature, LTC is related to health risks and financial constraints to overcome needs. We aim to investigate the effect of stated willingness to take health risks on purchasing LTC insurance. From our sample, on average, the financial respondent's willingness to take health risks on a categorical variable ranged between 0 and 10 is 2,91 (sd=2,71; N=5500), denoting a low willingness to take risks on health matters and lower than the financial respondent's willingness to take financial risks²¹.

Table 5.15 shows that, in general, the odds ratios associated with the financial respondent's willingness to take health risks are lower than those observed for willingness to take financial risks (Table 5.5). In the Intermediate model, a medium level of willingness to take health risks is associated with lower odds of purchasing LTC insurance. In contrast, at 2, 7, 8 and 9 levels of health risk, we observe higher odds, which suggests a non-monotone pattern. Full model results show that, compared to the unwillingness to take health risks, the willingness to take health

²⁰Stated risk preferences on health matters are asked by HRS in the exact question wording as the financial matters. HRS routing of the interview closes questions about the individuals' willingness to take risks on financial and health matters.

²¹Weighted data using respondent-level sampling weights for the Leave-behind questionnaire and the base-year weight adopted is 2014.

risks is more likely at level 2 and level 9, while the other levels show negative but non-significant odds values. We also find higher odds of purchasing LTC insurance among females compared to males, as well as among financial respondents with higher education and those with a higher number of diagnosed diseases.

We also ran our models using one of the most common high-risk health behaviors identified in the literature: drinking alcoholic beverages. We aim to investigate if substituting our variable of willingness to take health risks from another variable that expresses high-risk behaviors self-reported by the financial respondent could also be a good predictor of buying LTC insurance. Our binary variable equals 1 if the financial respondent in the last seven days drank alcoholic beverages and 0 otherwise. On average, 47,5% of the financial respondents drank alcoholic beverages in the last seven days ($N=16833$)²². Table 5.16 shows our results. The Intermediate model shows that financial respondents who consumed alcohol in the past seven days have higher odds of LTC insurance coverage. However, this association becomes negative and statistically insignificant in the Full model, after adjusting for demographic, social, and economic variables.

5.6 Discussion

Our research reveals that older USA couples who are willing to take financial risks prefer to cover their future LTC costs by acquiring insurance for at least one of the spouses. Theory suggests that more risk-averse consumers should be the individuals more likely to be insured (Boyer et al., 2019). Our results contradict that hypothesis. We found a positive effect on the odds of a couple being insured of lower levels of willingness to take risks on financial matters but also for upper moderate levels of willingness to take financial risks. Our findings are aligned with Wang et al. (2023b) and Cramer & Jensen (2006) perspectives on the positive effect of being married on the demand for insurance, but also on the findings that older people tend to be more risk averse. Josef et al. (2016) and Dohmen et al. (2017) found that the willingness to take risks decreases with age, i.e., people become more risk averse with age. By sharing life event risks, older married people are more prone to increase their demand for private LTC insurance, independently of their risk aversion level. The uptake of an insurance policy that covers unpredictable costs at the end of life is an assurance that care will be paid for but also that the survival element of the couple will not be deprived of necessary wealth and pushed into impoverishment. Pauly (1990) explained that “the elderly with a surviving spouse sharing the same household” is a more complex case as “impoverishing one’s spouse, rather than one’s children, seems to be the major fear of many married elderly”. The fact that we find a positive correlation between willingness to take financial risks and ownership of LTC insurance suggests that couples who are likely to take a riskier stance on their assets also feel a need to safeguard the financial position of the surviving spouse. By the same token, our finding also suggests that the riskier couples may be aware that they may be faced with a scenario of lack of funds when they need to receive care and not have the necessary bequest that incentivizes family members to provide care. The protection against that situation is to own LTC insurance that covers future LTC expenses. By using the financial respondents’ answers, we capture elements that reflect both spouses’ characteristics, individuals’ heterogeneity, and willingness to take risks. Our model is stronger as we control for any gender and age bias, as well as individual-specific and risk preferences. We also explored the youngest spouse’s perspective, which is mainly composed of women. Our results confirm the main regression findings, but the highest level of risk seeker decreases the couple’s insurance coverage. This result could indicate a gender and age effect. The current demographic data confirms that women live longer than men but face increased risks associated with the likely need to rely more on LTC services during longer periods and at higher costs.

²²Weighted data using respondent-level sampling weights and the base-year weight adopted is 2014.

New familiar dynamics derived from the lower or near absent care role provided by women will likely generate issues in LTC provision and public policy governance. Our results capture these dynamics, showing higher insurance coverage even with Medicaid and also when the financial respondents have a higher probability of entering a nursing home. We conclude that future unpaid intra-couple care will likely diminish, and policies that overcome these shortcomings must be implemented.

In the last few years, in the USA, purchasing LTC insurance combined with life insurance became a common practice (AARP, 2024). However, consumers sometimes need more information about the benefits yielded by each type of policy. In general, we observe significant increased odds of couples owning life insurance, specifically at higher levels of willingness to take risks. Private health insurance is also very commonly associated with LTC insurance. Our sample is from the USA, one of the most significant private LTC and health insurance markets. Our findings support the hypothesis that the USA's older couples perceive LTC and health insurance as two different insurance products, that require different approaches. We observed similar effects between life and LTC insurance but opposite ones on health insurance. Our results provide insights into couples' decisions to insure at least one spouse differently according to the insurance product under analysis. On the health insurance case, independently from analyzing the willingness to take financial or health risks, the results show lower odds of owning health insurance as the willingness to take risks increases. In the United States, beyond the highly regulated public support, health insurance coverage was mandatory prior to 2019, and healthcare remains a significant source of risk, particularly for older people. To test this, we ran regressions of both the willingness to take financial and health risks and the results show that the older couple's decision to purchase private health insurance coverage is negatively affected, independent of their willingness to take risks²³.

Our last robustness check suggests that being moderately risk-averse to taking health risks significantly decreases the demand for LTC insurance at the Intermediate model but increases when the financial respondent is at levels 2, 7, 8 and 9. The Full model includes covariates and shows a significant positive coefficient on the couple's insurance particularly at lower levels of risk seeking. When we analyze the risk behavior of the couple financial respondent drinking alcoholic beverages in the last seven days, we found evidence of a significant increase odds of couple coverage with LTC insurance, but only at the Intermediate model, and a nonsignificant decrease at the Full model. From AARP (2024), it is usual when the individual has an alcoholism condition to be denied private LTC insurance. Furthermore, our results could indicate that, at the couple's level, private LTC insurance is purchased when any health condition could produce adverse risks for spouses.

Our research faces limitations. First, the variable willingness to take financial risks is problematic. On one side, it is available only after wave 12 (the year 2014) and is a biennial wave variable, implying a short panel period available. Although we have our dependent variable since the first HRS wave (1992), we could only run regressions between 2014 and 2020. On the other hand, it is a self-completion question, and it raises doubts about its reliability. Second, we do not control for the USA State's effect, the heterogeneity of public Medicaid eligibility rules applied, or the heterogeneous cost of purchasing care services on the market. By accounting for the USA State's differences, we could treat it as fixed effects. Third, the spouse-nominated "financial respondent" remains almost unchanged across waves. Since we do not have larger panel data to allow more significant changes on the spouse-nominated "financial respondent", we assume that it could diminish the possibility of capturing even more variability of both spouses' preferences. Fourth, we do not control the financial respondents' level of information about private LTC insurance.

This study makes significant contributions. First, aging raises new challenges to countries' economic growth, welfare state sustainability, provision of health and social care services, and

²³Please see more information at <https://www.investopedia.com/is-health-insurance-mandatory-4773106>

labor markets. Under the possibility of having more women engaged in the labor market in the future, our study emphasizes future demand for private LTC financing sources and how to guarantee effective LTC policies based on older people’s needs and social challenges.

Second, our study is centered on understanding people who are married or partnered. We include both spouses’ perspectives, which is innovative compared to other studies that divide their analysis by spouses’ gender and decision power within couples. We focus on married people, emphasizing couples’ decisions about their future dependence and focusing on how they will manage their needs. The scope of our research is the couple, and we observe the intra-couple decision of how to finance care.

Third, our study contributes to and highlights the importance of conducting more research about the behavioral factors associated with the insurance market, in particular those embedded in behavioral preferences.

Fourth, we reinforce the importance of accounting for “who” among the couple is selected to provide data, especially when we analyze a decision that produces effects over the two spouses.

Finally, our results carry significant implications for different stakeholders. OECD (2024) highlights that public expenditures must be adapted to the demographic challenge of an aging population. Our results contribute to informing public decisions on finances, sustainability, and welfare policies. From the business and markets side, our findings could support formulating more effective insurance products, taking a particular focus on couples, as well as new future social dynamics. For health and social care providers, it contributes to a better understanding of the willingness of older couples to be covered with private insurance and use this benefit to pay for care services. From the labor market side, our research could inform group long-term care insurance policies that could be introduced on proposed labor contracts.

Applying our models to other contexts, such as Europe and Asia, could be an interesting extension. The aim is to test if older couple’s willingness to take financial risks also increases the purchase of LTC insurance, even in countries with higher public benefits, universal access to public care, mandatory social LTC insurance implemented, underdeveloped private insurance markets, and divergent cultural and social structures around women roles and gender equality. On the other hand, our research could be extended by including more waves, as well as another observation level in our multilevel analysis regressions, such as if we consider the effect of the USA States or European LTC countries’ policies typologies.

5.7 Conclusion

Only approximately 17% of the couples in our sample have at least one of the spouses covered with private LTC insurance. Understanding the reasons behind couples’ purchase (or decision not to purchase) of private LTC insurance is of paramount importance. This paper aims to provide additional evidence on the extent to which older couple’s willingness to take financial risks affects the purchase of private LTC insurance. By using panel data from the Health and Retirement Study, we study older couples from the USA, where the private LTC insurance market is more developed. We implement an econometric strategy based on the multilevel mixed-effects logit model, taking advantage of our panel data and including answers from both spouses, nested on a couple-specific random intercept.

Our paper provides evidence that couples purchasing LTC insurance is positively correlated with their willingness to take financial risks. These findings are, at some point, contradictory to the theories around risk aversion and self-insurance purchase. Still, they are consistent with theories of older people being more risk-averse and with the hypothesis that couples demand more insurance because they care about guaranteeing financial stability and care for the surviving spouse. In addition, when we isolate women’s education effect, an increased purchase of LTC insurance is estimated, corroborating the idea that a better-informed surviving spouse may exert pressure for the couple to own insurance and not use savings in the care of the oldest

spouse. The significant positive effect of couples' risk preference on the decision to purchase long-term care insurance policies extends the understanding of the decision processes in older couples about their end-of-life financing. It also reinforces the idea that the intra-couple dynamics may be more relevant than risk aversion as a driver for insurance purchase decisions. Our findings indicate that studying married people is an issue that needs differentiated research from observing individual decisions, highlighting why the traditional rational theory of the risk-averse individuals should be considered differently when the study is oriented to deciding *mine* and *my spouse's* dependence financing. Additional analyses of couple-centered decisions that account for spousal heterogeneity should also be considered in future research.

5.8 Appendix

5.8.1 Collinearity diagnostics

Our dependent variable is binary and according to Williams (2015), in the cases of binary variables, "much of the diagnostic information for multicollinearity (e.g., Variance inflation factors)" can be obtained through the Stata command *collin* by calculating the VIF for each independent variable to identify correlations between variables and determine the strength of the relationships²⁴. VIFs are constructed from the R-squared, such that $VIF = 1/(1 - R^2)$.

From Table 5.6, we verify that our variables have values of VIF close to 1, which denotes that variables are not correlated and multicollinearity does not exist in our regression models. By analyzing the R-squared we get small values which indicate that the independent variables can't be explained by other independent variables, and each one provides additional information to our model.

Table 5.6: Collinearity diagnostics

	VIF	Sqrt. VIF	R-Squared
Risk aversion on financial matters	1,08	1,04	0,07
Age	1,26	1,12	0,21
Oldest	1,42	1,19	0,30
Gender	1,46	1,21	0,32
Education	1,39	1,18	0,28
White race	1,12	1,06	0,11
Retired	1,16	1,08	0,14
Couple number of children	1,09	1,05	0,08
Couple log income quartile	1,57	1,25	0,36
Couple log wealth quartile	1,56	1,25	0,36
Probability to nursing home in the next 5 years	1,08	1,04	0,07
Sum of diseases diagnosed	1,27	1,13	0,22
Self-reported general health status	1,34	1,16	0,25
Covered by Medicaid	1,12	1,06	0,11

Notes: Calculated using the Stata command *collin* which computes several collinearity diagnostic measures. Variance inflation factors (VIF). If all of the variables are orthogonal to each other, i.e., completely uncorrelated with each other, the VIFs' are 1. If a variable is very closely related to another variable(s), the VIFs are very large.

²⁴VIF runs auxiliary regressions to explain the independent variables using all independent variables of the model.

5.8.2 Econometric model

We implement the Hausman’s test, and since we do not have a significant result (we get a Prob $\chi^2 = 0,93$), we favor the random-effects model over the fixed-effects model. Table 5.7 compares regression results with panel data random-effects logit model by running Stata commands *xtlogit* and *melogit*. Both commands use different algorithm settings²⁵, but we get similar results. To run our models, we select the *melogit* because sampling weights are applied at a couple’s level (couple ID level) as it is recommended by Health and Retirement Study (2024) and HRS Staff (2019), and it is not allowed at *xtlogit* random-effect. Furthermore, *melogit* is advantageous when applied to clusters and on assuming that observations in the same couple/cluster are related, sharing common cluster-level random effects. It allows us to get more accurate results since we can estimate more complicated random effects models (Rabe-Hesketh, 2022; Williams, 2022; StataCorp, 2023b).

Table 5.7: Comparison of coefficients obtained by running Random-effects logistic model for purchasing LTC insurance vs Multilevel mixed-effects logistic model

	Couple LTC insurance coverage (DV) = 1 if at least one couple member is insured;= 0 otherwise	
	xtlogit, re	melogit
WTFR (IV):		
0 (Unwilling)	(ref.)	(ref.)
1	0,97**	3,07***
2	1,25***	3,13***
3	1,46***	3,38***
4	0,92*	3,07**
5	1,24***	3,76***
6	1,81***	5,46***
7	1,19**	2,88***
8	0,62	2,08**
9	1,68*	3,77***
10 (Fully prepared)	0,57	1,79
Age	0,03	-0,01
FR Oldest (=1 Yes)	-0,52	0,26
Gender (=1 Female)	-0,21	0,21
Education	0,24***	-0,01
White race (=1 Yes)	-0,50	-0,39*
Retired (=1 Yes)	0,90**	0,32
Number of children	-0,07	-0,14**
Income quartile:		
Q1	(ref.)	(ref.)
Q2	0,13	-0,09
Q3	0,77**	0,94*
Q4	1,11**	0,60
Wealth quartile:		
Q1	(ref.)	(ref.)
Q2	0,69	1,85**
Q3	0,87*	1,58**
Q4	1,37***	1,18
NH probability	0,01*	0,003
Sum of diseases	0,11	0,46***
Health status (category):		
1.Poor	(ref.)	(ref.)
2.Fair	0,07	0,99
3.Good	0,55	0,85
4.Very good	0,74	1,68
5.Excellent	0,50	1,39
Medicaid (=1 Yes)	0,92	-0,49
Time		
2014	(ref.)	(ref.)
2016	0,26	0,18
2018	0,24	0,31
2020	-0,21	-0,29
Intercept	-15,55***	-43,45***
Wald χ^2	91,84***	76,74***
Number of observations	3747	3700

Notes: Data sources are described in Table 5.4. *melogit* and *xtlogit* results are estimates coefficients. *melogit* apply sampling weights at a couple level (couple ID level) (HRS Staff, 2019) and it is recommended by the Health and Retirement Study (2024): "Since the HRS sample is a multi-stage area probability sample of the United States, with oversamples of Blacks and Hispanics, unbiased estimates of population parameters require the use of these sampling weights". Random intercept at couple level (couple ID level). *xtlogit* are unweighted. We tested by applying `vce(cluster id)`, but we did not get the LR test, standard errors, or confidence intervals in the model evaluations. Statistical significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Dependent variable (DV). Independent variable (IV). Willingness to take risks on financial matters (WTFR). Quartile (Q). Nursing home (NH). Financial respondent (FR). All variables are related to the financial respondent unless the number of children, couple log income quartiles, and couple log wealth quartiles are at the couple level. We declared to Stata a panel dataset with panel identifier (couple ID) and time variable (wave year).

²⁵Note that both commands use different versions of adaptive quadrature; the *xtlogit* use Gauss–Hermite quadrature while the *melogit* use nonadaptive Gauss–Hermite quadrature.

5.8.3 Descriptive statistics of the youngest spouse sample

Table 5.8: Descriptive statistics of the youngest spouse sample

Variable	Description and measurement	Time period	Mean or %	SD	N
Couple LTC insurance coverage (binary)	= 1 if at least one couple member is insured = 0 if neither couple member is insured	2014-2020	0,18	0,39	16876
YS willingness to take financial risks (category range 0-10)	= 0 if YS is unwilling to take financial risks = 10 if YS is fully prepared to take financial risks	2014-2020	3,29	2,58	5352
YS age	Age of the youngest spouse (in years)	2014-2020	64,13	9,16	16900
Age gap	Age difference between the two spouses (in years)	2014-2020	4,51	4,58	16900
FR aged (binary)	= 1 if FR is the oldest spouse = 0 otherwise	2014-2020	0,54	0,50	16898
YS gender (binary)	= 1 if YS is female = 0 otherwise	2014-2020	0,75	0,44	16900
YS education	YS education (in years)	2014-2020	13,51	2,81	16825
YS white race (binary)	= 1 if YS is white/caucasian = 0 if YS is other race	2014-2020	0,85	0,35	16900
YS is retired (binary)	= 1 if YS is retired or partially retired = 0 if otherwise	2014-2020	0,54	0,50	16900
Couple number of children	Couple number of living children (in number)	2014-2020	2,99	1,75	16596
Couple log income	Couple log income (in quartiles range 1-4)	2014-2020	2,71	1,09	16900
Couple log wealth	Couple log wealth (in quartiles range 1-4)	2014-2020	2,77	1,08	16900
YS probability of moving to NH	YS self-reported probability of moving to NH in next 5 years (in percent)	2014-2020	14,74	19,97	8350
YS chronic conditions	YS number of health chronic conditions diagnosed among 9 possible diseases	2014-2020	1,96	1,46	16887
YS self-reported general health status (category range 1-5)	= 1 if Poor; = 2 if Fair; = 3 if Good; = 4 if Very good; = 5 if Excellent	2014-2020	3,32	1,00	16891
YS covered by Medicaid	=1 if YS is currently covered by Medicaid = 0 otherwise	2014-2020	0,05	0,22	16761

Notes: Data sources are the RAND HRS Longitudinal File (RAND HRS, 2024), except the youngest willingness to take financial risks data is from HRS (Health and Retirement Study, 2023). Weighted data. Respondent-level sampling weights, except for variables of the number of children, income, and wealth that apply household-level sampling weights. Willingness to take financial risks uses respondent-level sampling weights from the leave-behind questionnaire. The base-year weight adopted is 2014 for all variables. Our weighting strategy followed HRS Staff (2019). Youngest spouse (YS). Financial respondent (FR). Nursing home (NH). Standard deviation (SD). N (Number of observations).

5.8.4 Youngest spouse estimation

Table 5.9: Multilevel mixed effects models for purchasing LTC insurance - the youngest spouse's perspective

Couple LTC insurance coverage (DV) = 1 if at least one couple member is insured;= 0 otherwise Estimated OR (95% CI)			
	Null model	Intermediate Model	Full Model
WTFR (IV):			
0 (Unwilling)		(ref.)	(ref.)
1		2,49 (1,26;4,93)***	11,88 (1,19;118,57)**
2		2,26 (1,18;4,31)**	19,80 (2,52;155,77)***
3		2,14 (0,83;5,52)	30,71 (3,15;299,43)***
4		2,35 (1,05;5,26)**	18,50 (2,21;154,50)***
5		2,19 (0,83;5,77)	28,49 (2,22;365,88)**
6		4,20 (1,13;15,59)**	370,66 (28,22;4868,09)***
7		4,39 (1,42;13,56)**	37,61 (2,41;587,05)**
8		7,35 (1,82;29,60)***	9,74 (0,56;170,85)
9		29,96 (3,73;240,84)***	1,99 (0,07;53,07)
10 (Fully prepared)		10,23 (2,63;39,74)***	0,0005 (0,00001; 0,02)***
Age gap			0,98 (0,93;1,04)
FR Oldest (=1 Yes)			1,21 (0,68;2,17)
Gender (=1 Female)			4,13 (2,03;8,39)***
Education			1,23 (1,09;1,39)***
White race (=1 Yes)			1,66 (0,91;3,04)*
Retired (=1 Yes)			3,30 (1,23;8,86)*
Number of children			0,87 (0,76;0,98)**
Income quartile:			
Q1			(ref.)
Q2			1,61 (0,38;6,82)
Q3			1,84 (0,44;7,61)
Q4			2,71 (0,49;15,11)
Wealth quartile:			
Q1			(ref.)
Q2			2,04 (0,46;9,16)
Q3			0,68 (0,15;3,09)
Q4			0,07 (0,01;0,47)***
NH probability			0,94 (0,91;0,97)***
Sum of diseases			0,62 (0,46;0,83)***
Health status (category):			
1.Poor			(ref.)
2.Fair			1,83 (0,16;20,73)
3.Good			0,21 (0,02;2,36)
4.Very good			0,16 (0,01;1,94)
5.Excellent			0,36 (0,02;7,51)
Medicaid (=1 Yes)			0,47 (0,18;1,23)
Time:			
2014			(ref.)
2016			3,27 (1,10;9,69)**
2018			4,50 (1,07;18,92)**
2020			2,68 (0,88;8,20)*
Intercept	0,0002 (5,51e-06;0,005)***	9,11e-09 (4,46e-10;1,86e-07)***	2,71e-24 (4,39e-30;1,68e-18)***
RE variance	104,77 (52,24)	447,80 (82,56)	3358,22 (794,39)
AIC	5,66x 10 ⁷	2,69x10 ⁷	1,21x10 ⁷
ICC	0,97 (0,01)	0,99 (0,00)	0,99 (0,00)
Wald χ^2		29,86***	67,73***
Number of observations	16667	6149	3041

Notes: Data sources are described in Table 5.4. Data from 2014 to 2020. We apply sampling weights at a couple level (couple ID level) (HRS Staff, 2019), and it is recommended by the Health and Retirement Study (2024): "Since the HRS sample is a multi-stage area probability sample of the United States, with oversamples of Blacks and Hispanics, unbiased estimates of population parameters require the use of these sampling weights". Random intercept at couple level (couple ID level). Statistical significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Dependent variable (DV). Independent variable (IV). Willingness to take risks on financial matters (WTFR). Quartile (Q). Nursing home (NH). Akaike information criterion (AIC). Financial respondent (FR). Intraclass correlation coefficient (ICC). Standard deviation in parenthesis. RE variance is estimated random-effects variances. All variables are related to the financial respondent unless the number of children, couple log income quartiles, and couple log wealth quartiles are at the couple level. We declared to Stata a panel dataset with panel identifier (couple ID) and time variable (wave year). The Null model includes only the random intercept term. The Intermediate model includes only the willingness to take risks and the random intercept term. The Full model includes willingness to take risks, covariates as fixed effects and the random intercept term. Estimates are odds ratios (OR) and their 95% confidence intervals (CI).

5.8.5 Descriptive statistics of the sample when the wife has a higher education level than the husband

Table 5.10: Descriptive statistics of the sample when the wife has a higher education level than the husband

Variable	Description and measurement	Time period	Mean or %	SD	N
Couple LTC insurance coverage (binary)	= 1 if at least one couple member is insured = 0 if neither couple member is insured	2014-2020	0,18	0,38	10512
FR willingness to take financial risks (category range 0-10)	= 0 if FR is unwilling to take financial risks = 10 if FR is fully prepared to take financial risks	2014-2020	3,64	2,60	3503
FR age	FR age (in years)	2014-2020	66,77	8,75	10516
FR aged (binary)	= 1 if FR is the oldest spouse = 0 otherwise	2014-2020	0,52	0,50	10525
FR gender (binary)	= 1 if FR is female = 0 otherwise	2014-2020	0,43	0,49	10516
FR education	FR education (in years)	2014-2020	13,52	2,91	10479
FR white race (binary)	= 1 if FR is white/caucasian = 0 if FR is other race	2014-2020	0,85	0,35	10526
FR is retired (binary)	= 1 if FR is retired or partially retired = 0 if otherwise	2014-2020	0,60	0,49	10516
Couple number of children	Couple number of living children (in number)	2014-2020	2,92	1,70	10339
Couple log income	Couple log income (in quartiles range 1-4)	2014-2020	2,70	1,10	10526
Couple log wealth	Couple log wealth (in quartiles range 1-4)	2014-2020	2,75	1,09	10526
FR probability of moving to NH	FR self-reported probability of moving to NH in next 5 years (in percent)	2014-2020	14,74	19,28	6167
FR chronic conditions	FR number of health chronic conditions diagnosed among 9 possible diseases	2014-2020	2,14	1,49	10508
FR self-reported general health status (category range 1-5)	= 1 if Poor; = 2 if Fair; = 3 if Good; = 4 if Very good; = 5 if Excellent	2014-2020	3,29	0,98	10513
FR covered by Medicaid	= 1 if FR is currently covered by Medicaid = 0 otherwise	2014-2020	0,05	0,22	10431

Notes: Data sources are the RAND HRS Longitudinal File (RAND HRS, 2024), except financial respondent willingness to take financial risks data is from HRS (Health and Retirement Study, 2023). Weighted data. All variables are related to the financial respondent unless the number of children, couple log income quartiles, and couple log wealth quartiles are at the couple level. Willingness to take financial risks uses respondent-level sampling weights from the leave-behind questionnaire. The base-year weight adopted is 2014 for all variables. Our weighting strategy followed HRS Staff (2019). Financial respondent (FR). Nursing home (NH). Standard deviation (SD). N (Number of observations).

5.8.6 The wife has a higher education level than the husband estimation

Table 5.11: Multilevel mixed effects models for purchasing LTC insurance - The wife has a higher education level than the husband

Couple LTC insurance coverage (DV) = 1 if at least one couple member is insured;= 0 otherwise Estimated OR (95% CI)			
	Null model	Intermediate Model	Full Model
WTFR (IV):			
0 (Unwilling)		(ref.)	(ref.)
1		4,81 (1,49;15,56)***	106,50 (8,79;1289,60)***
2		5,34 (1,54;18,54)***	28,01 (2,37;330,46)***
3		2,98 (0,58;15,37)	70,59 (6,45;772,56)***
4		2,50 (0,52;12,07)	5,87 (0,53;65,65)
5		5,22 (1,41;19,25)**	204,59 (13,02;3213,66)***
6		0,64 (0,11;3,66)	271,02 (12,22;6013,12)***
7		2,87 (0,86;9,60)*	18,43 (1,76;193,39)**
8		6,80 (0,98;47,16)*	22,34 (1,30;382,66)**
9		7,36 (1,71;31,68)***	40,99 (3,76;445,17)***
10 (Fully prepared)		14,01 (2,57;76,36)***	1,75 (0,02;138,59)
Age			0,91 (0,85;0,97)***
FR Oldest (=1 Yes)			1,30 (0,78;2,19)
Gender (=1 Female)			1,06 (0,58;1,93)
Education			1,22 (1,10;1,37)***
White race (=1 Yes)			0,57 (0,33;0,99)**
Retired (=1 Yes)			0,36 (0,09;1,46)
Number of children			1,06 (0,95;1,19)
Income quartile:			
Q1			(ref.)
Q2			0,32 (0,09;1,22)*
Q3			0,75 (0,25;2,30)
Q4			0,35 (0,07;1,65)
Wealth quartile:			
Q1			(ref.)
Q2			24,37 (2,60;228,14)**
Q3			20,10 (2,73;148,20)***
Q4			17,02 (2,50;116,10)***
NH probability			1,04 (1,01;1,06)***
Sum of diseases			1,92 (1,31;2,82)***
Health status (category):			
1.Poor			(ref.)
2.Fair			1,60 (0,28;9,01)
3.Good			0,47 (0,08;2,64)
4.Very good			0,63 (0,08;4,70)
5.Excellent			1,75 (0,19;16,39)
Medicaid (=1 Yes)			14,83 (3,89;56,54)***
Time:			
2014			(ref.)
2016			1,31 (0,52;3,30)
2018			1,40 (0,36;5,42)
2020			0,30 (0,08;1,16)*
Intercept	0,0010 (0,0003;0,003)***	1,34e-07 (1,10e-9;0,00002)***	6,68e-20 (4,00e-25;1,12e-14)***
RE variance	53,18 (14,06)	299,91 (105,97)	2397,92 (647,77)
AIC	3,47x 10 ⁷	1,67x10 ⁷	8906110
ICC	0,94 (0,00)	0,99 (0,00)	0,99 (0,00)
Wald χ^2		20,42**	60,51***
Number of observations	10388	3916	2289

Notes: Data sources are described in Table 5.4. Data from 2014 to 2020. We apply sampling weights at a couple level (couple ID level) (HRS Staff, 2019), and it is recommended by the Health and Retirement Study (2024): "Since the HRS sample is a multi-stage area probability sample of the United States, with oversamples of Blacks and Hispanics, unbiased estimates of population parameters require the use of these sampling weights". Random intercept at couple level (couple ID level). Statistical significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Dependent variable (DV). Independent variable (IV). Quartile (Q). Nursing home (NH). Akaike information criterion (AIC). Financial respondent (FR). Intraclass correlation coefficient (ICC). Standard deviation in parenthesis. RE variance is estimated random-effects variances. All variables are related to the financial respondent unless the number of children, couple log income quartiles, and couple log wealth quartiles are at the couple level. We declared to Stata a panel dataset with panel identifier (couple ID) and time variable (wave year). We restrict our sample to couples where the wife has higher or equal education (in years) than the husband (deleted observations n=7537). The Null model includes only the random intercept term. The Intermediate model includes only the willingness to take risks and the random intercept term. The Full model includes willingness to take risks, covariates as fixed effects and the random intercept term.

5.8.7 Life insurance estimation

Table 5.12: Multilevel mixed effects models for purchasing life insurance

Couple life insurance coverage (DV) = 1 if at least one couple member is insured;= 0 otherwise Estimated OR (95% CI)			
	Null model	Intermediate Model	Full Model
WTFR (IV):			
0 (Unwilling)		(ref.)	(ref.)
1		0,82 (0,37;1,80)	1,61 (0,48;5,32)
2		2,18 (0,98;4,83)*	1,67 (0,65;4,30)
3		1,22 (0,65;2,27)	0,68 (0,24;1,89)
4		0,50 (0,19;1,30)	1,76 (0,56;5,50)
5		3,37 (0,98;11,61)*	10,50 (2,63;41,85)***
6		0,45 (0,22;0,90)**	0,66 (0,18;2,46)
7		1,03 (0,43;2,44)	1,99 (0,66;6,07)
8		1,32 (0,41;4,29)	18,78 (2,75;128,27)***
9		3,92 (0,42;37,04)	40,48 (0,58;2806,92)*
10 (Fully prepared)		0,42 (0,07;2,49)	1,55 (0,04;60,33)
Age			0,91 (0,88;0,95)***
FR Oldest (=1 Yes)			0,90 (0,61;1,33)
Gender (=1 Female)			0,52 (0,34;0,79)***
Education			0,94 (0,89;0,99)**
White race (=1 Yes)			1,58 (1,08;2,31)
Retired (=1 Yes)			0,11 (0,03;0,48)***
Number of children			1,04 (0,97;1,12)
Income quartile:			
Q1			(ref.)
Q2			2,66 (1,47;4,80)***
Q3			16,08 (5,84;44,26)***
Q4			12,05 (5,01;28,98)***
Wealth quartile:			
Q1			(ref.)
Q2			5,46 (2,23;13,35)***
Q3			2,67 (1,29;5,55)***
Q4			0,77 (0,38;1,54)
NH probability			1,01 (0,99;1,02)
Sum of diseases			0,95 (0,80;1,11)
Health status (category):			
1.Poor			(ref.)
2.Fair			2,37 (1,26;4,46)***
3.Good			2,75 (1,41;5,38)***
4.Very good			0,93 (0,44;1,96)
5.Excellent			1,75 (0,28;10,99)
Medicaid (=1 Yes)			0,04 (0,02;0,08)***
Time:			
2014			(ref.)
2016			1,42 (0,59;3,40)
2018			0,06 (0,02;0,20)***
2020			0,03 (0,01;0,09)***
Intercept	180,16 (67,91;477,96)***	5,13e+09 (7,76e+08;3,40e+10)***	2,12e+19 (9,67e+14;4,66e+23)***
RE variance	46,11 (11,94)	778,32 (70,93)	1918,36 (407,29)
AIC	6,78x 10 ⁷	3,06x10 ⁷	1,68x10 ⁷
ICC	0,93 (0,02)	0,99 (0,00)	0,99 (0,00)
Wald χ^2		23,50***	174,12***
Number of observations	16659	6256	3702

Notes: Data sources are described in Table 5.4. The life insurance data source is the RAND HRS Longitudinal File (RAND HRS, 2024). Data from 2014 to 2020. We apply sampling weights at a couple's level (couple ID level) (HRS Staff, 2019), and it is recommended by the Health and Retirement Study (2024): "Since the HRS sample is a multi-stage area probability sample of the United States, with oversamples of Blacks and Hispanics, unbiased estimates of population parameters require the use of these sampling weights". Random intercept at couple level (couple ID level). Statistical significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Dependent variable (DV). Willingness to take risks on financial matters (WTFR). Independent variable (IV). Quartile (Q). Nursing home (NH). Akaike information criterion (AIC). Financial respondent (FR). Intraclass correlation coefficient (ICC). Standard deviation in parenthesis. RE variance is estimated random-effects variances. All variables are related to the financial respondent unless the number of children, couple log income quartiles, and couple log wealth quartiles are at the couple level. We declared to Stata a panel dataset with panel identifier (couple ID) and time variable (wave year). The Null model includes only the random intercept term. The Intermediate model includes only the willingness to take risks and the random intercept term. The Full model includes willingness to take risks, covariates as fixed effects and the random intercept term. Estimates are odds ratios (OR) and their 95% confidence intervals (CI).

5.8.8 Health insurance estimation

Table 5.13: Multilevel mixed effects models for purchasing health insurance

Couple health insurance coverage (DV) = 1 if at least one couple member is insured;= 0 otherwise Estimated OR (95% CI)			
	Null model	Intermediate Model	Full Model
WTFR (IV):			
0 (Unwilling)		(ref.)	(ref.)
1		2,25 (1,36;3,71)***	1,05 (0,56;1,97)
2		1,73 (1,05;2,84)**	0,53 (0,29;0,97)**
3		2,32 (1,43;3,76)***	0,60 (0,32;1,10)
4		3,15 (1,80;5,50)***	1,03 (0,51;2,06)
5		2,60 (1,61;4,19)***	0,52 (0,28;0,97)**
6		4,95 (2,79;8,78)***	1,10 (0,48;2,15)
7		2,62 (1,54;4,48)***	0,40 (0,19;0,82)**
8		3,35 (1,75;6,40)***	0,63 (0,28;1,41)
9		3,85 (1,67;8,86)***	2,61 (0,85;8,06)*
10 (Fully prepared)		0,44 (0,15;1,30)	0,31 (0,09;1,00)*
Age			0,90 (0,87;0,93)***
FR Oldest (=1 Yes)			2,05 (1,32;3,17)***
Gender (=1 Female)			0,76 (0,48;1,21)
Education			1,11 (1,03;1,20)***
White race (=1 Yes)			3,11 (1,67;5,81)***
Retired (=1 Yes)			0,48 (0,28;0,81)***
Number of children			0,95 (0,86;1,05)
Income quartile:			
Q1			(ref.)
Q2			1,62 (0,10;2,63)*
Q3			2,36 (1,38;4,03)***
Q4			6,52 (3,39;12,55)***
Wealth quartile:			
Q1			(ref.)
Q2			2,75 (1,49;5,07)***
Q3			3,00 (1,59;5,67)***
Q4			3,80 (1,93;7,50)***
NH probability			1,00 (0,99;1,01)
Sum of diseases			0,96 (0,84;1,09)
Health status (category):			
1.Poor			(ref.)
2.Fair			1,25 (0,50;3,13)
3.Good			1,51 (0,62;3,72)
4.Very good			1,73 (0,69;4,33)
5.Excellent			1,71 (0,57;5,14)
Medicaid (=1 Yes)			0,19 (0,07;0,53)***
Time:			
2014			(ref.)
2016			0,75 (0,48;1,17)
2018			0,63 (0,43;0,91)**
2020			0,59 (0,37;0,95)**
Intercept	10,39 (8,47;12,75)***	5,80 (2,97;11,35)***	271,65 (18,29;4034,97)***
RE variance	12,58 (1,15)	12,32 (3,41)	8,51 (1,69)
AIC	8,07x 10 ⁷	3,50x10 ⁷	1,98x10 ⁷
ICC	0,79 (0,02)	0,79 (0,05)	0,72 (0,04)
Wald χ^2		51,14***	132,26***
Number of observations	16673	6260	3704

Notes: Data sources are described in Table 5.4. The health insurance data source is the RAND HRS Longitudinal File (RAND HRS, 2024). Data from 2014 to 2020. We apply sampling weights at a couple's level (couple ID level) (HRS Staff, 2019), and it is recommended by the Health and Retirement Study (2024): "Since the HRS sample is a multi-stage area probability sample of the United States, with oversamples of Blacks and Hispanics, unbiased estimates of population parameters require the use of these sampling weights". Random intercept at couple level (couple ID level). Statistical significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Dependent variable (DV). Willingness to take risks on financial matters (WTFR). Independent variable (IV). Quartile (Q). Nursing home (NH). Akaike information criterion (AIC). Financial respondent (FR). Intraclass correlation coefficient (ICC). Standard deviation in parenthesis. RE variance is estimated random-effects variances. All variables are related to the financial respondent unless the number of children, couple log income quartiles, and couple log wealth quartiles are at the couple level. We declared to Stata a panel dataset with panel identifier (couple ID) and time variable (wave year). The Null model includes only the random intercept term. The Intermediate model includes only the willingness to take risks and the random intercept term. The Full model includes willingness to take risks, covariates as fixed effects and the random intercept term. Estimates are odds ratios (OR) and their 95% confidence intervals (CI).

5.8.9 Private health insurance and willingness to take risks on own health estimation

Table 5.14: Multilevel mixed effects models for purchasing health insurance - Willingness to take risks on health matters (IV)

Couple health insurance coverage (DV) = 1 if at least one couple member is insured;= 0 otherwise Estimated OR (95% CI)			
	Null model	Intermediate Model	Full Model
WTHR (IV):			
0 (Unwilling)		(ref.)	(ref.)
1		2,99 (1,97;4,53)***	1,07 (0,63;1,82)
2		2,15 (1,41;3,29)***	0,84 (0,48;1,46)
3		2,62 (1,69;4,05)***	0,66 (0,36;1,20)
4		2,57 (1,44;4,60)***	0,92 (0,44;1,94)
5		2,33 (1,46;3,74)***	0,82 (0,44;1,53)
6		1,70 (0,94;3,10)*	0,49 (0,21;1,14)*
7		1,75 (0,89;3,45)	1,35 (0,54;3,39)
8		2,18 (1,13;4,20)**	0,63 (0,26;1,57)
9		1,14 (0,49;2,65)	0,67 (0,20;2,30)
10 (Fully prepared)		0,21 (0,08;0,51)***	0,21 (0,07;0,58)***
Age			0,90 (0,87;0,93)***
FR Oldest (=1 Yes)			2,06 (1,32;3,21)***
Gender (=1 Female)			0,79 (0,50;1,26)
Education			1,11 (1,03;1,20)***
White race (=1 Yes)			3,02 (1,59;5,74)***
Retired (=1 Yes)			0,45 (0,27;0,77)***
Number of children			0,96 (0,87;1,06)
Income quartile:			
Q1			(ref.)
Q2			1,56 (0,96;2,55)*
Q3			2,19 (1,27;3,75)***
Q4			6,03 (3,13;11,64)***
Wealth quartile:			
Q1			(ref.)
Q2			2,94 (1,57;5,49)***
Q3			3,26 (1,70;6,23)***
Q4			3,93 (1,97;7,83)***
NH probability			1,00 (0,99;1,01)
Sum of diseases			0,97 (0,84;1,11)
Health status (category):			
1.Poor			(ref.)
2.Fair			1,43 (0,55;3,73)
3.Good			1,80 (0,70;4,62)
4.Very good			2,03 (0,78;5,32)
5.Excellent			1,93 (0,62;6,03)
Medicaid (=1 Yes)			0,21 (0,08;0,56)***
Time			
2014			(ref.)
2016			0,73 (0,47;1,14)
2018			0,63 (0,44;0,92)**
2020			0,58 (0,36;0,94)**
Intercept	10,39 (8,47;12,75)***	7,10 (3,87;13,03)***	173,63 (11,50;2620,49)***
RE variance	12,58 (1,15)	12,01 (3,20)	8,87 (1,80)
AIC	8,07x 10 ⁷	3,49x10 ⁷	1,99x10 ⁷
ICC	0,79 (0,02)	0,79 (0,04)	0,73 (0,04)
Wald χ^2		57,99***	127,12***
Number of observations	16673	6272	3714

Notes: Data sources are described in Table 5.4. Willingness to take health risks data source is from HRS (Health and Retirement Study, 2023), and private health insurance is from RAND HRS (2024). We apply sampling weights at a couple's level (couple ID level) (HRS Staff, 2019), and it is recommended by the Health and Retirement Study (2024): "Since the HRS sample is a multi-stage area probability sample of the United States, with oversamples of Blacks and Hispanics, unbiased estimates of population parameters require the use of these sampling weights". Random intercept at couple level (couple ID level). Statistical significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Dependent variable (DV). Independent variable (IV). Quartile (Q). Nursing home (NH). Akaike information criterion (AIC). Financial respondent (FR). Intraclass correlation coefficient (ICC). Standard deviation in parenthesis. RE variance is estimated random-effects variances. All variables are related to the financial respondent unless the number of children, couple log income quartiles, and couple log wealth quartiles are at the couple level. We declared to Stata a panel dataset with panel identifier (couple ID) and time variable (wave year). The Null model includes only the random intercept term. The Intermediate model includes only the willingness to take risks and the random intercept term. The Full model includes willingness to take risks, covariates as fixed effects and the random intercept term. Estimates are odds ratios (OR) and their 95% confidence intervals (CI).

5.8.10 Health risk aversion estimation

Table 5.15: Multilevel mixed effects models for purchasing LTC insurance - Willingness to take risks on health matters (IV)

Couple LTC insurance coverage (DV) = 1 if at least one couple member is insured;= 0 otherwise Estimated OR (95% CI)			
	Null model	Intermediate Model	Full Model
WTHR (IV):			
0 (Unwilling)		(ref.)	(ref.)
1		1,30 (0,50;3,35)	0,71 (0,18;2,80)
2		1,99 (0,99;3,99)*	5,53 (1,74;17,52)***
3		1,46 (0,64;3,35)	1,82 (0,48;6,89)
4		0,50 (0,20;1,29)	1,25 (0,29;5,46)
5		0,21 (0,07;0,62)***	0,83 (0,17;4,02)
6		0,68 (0,24;1,94)	0,68 (0,08;5,98)
7		3,24 (1,13;9,26)**	2,82 (0,32;24,74)
8		3,18 (0,90;11,18)*	0,24 (0,02;2,54)
9		1,28 (0,45;3,68)**	3,83 (1,16;12,57)**
10 (Fully prepared)		0,59 (0,16;2,21)	0,38 (0,03;4,21)
Age			0,96 (0,92;1,00)*
FR Oldest (=1 Yes)			1,43 (0,85;2,41)
Gender (=1 Female)			1,60 (0,92;2,78)*
Education			1,13 (1,04;1,22)***
White race (=1 Yes)			1,07 (0,65;1,77)
Retired (=1 Yes)			1,23 (0,49;3,11)
Number of children			1,02 (0,93;1,12)
Income quartile:			
Q1			(ref.)
Q2			1,07 (0,34;3,39)
Q3			2,21 (0,77;6,32)
Q4			2,27 (0,68;7,61)
Wealth quartile:			
Q1			(ref.)
Q2			2,31 (0,78;6,86)
Q3			1,06 (0,35;3,24)
Q4			0,81 (0,27;2,37)
NH probability			0,99 (0,98;1,02)
Sum of diseases			1,38 (1,13;1,70)***
Health status (category):			
1.Poor			(ref.)
2.Fair			0,79 (0,06;9,83)
3.Good			0,96 (0,09;10,05)
4.Very good			1,66 (0,15;17,96)
5.Excellent			1,04 (0,08;13,59)
Medicaid (=1 Yes)			0,71 (0,13;3,87)
Time:			
2014			(ref.)
2016			0,99 (0,45;2,20)
2018			1,76 (0,67;4,65)
2020			1,09 (0,50;2,37)
Intercept	0,0002 (5,51e-06;0,005)***	9,95e-09 (2,64e-10;3,75e-10)***	8,25e-16 (3,82e-19;1,78e-12)***
RE variance	104,77 (52,24)	486,01 (107,35)	1526,89 (321,27)
AIC	5,66x 10 ⁷	2,73x10 ⁷	1,50x10 ⁷
ICC	0,97 (0,01)	0,99 (0,00)	0,99 (0,00)
Wald χ^2		18,93**	65,11***
Number of observations	16667	6269	3711

Notes: Data sources are described in Table 5.4. Willingness to take health risks data source is from HRS (Health and Retirement Study, 2023). Data from 2014 to 2020. We apply sampling weights at a couple's level (couple ID level) (HRS Staff, 2019), and it is recommended by the Health and Retirement Study (2024): "Since the HRS sample is a multi-stage area probability sample of the United States, with oversamples of Blacks and Hispanics, unbiased estimates of population parameters require the use of these sampling weights". Random intercept at couple level (couple ID level). Statistical significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Dependent variable (DV). Willingness to take risks on health matters (WTHR).Independent variable (IV). Quartile (Q). Nursing home (NH). Akaike information criterion (AIC). Financial respondent (FR). Intraclass correlation coefficient (ICC). Standard deviation in parenthesis. RE variance is estimated random-effects variances. All variables are related to the financial respondent unless the number of children, couple log income quartiles, and couple log wealth quartiles are at the couple level. We declared to Stata a panel dataset with panel identifier (couple ID) and time variable (wave year). The Null model includes only the random intercept term. The Intermediate model includes only the willingness to take risks and the random intercept term. The Full model includes willingness to take risks, covariates as fixed effects and the random intercept term. Estimates are odds ratios (OR) and their 95% confidence intervals (CI).

Table 5.16: Models: Drink alcoholic beverages in the last 7 days (IV) and at least one couple member is covered by private LTC insurance (DV)

Couple LTC insurance coverage (DV) = 1 if at least one couple member is insured;= 0 otherwise Estimated OR (95% CI)			
	Null model	Intermediate Model	Full Model
Drink alcoholic beverages:			
0 (=0 No)		(ref.)	(ref.)
1 (=1 Yes)		1,20 (0,97;1,49)*	0,74 (0,48;1,14)
Age			1,07 (0,10;1,15)*
FR Oldest (=1 Yes)			0,76 (0,48;1,22)
Gender (=1 Female)			0,98 (0,61;1,59)
Education			1,50 (1,00;2,23)**
White race (=1 Yes)			0,76 (0,51;1,12)
Retired (=1 Yes)			1,28 (0,74;2,22)
Number of children			0,88 (0,74;1,04)
Income quartile:			
Q1			(ref.)
Q2			0,77 (0,42;1,43)
Q3			1,36 (0,77;2,43)
Q4			1,57 (0,83;2,97)
Wealth quartile:			
Q1			(ref.)
Q2			1,32 (0,46;3,79)
Q3			1,68 (0,67;4,19)
Q4			2,12 (0,71;6,28)
NH probability			0,99 (0,98;1,00)
Sum of diseases			1,04 (0,88;1,22)
Health status (category):			
1.Poor			(ref.)
2.Fair			1,05 (0,38;2,89)
3.Good			1,27 (0,42;3,81)
4.Very good			1,51 (0,45;5,08)
5.Excellent			2,24 (0,52;9,71)
Medicaid (=1 Yes)			2,42 (0,96;6,10)*
Time:			
2014			(ref.)
2016			0,81 (0,55;1,20)
2018			0,70 (0,46;1,06)*
2020			0,59 (0,34;0,10)*
Intercept	0,0002 (5,51e-06;0,005)***	0,0002 (6,04e-08;0,56)***	1,82e-12 (2,63e-24;1,26)***
RE variance	104,77 (52,24)	99,17 (123,41)	407,95 (467,64)
AIC	5,66x 10 ⁷	5,65x10 ⁷	2,94x10 ⁷
ICC	0,97 (0,01)	0,97 (0,04)	0,99 (0,01)
Wald χ^2		2,86*	32,07
Number of observations	16667	16596	9074

Notes: Data sources are described in Table 5.4. Drink alcoholic beverages in the last 7 days data source is the RAND HRS Longitudinal File (RAND HRS, 2024). Data from 2014 to 2020. We apply sampling weights at a couple's level (couple ID level) (HRS Staff, 2019), and it is recommended by the Health and Retirement Study (2024): "Since the HRS sample is a multi-stage area probability sample of the United States, with oversamples of Blacks and Hispanics, unbiased estimates of population parameters require the use of these sampling weights". Random intercept at couple level (couple ID level). Statistical significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Dependent variable (DV). Independent variable (IV). Quartile (Q). Nursing home (NH). Akaike information criterion (AIC). Financial respondent (FR). Intraclass correlation coefficient (ICC). Standard deviation in parenthesis. RE variance is estimated random-effects variances. All variables are related to the financial respondent unless the number of children, couple log income quartiles, and couple log wealth quartiles are at the couple level. We declared to Stata a panel dataset with panel identifier (couple ID) and time variable (wave year). The Null model includes only the random intercept term. The Intermediate model includes only drink alcoholic beverages and the random intercept term. The Full model includes drink alcoholic beverages, covariates as fixed effects and the random intercept term. Estimates are odds ratios (OR) and their 95% confidence intervals (CI).

Chapter 6

Conclusion

An increasing proportion of the population requires LTC in their later years. This care must be financed and delivered over an uncertain period to ensure support for basic daily activities and a dignified end-of-life experience.

The demographic landscape is further shaped by evolving social behaviors and preferences, such as reduced family caregiving capacity, lower fertility rates, and increasingly diverse retirement decisions. The traditional model of informal care provided by family members, supplemented by public funding, is no longer sufficient. However, living with a partner continues to serve as a form of informal insurance against LTC needs. This thesis places particular emphasis on the role of couples in LTC decision-making, accounting for both spouses' preferences.

Governments worldwide recognize LTC as a growing challenge for social and healthcare systems, public finances, labor markets, and the sustainability of the welfare state. Diverse public policy responses have emerged, making the analysis of strategic orientations in LTC a vital area of research. Financing such an unpredictable need poses a significant challenge for individuals, requiring a balance between public, private, and informal support, and decisions about saving versus insuring from an early age.

This thesis addresses two central issues in the Economics of LTC: public policy design and private insurance coverage. The first two essays focus on public LTC policy orientations. Essay 1 reviews the conceptual foundations of LTC and examines key policy features and financing mechanisms. Essay 2 builds on this foundation by identifying four core dimensions of LTC (supply, demand, financing, and regulation), and applies a clustering ensemble approach (FCM, PAM, SOM) to classify 30 OECD countries into seven distinct LTC policy typologies. Essays 3 and 4 shift the focus to older couples' decisions regarding private LTC insurance. Essay 3 develops a theoretical Principal-Agent model to represent intra-couple dynamics, accounting for differences in LTC risk and the costs of care provision. Essay 4 empirically investigates how financial risk preferences influence the decision to purchase LTC insurance, using panel data from the Health and Retirement Study (HRS) in the United States. The findings show a positive relationship between willingness to take financial risks and insurance uptake, with variations across different types of insurance products.

From these four essays, several important insights and policy implications emerge:

- **Public policy design:** Effective LTC policy must reflect evolving family structures, labor market dynamics, and broader societal changes. Essay 4, for example, highlights the relevance of gender roles and educational attainment in shaping LTC decisions, suggesting the need to consider younger generations' perspectives in future policy design.
- **Micro and macro agents in LTC:** The thesis underscores the complementary roles of individuals (as micro agents) and governments and insurers (as macro agents) in financing and providing LTC. Coordinated strategies are essential to ensure sustainable and equitable coverage.

- Methodological innovation: Each essay employs a distinct methodological approach—literature review, clustering analysis, theoretical modeling, and empirical econometrics—contributing to the diversification and enrichment of research methods in the Economics of LTC.

This thesis opens several avenues for future research. Further exploration of clustering techniques could deepen our understanding of LTC policy governance and organization. Psychological and social factors influencing insurance decisions warrant closer examination, and expanding the dataset to include more countries and variables could enhance comparative analysis. Each essay identifies specific limitations and proposes improvements, laying the groundwork for continued inquiry into this critical area of economic research. It is hoped that the findings and approaches presented here will inspire further contributions to the evolving field of LTC economics.

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