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Wealth, Income, State Dependence and Other Determinants of Depression Among Elderly Europeans

Master's thesis

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Declaration of Authorship

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Abstract

This thesis investigates the determinants of depression among elderly Europeans, with a particular focus on the roles of wealth, income, and prior episodes of depression. Utilizing data from the Survey of Health, Ageing and Retirement in Europe (SHARE), the study employs both static and dynamic logistic regression models to analyze the impact of various socioeconomic factors on the prevalence of depression in older adults. Key findings indicate that wealth is a stronger predictor of depression than income, and there is a significant state dependence effect, where past depression increases the likelihood of future depressive episodes. Additionally, elderly women face a considerably higher risk of depression compared to their male counterparts, and physical health significantly influences depression levels. Depression among the elderly significantly increased during COVID-19 period. This research provides valuable insights for policymakers aiming to mitigate the adverse effects of depression on the aging population by identifying the endangered groups and factors that significantly affect depression.

JEL Classification	I12, I14, J14, C23
Keywords	Depression, SHARE, state dependence, wealth, income
Title	Wealth, Income, State Dependence and Other Determinants of Depression Among Elderly Europeans

Abstrakt

Tato diplomová práce zkoumá determinanty deprese mezi staršími Evropany, se zvláštním zaměřením na role bohatství, příjmu a předchozích epizod deprese. Využívajíc data ze Survey of Health, Ageing and Retirement in Europe (SHARE), studie používá statické i dynamické logistické regresní modely k analýze vlivu různých socioekonomických faktorů na výskyt deprese u starších dospělých. Klíčové výsledky ukazují, že bohatství je silnějším prediktorem deprese než příjem a že existuje významný efekt závislosti na předchozím časovém období, kde deprese v minulém období zvyšuje pravděpodobnost budoucích depresivních epizod. Dále starší ženy čelí podstatně vyššímu riziku deprese ve srovnání se svými mužskými protějšky a fyzické zdraví významně ovlivňuje riziko deprese. Výskyt deprese se mezi staršími výrazně zvýšil během období COVID-19. Tento výzkum poskytuje cenné poznatky pro tvůrce politik zaměřených na zmírnění nepříznivých dopadů deprese na stárnoucí populaci, identifikováním ohrožených skupin a faktorů, které významně ovlivňují depresi.

Klasifikace JEL	I12, I14, J14, C23
Klíčová slova	Deprese, SHARE, laggované vlastní proměnné, bohatství, příjem
Název práce	Bohatství, příjem a psychický stav v minulosti jako determinanty deprese mezi starší generací Evropanů

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Acronyms

SHARE The Survey of Health, Ageing and Retirement in Europe

FE Fixed effects

RE Random effects

iid Independent and Identically Distributed

STATA STAtistics and daTA, software for statistics and data science

CAPI Computer-Assisted Personal Interviewing

JEL Journal of Economic Literature classification system

EU European Union

Chapter 1

Introduction

The population of Europe is expected to peak at 453 million in 2026 before falling to 432 million by 2070. At the same time, a strong upward shift in the age distribution will affect all member states due to increasing longevity and a long-term decline in birth rates. As a result, the old-age dependency ratio will grow rapidly in the coming decades. This ratio, which measures the relative number of potential retirees to potential workers, illustrates how an aging population affects the balance between beneficiaries and contributors. From about 29% in 2010 in the EU, it rose to 36% in 2022 and is projected to reach 59% by 2070, with most of the increase expected by 2045. In other words, the EU will shift from having nearly three people aged 20 to 64 for every one person aged over 65 in 2022, to having less than two people in this age group for every one person aged over 65 by 2045 (European Commission 2024).

Depression is the greatest contributor to global disability, measured by years lived with disability (YLDs), with 5.7% of Europeans over 60 suffering from depression (WHO 2023). Depressed elderly individuals incur and face significantly higher direct costs than their non-depressed counterparts of the same age, making them more susceptible to poverty and its associated adverse effects. (Luppa *et al.* 2008). However, the negatives are not only economic. Suicide is most strongly associated with depression among the elderly compared to other age groups, and approximately 85% of older adults who died by suicide were depressed (Conwell & Brent 1995).

Despite the severe implications, most individuals diagnosed with depression can be successfully treated and overcome the disease (WHO 2012). Given the forthcoming sociodemographic changes, the topic of depression among elderly Europeans is increasingly important.

Current research on elderly depression has identified several key determinants, such as socioeconomic status, gender, marital status, health, children, social support nets and health system characteristics (Semyonov *et al.* 2013; Zhao *et al.* 2012; WHO 2017; Yaka *et al.* 2014; Kourouklis *et al.* 2020). However, many studies have limitations, including cross-sectional designs and insufficient control for confounding variables. We analyze 345 728 observations from 28 countries. We control for multiple determinants inspired by the empirical research and account for an initial condition value often omitted in the literature. Specifically, three hypotheses are tested:

- **Hypothesis 1** - Wealth is a stronger predictor of depression among elderly individuals compared to income.
- **Hypothesis 2** - State dependence has a statistically significant effect on the presence of depression among elderly individuals.
- **Hypothesis 3** - COVID-19 increased the risk of depression among the elderly by limiting social interactions and making healthcare access more difficult.

Fixed and random effects panel data models are estimated. In addition, a static random effects model is compared to the dynamic random effects models to uncover the effect of initial condition value. The results suggest that a dynamic model significantly improves the explanatory power of the model pointing out to the importance of the initial condition value in the social science research. We found that COVID-19 negatively affected the mental health of the elderly. Evidence shows that widowhood impacts males more adversely than females. Additionally, results suggest that women have a higher probability of depression.

The thesis follows this structure: Chapter 2 presents the literature review. Chapter 3 introduces the dataset and relevant data treatments. The methodology and specific model specifications are detailed in Chapter 4. Chapter 5 presents and interprets the results. Possible extensions, shortcomings, and policy implications are described in Chapter 6. Chapter 7 concludes the thesis.

Chapter 2

Literature review

This chapter starts by presenting stylized facts about depression and its epidemiology. Subsequently, it explores the impact of depression on the elderly. Following this, the two main determinants investigated in this thesis - state dependence and income & wealth - are introduced. Lastly, other determinants of depression, widely addressed in the literature are discussed, including age, gender, marital status, education, work situation, family structure, health & habits & activity, and country.

2.1 Stylized facts/Epidemiology

Depressive disorders have consistently ranked within the top three causes of non-fatal health burden worldwide over the past three decades (Vos *et al.* 2017). The emphasis on depression is more important than ever, as per OECD and European Commision (2022) findings, the prevalence of depressive symptoms doubled since the onset of the COVID-19 pandemic. WHO ranks depression as the single largest contributor to global disability using the years lived with disability metric (YLDs) and estimates that 3.8% of the global population suffers from depression, with the rate increasing to 5.7% among adults older than 60 years (WHO 2023).

Depression is often underdiagnosed due to the stigma surrounding mental health and the episodic nature of the condition, where severe episodes can quickly shift to periods of improvement, leading individuals to forgo seeking care. According to Faisal-Cury *et al.* (2022) the underdiagnosis ranges from 8.5% to up to 50%.

The issue of underdiagnosis is important, given the existence of effective treatment plans for depression (Cuijpers *et al.* 2020).

As reported by Eurostat, 21.1% of the total population living in the EU-27 are citizens aged 65 or older. Because of the ever-increasing longevity and steady decline in fertility rates, this share is expected to reach 29.4% of total EU population by 2050. In absolute terms, we expect that this age group will expand from 94 million to 130 million (Eurostat *et al.* 2020).

According to Luppa *et al.* (2008) depressed elderly individuals incur significantly higher direct costs than their nondepressed counterparts of the same age, this relationship persists even after controlling for chronic medical illness, cognitive functions, and sociodemographic characteristics. This renders them more prone to elderly poverty and adversities associated with it. The incidence of major depression is higher among older adults receiving medical and surgical care during hospitalization. Furthermore, the highest prevalence of depression is observed among individuals residing in long-term care facilities (Blazer 2003).

2.2 Depression and how it affects the elderly

Depression constitutes a severe mental disorder with detrimental impacts on one's emotions, cognition, and behavior. Manifesting through a spectrum of varying symptoms which include:

- Profound feeling of sadness
- Loss of interest in living and everyday activities
- Weight fluctuations not caused by change of diet
- Disturbance of natural sleep pattern
- Increased fatigue
- Feelings of worthlessness or inappropriate guilt
- Irritability
- Impaired cognitive and decision making abilities
- Contemplation of death or suicide

- Suicide attempts

Fortunately, through accurate diagnosis and effective treatment, the majority of individuals diagnosed with depression can successfully overcome the condition (WHO 2012).

Disparities exist in the manifestation of depression between the elderly and younger generations. Older individuals are more prone to encountering symptoms such as sleep disturbance, increased fatigue, loss of interest in living and hopelessness about the future. On the other hand, they exhibit a lower likelihood of experiencing emotions like sadness, worthlessness, or guilt compared to younger generations (Fiske *et al.* 2009). Regarding gender differences in experienced depressive symptoms among the elderly, a significant distinction emerges: elderly women more frequently encounter appetite disturbances, whereas elderly men tend to experience heightened levels of agitation (Kockler & Heun 2002).

Depression is a major risk factor for disability and mortality in older patients even if controlled for other factors that are usually connected to both such as smoking or cognitive impairment. Blazer *et al.* (2001) suggest that depression might affect mortality through many independent pathways which may be leading to double feedback loops. Cognitive impairment, including conditions like dementia or Alzheimer's disease, frequently coexists with depression in the elderly. Individuals facing both conditions face increased risk of adverse outcomes. Treatment is often complicated by cognitive impairment resulting from depression, potentially resulting in continuous problems with both mood and cognition (Steffens & Potter 2008).

Depression can also aggravate functional impairments linked to physical illness, hinder treatment and rehabilitation efficacy, and contribute to a decline in physical capabilities (Mogga *et al.* 2006), while also decreasing the overall quality of life among the elderly (Fiske *et al.* 2009).

Kiecolt-Glaser & Glaser (2002) discuss how biological conditions linked to age-related diseases, including cardiovascular disease, certain cancers, arthritis, and type 2 diabetes, are associated with depression. They also highlight that depression negatively impacts the healing process of wounds and prolongs infections. Consequently, they argue that the interaction between aging and depression heightens the risks of morbidity and mortality among the elderly.

Suicide is an exceptionally dreadful potential effect of depression. Over the course of an individual's life, among those who exhibited suicidal tendencies and required inpatient care, approximately 8.6% will commit suicide. For those who required inpatient care due to depression but did not show suicidal tendencies, the rate is around 4.0%. Among individuals who did not need inpatient care, the rate drops to 2.2%. In contrast, the general population has a suicide rate close to 0.5% (Bostwick & Pankratz 2000). This raises a critical question: how many individuals in the general population, potentially contributing to the 0.5% suicide rate, are suffering from undiagnosed depression?

To offer an alternative perspective, it is important to recognize that a significant majority of individuals who die by suicide were affected by depression. Approximately 85% of older adults who died by suicide had been diagnosed with depression. Furthermore, suicide among older adults exhibits a stronger association with depression compared to suicide in any other age group (Conwell & Brent 1995).

2.3 State dependence, wealth and income

2.3.1 Income & Wealth

The relationship between income and depression among the elderly is quite established by many years of research. For this reason, this section will focus more on the impact of wealth on elderly depression. Low income is very often mentioned as a major risk factor when it comes to elderly depression (Blazer *et al.* 1991; West *et al.* 1998; Yaka *et al.* 2014).

Semyonov *et al.* (2013) report that the positive association between wealth and health holds even after controlling for socio-demographic attributes and household income. Suggesting that wealth could be an important driver of elderly depression. Wealth can function as a protective buffer when individuals experience a health decline. Those with wealth exceeding the median exhibit a significantly smaller decrease in well-being after encountering a new disability compared to counterparts with lower wealth. This phenomenon could be really important in the context of developed European countries, where many aging Europeans may face health deterioration, and sufficient wealth could serve as a protective factor against the development of depressive symptoms (Smith *et al.* 2005).

Schwandt (2018) presents compelling evidence indicating that positive wealth shocks have significantly positive impacts on the health outcomes of stock-holding retirees in the United States. The study reveals that a 10 percent wealth shock is correlated with a 2–3 percent improvement in physical, self-reported and mental health. McInerney *et al.* (2013) establishes a similar relationship while examining the impact of the 2008 stock market crash. The study reveals a connection between decreased wealth, heightened prevalence of depression, and increased usage of antidepressant drugs, particularly among individuals with substantial exposure to the stock market.

Back & Lee (2011) report gender differences in the impact of wealth and income on depression. Specifically, income is notably linked to depression among elderly women, whereas wealth emerges as a significant predictor of depression among elderly men.

Kourouklis *et al.* (2020) focus on investigating the impact of income and wealth across various regions in Europe. The study reveals that income and wealth inequalities are most pronounced in economically disadvantaged regions and areas with weaker welfare systems. Additionally, the study reports that income consistently emerges as a stronger predictor than wealth across all examined countries.

2.3.2 History of depression and state dependence

Numerous prior studies consistently identify a history of depression as one of the most significant predictors of elderly depression (Cole *et al.* 1999; Cole & Dendukuri 2003; Beekman *et al.* 1995; Djernes 2006). Approximately 50% of elderly individuals experiencing depression persist in their depressive state over the following 2-3 years. The impact of prior depression is not uniform, as the severity of depression at baseline strongly correlates with future persistence (Cole *et al.* 1999; Gallagher *et al.* 2013).

The robust presence of this persistence implies that depression is not merely a temporary or transient state. Depression needs to be understood as not only an outcome of an individual's current circumstances, but also as an outcome of their history and and latent characteristics that are impossible to be uncovered by current data collecting techniques. Individuals with a history of depression may have a predisposition to recurrent depressive episodes, emphasizing the importance of accounting for this factor when investigating determinants of elderly depression.

The importance of state dependence is not limited to depression and has already been researched in other domains of health economics. For instance, Nargis *et al.* (2022) utilize dynamic models to capture state dependence in smoking. They have shown that smoking habits persist over time due to the addictive nature of nicotine and behavioral reinforcement, with significant economic losses attributed to smoking-related illnesses. Similarly, Hasin *et al.* (2007) demonstrate through extensive statistical analysis that individuals with a history of alcohol abuse are significantly more likely to relapse even after periods of abstinence, with alcohol dependence associated with a higher prevalence of psychiatric disorders and disabilities. Obesity, another significant health issue, also shows state dependence. Obesity tends to persist due to a combination of metabolic, lifestyle, and environmental factors. About 11.4% to 11.8% of current weight is influenced by past weight, while declines in physical activity accounted for about 6.1% of weight gain and dietary changes contributed 2.9-3.8% to weight gain over a 15-year period. These results show the importance of state dependence and highlight the importance of early interventions when it comes adverse health situations (Ng *et al.* 2010).

2.4 Other determinants of depression

Current research has identified various determinants of depression among older Europeans. However, these determinants have often been studied in isolation due to limitations in data availability or a lack of comprehensive analyses.

2.4.1 Age

Age stands out as one of the foremost factors influencing both depression and elderly depression. Despite the considerable attention this topic has received, research outcomes continue to vary among scholars, and numerous hypotheses persist regarding this phenomenon.

According to Zhao *et al.* (2012), in their meta-analysis focusing specifically on age and risk of depression among the elderly, age is acknowledged as an important risk factor for depression, the risk steadily increases within the age range of 55-89 and plateaus when individuals reach 90 years of age.

Stordal *et al.* (2003) reached a similar conclusion, identifying a linear increase in the prevalence of depression with advancing age. These findings remained consistent even after controlling for various variables connected to health impairments, educational background, gender, sociodemographic variables, and other health-related behaviors, including smoking or regular alcohol intake.

On the contrary, Henderson *et al.* (1998) asserts that depressive symptoms show a decrease with advancing age in both male and female populations. Although the paper presents compelling evidence supporting this claim, the robustness of the findings may be questioned due to the cross-sectional nature of the observations. Cohort effects, rather than age alone, may account for the observed decline in symptoms, suggesting that other factors contribute to this phenomenon. Additionally, the phenomenon of selective mortality is a source of potential bias, suggesting that the potential respondents that would report higher prevalence of depression symptoms already died at younger ages compared to their more advantaged (not depressed) peers.

The phenomenon highlighted at the start of this sub-section could be untangled by focusing on differences in methodologies. Recent research suggests that discrepancies in patterns of age-related differences in psycho-social adjustment across studies may be attributed, at least in part, to mode effects. Particularly, studies employing data collection modes with increased direct interviewer contact (e.g., in-person interviews) tend to reveal age-related decreases in reports of depressive symptoms, while those utilizing less direct contact modes (e.g., questionnaires) are more inclined to indicate age-related increases (Luong *et al.* 2015).

2.4.2 Gender

According to WHO (2017), the prevalence of depression is higher for women in all age cohorts and in all regions compared to their male counterparts.

Cole & Dendukuri (2003) identify that being a women is one of the 5 most significant risk factors when it comes to elderly depression. This assertion aligns with the findings of Djernes (2006) and Schmitz & Brandt (2019), the latter of which also highlights notable variations in the depression gender gap across European countries.

Acciai & Hardy (2017) also explored the gender gap in elderly depression. After adjusting for factors such as marital and employment status, education, wealth, and other health-related variables, the study concluded that only a portion of the gap could be explained by these compositional differences. In an attempt to investigate if the gender gap in elderly depression could be attributed to gender-specific response styles, proxy variables connected to respondent and gender-specific reporting behavior were introduced into the model. However, the inclusion of these variables did not yield any significant effects. The study also examined how genders react differently to adverse situations. Contrary to expectations, they found that women exhibit lower reactivity to adverse situations. This implies that, even though women are more likely to face challenging circumstances, those in less secure situations report fewer depressive symptoms than similarly challenged men.

Van de Velde *et al.* (2010) assert that men are more significantly affected by the loss of a partner, with both widowhood and singlehood posing more substantial risks for depression in men compared to women. In contrast, Schaan (2013) reports no statistically significant interaction between gender and widowhood concerning depression risks. This finding is consistent with Schmitz (2021), who concludes that gender disparities are absent in the impact of widowhood on depression among the elderly. Notably, loneliness stands out as a primary driver of these negative effects, overshadowing the influence of reduced financial resources.

Van de Velde *et al.* (2010) provides additional evidence supporting the gender gap in depression and proposes various channels that may contribute to this phenomenon. The key finding suggests that, although both genders experience a reduced likelihood of depression in favorable socioeconomic settings, education emerges as a more influential predictor for women, suggesting potential disparities in labor market outcomes. Furthermore, while emphasizing that socioeconomic status is the primary driver of depression among Europeans, the study notes substantial variations in the size of this effect across different European countries.

The exploration of gender inequality and cross-country variations in depression gender gap is further advanced by Bracke *et al.* (2020). Their findings indicate that social inequality between men and women is a significant concern. In nations where women have limited power and fewer opportunities, depression occurs more frequently, and its symptoms are more severe. This increased frequency is especially observed among the elderly and even more so in elderly women. Consequently, the mental health of older women in countries characterized by gender inequality is severely impaired.

Kuehner (2003) argues that while recognizing various contributors to the gender gap in depression, there's a need for integrated models considering psychological and psychosocial factors. Moreover, there is a need to reevaluate current diagnostic tools and classification systems, as they may currently exhibit a bias toward recognizing 'female' symptoms over 'male' symptoms.

2.4.3 Marital status

The current literature widely supports the idea that having a spouse helps lower the likelihood of depression in elderly individuals. Older adults with spouses often experience fewer signs of depression compared to those who are single or widowed. This phenomenon is probably explained by the emotional and social support provided by long-term partners. Having a spouse also brings practical benefits in dealing with the challenges of aging. Daily activities, healthcare, and financial responsibilities can be shared between partners, making it easier for individuals to handle the challenges of getting older (Prince *et al.* 1999a; Yaka *et al.* 2014; Zhang & Li 2011).

Pascual *et al.* (2019), proposes that being in a long-term relationship can serve as a double-edged sword. When one spouse experiences poor mental health, such as depression, the other may face a significantly decreased quality of life. This can be intuitively understood because the additional responsibility of caring for a mentally unwell spouse can be a significant burden, leading to adverse effects on the caregiver.

The impact of widowhood is not homogeneous, Carr *et al.* (2000) discovered that the negative effects of widowhood are greater among individuals who were reliant on their spouses and those who had a closer relationship with their spouse. The relationship between marital quality and the impact of widowhood on depression is further explored by Schaan (2013). Firstly, they demonstrate that individuals reporting higher marital quality show greater growth in depressive symptoms after losing their spouse compared to those reporting lower marital quality. Secondly, they provide evidence suggesting that non-caregiving individuals face a higher risk of depressive symptoms after becoming widowed, implying that caregivers may anticipate the loss of a loved one better, and the end of caregiving may lessen the negative effects of losing a spouse.

2.4.4 Education

Education is frequently examined in studies investigating the determinants of elderly depression. Sözeri-Varma (2012) identifies lower educational attainment as one of the top eight risk factors for elderly depression, a sentiment told by several other studies (Chang-Quan *et al.* 2010b; Yaka *et al.* 2014; Bjelland *et al.* 2008), suggesting that lower-educated elderly individuals may face an elevated risk of depression due to limited economic opportunities, fewer social connections, and disparities in accessing quality healthcare and mental health services.

On the contrary, some studies such as those by Cole & Dendukuri (2003) or Buys *et al.* (2008) propose that education is not statistically significant. However, it is plausible that these results stem from methodological shortcomings, such as focusing on a specific subgroup of the elderly or inadequately designing the research framework. An intriguing finding by Back & Lee (2011), suggests that education is a statistically significant predictor of elderly depression only for women.

2.4.5 Work situation

Unemployment among older individuals is widely acknowledged as a significant risk factor for depression in the existing literature (Yaka *et al.* 2014; Sidik *et al.*

2004).

Hyde *et al.* (2015) investigated the impact of involuntary retirement on depression. The study's results indicate that individuals who experienced involuntary retirement are over three times more likely to report major depression than those who voluntarily left work. This finding holds considerable economic significance, persisting even after controlling for various factors related to individuals' lives.

Choi *et al.* (2013) took a very interesting approach by examining the relationship between five different productive activities of the elderly (paid work, formal volunteering, caregiving, informal helping, and caring for grandchildren) and depression. According to the results, engaging in formal volunteering, paid work, and informal helping significantly reduces the likelihood of experiencing depression. In contrast, caregivers face a higher risk when it comes to elderly depression.

2.4.6 Family structure

In general, having children is commonly perceived as a protective factor against elderly depression by the current literature, however in the past, the general believe was that childlessness has no impact on individuals mental health (Koropeckyj-Cox 1998).

Buber & Engelhardt (2008) conducted an analysis examining how the number of children, their proximity to parents, and the frequency of contact impact the mental health of elderly individuals. The results confirm, that childless individuals face an increased risk of depression. However, a significant double-edged phenomenon is presented in the study — elderly individuals with children, but limited contact with them, report even more depressive symptoms, suggesting that having children can also be a source of traumatic dispute. The authors also claim that although the effect of children is statistically significant, it is not as substantial as the impact of marital status, as discussed in section 2.4.3. This is likely because individuals spend the majority of their elderly life with a spouse rather than with their adult children.

Kruk & Reinhold (2014) pursue an interesting research avenue by examining the impact of the number of biological children on the mental health of elderly Europeans. They do so by introducing variables indicating whether the first two births are multiple births and whether the first two children share gender. Two notable findings emerge: first, the transition from one child to two children has no negative effects on parents. Second, for women, experiencing a twin birth during the second childbirth increases the risk of depression later in life by up to 20% compared to mothers with two children from separate births; however, no statistically significant effect is observed for men.

A noteworthy study from China by Jia (2020) investigates the impact of the frequency of visits and the monetary value of gifts given by children to their parents on the mental health of the elderly. The study reveals a statistically significant negative association between the frequency of visits and the level of depression among the elderly. In contrast, the level of depression does not seem to be significantly affected by monetary support received by parents.

2.4.7 Health & Habits & Activity

The literature on health and its association with the risk of depression in later life consistently acknowledges two primary research avenues. The first explores the impact of the presence and number of chronic diseases on the risk of depression among the elderly. The second avenue focuses on self-perceived health. Both of these characteristics significantly influence the risk of depression. Individuals reporting poorer self-perceived health and a greater number of chronic illnesses are at a higher risk of experiencing depression in later life compared to their healthier peers. When comparing the two factors, it is observed that poor self-reported health status exhibits a stronger association with depression than the presence of chronic illnesses (Chang-Quan *et al.* 2010a; Beekman *et al.* 1995; Cole & Dendukuri 2003; Yaka *et al.* 2014).

It is acknowledged that lifestyle factors related to health, such as smoking or the level of alcohol consumption, can potentially influence depression among the elderly, though findings in the literature are not consistently conclusive suggesting that the effects are not on the surface level. Weyerer *et al.* (2013) report a significant and robust association between smoking and depression among primary care patients aged 75+, with no observed relationship with alcohol consumption. Shahab *et al.* (2015) present an intriguing phenomenon from the English Longitudinal Study of Ageing - after modelling depression and smoking concurrently, they conclude that depression may act as a barrier to quitting smoking, but quitting smoking does not have a long-term impact on elderly depression. Cheng *et al.* (2016) report, based on their two-wave survey, that baseline drinkers and smokers are less likely to develop depression, and vice versa; individuals experiencing depression in the first wave are less likely to initiate drinking or smoking compared to their nondepressed peers. They explain the findings by suggesting that cultural factors and different motivations for smoking and drinking, such as social bonding rather than individual mood regulation, play a significant role in this relationship.

Physical activity is linked to reduced levels of depression among the elderly, and it is suggested that physical activity should be implemented as a preventive measure for age-related diseases including depression (Teixeira *et al.* 2013; Nelson *et al.* 2007). In a comprehensive three-year longitudinal study in Korea, Roh *et al.* (2015) focused on not only physical, but also social and religious activities. They concluded that participation in these activities was associated with a decreased risk of depression in the elderly. Notably, individuals engaged in at least two of these activities faced an even smaller risk of depression compared to those involved in only one. Croezen *et al.* (2015) argue that the impact of social participation on depression is nuanced, with the direction and strength varying based on the nature of the social activity. While participation in religious activities had a positive effect, engagement in political or community activities showed an increase in depressive symptoms in later years.

2.4.8 Country

Various sources consistently emphasize the influence of different country-specific factors on elderly depression, implying that differences in culture, welfare regimes and other nation-specific characteristics in understanding the determinants of depression among older individuals (Copeland *et al.* 1999; Horackova *et al.* 2019). Notably, Kourouklis *et al.* (2020) highlights more pronounced income and wealth effects in central, southern, and eastern European regions, with comparatively lower effects observed in Nordic countries. Additionally, Schmitz & Brandt (2019) propose variations in the gender gap related to depression, noting the smallest gap in northern countries and the largest in southern countries.

Regional differences can also be observed in persistence of depression - France, Italy and Belgium are associated with increased persistence (Gallagher *et al.* 2013). Investigating socioeconomic inequalities in the life outcomes of older Europeans, Niedzwiedz *et al.* (2014) reveal substantial differences associated with diverse welfare regimes. Notably, the disparities are minimal in Scandinavian and Bismarckian regimes, whereas they are more pronounced in Southern and post-communist regimes.

Horackova *et al.* (2019) reports prevalence rate across european regions: 17 % in Scandinavia, 26% in Western Europe, 32% in central and Eastern Europe and 35% in Southern Europe. The study places significant emphasis on the gap in mental health service utilization, defined as the proportion of individuals with a diagnosable mental health disorder who do not seek mental health services.This gap is reported to be 83% in Scandinavia, Central and Eastern Europe, and 76% for the elderly in Western and Southern Europe. Aligning with the findings of Park *et al.* (2015), both studies highlight the importance of reducing social stigma associated with seeking professional help for depression and mental illnesses, emphasizing the need to promote help-seeking behaviors among older adults.

Chapter 3

Data

This chapter will first present the dataset used for the analysis. Next, the methodology of imputations and other data treatments will be discussed. Consequently, the dependent variable of depression will be presented in detail. Lastly, the independent variables, along with their distributions and economic rationale, will be introduced.

3.1 Data set

All data used in this thesis come from the Survey of Health, Ageing and Retirement in Europe (SHARE), the largest panel dataset providing internationally comparable longitudinal microdata. SHARE started in 2001 and currently includes 29 participating countries. As of now, nine waves of data have been collected and processed, however this thesis utilizes eight of those waves as wave three had a different structure and a significant number of missing observations. SHARE tracks a wide range of variables from different domains of individuals' lives, including health, biomarkers, sociodemographic characteristics, socio-economic status, and social and family networks.

SHARE data is collected every other year and adheres to high quality control standards. This high quality is achieved through Computer-Assisted Personal Interviewing (CAPI). CAPI involves face-to-face interviews conducted using laptops equipped with CAPI software. The questionnaire is first prepared and then translated into all required languages, with adjustments made for country-specific variables to ensure cross-country comparability (Börsch-Supan *et al.* 2013).

Participants younger than 50 were excluded from the sample, as they were included only because they were married to someone 50 or older and are not considered elderly Europeans for the purpose of this study.

3.2 Imputations and other data adjustments

Most of the variables used for estimations in this thesis come from EasySHARE. EasySHARE is a smaller dataset with many advantageous features, including pre-transformed variables ready for research and minimal missing observations. In addition to EasySHARE, I will use specific SHARE datasets focusing on wealth and health, as EasySHARE does not sufficiently cover these domains for the objectives of this thesis.

SHARE uses imputations to minimize the number of missing observations. Imputing variables is a statistical method to estimate missing data entries when actual responses are unavailable. This approach results in a less biased dataset by estimating missing values based on respondents most similar to those with missing responses. In EasySHARE and SHARE, household wealth and income variables are imputed to provide more observations. SHARE employs two imputation methods: fully conditional specification (FCS) and the hot-deck method, depending on the prevalence of missing responses. These methods reduce bias and ensure more complete data for analysis (Trevisan *et al.* 2015).

3.3 Depression as the dependent variable

This subsection introduces the dependent variable of the thesis, a binary indicator of whether an individual is depressed. This variable is based on the EURO-D scale, collected as part of the mental health module in SHARE. The EURO-D scale, developed by Prince *et al.* (1999b), is a common depression symptom scale that enables the comparison of various depression risk factors across different research entities. The EURO-D scale is a number between 0 and 12 indicating how many symptoms of depression the respondent suffers from. The symptoms include: depressed mood, pessimism, wishing death, self blame, trouble sleeping, loss of interest, irritability, loss of appetite, fatigue, difficulty concentrating, no enjoyment and tearfulness. The particular questions which determine the number of symptoms the respondent suffers from are presented in the appendix A.1.

My dependent variable indicating whether an individual is depressed has a value of "not depressed" if the individual has 3 or fewer symptoms at the time of the interview, and "depressed" if they have 4 or more depressive symptoms. The threshold of 4 symptoms is commonly used in the literature, as seen (Horackova *et al.* 2019; Prince *et al.* 1999b; Kourouklis *et al.* 2020). This threshold is considered the optimal cut-off point for identifying respondents who would most likely be diagnosed with depression using a more sophisticated approach.

Figure 3.1 shows the distribution of the EURO-D scale across observations.

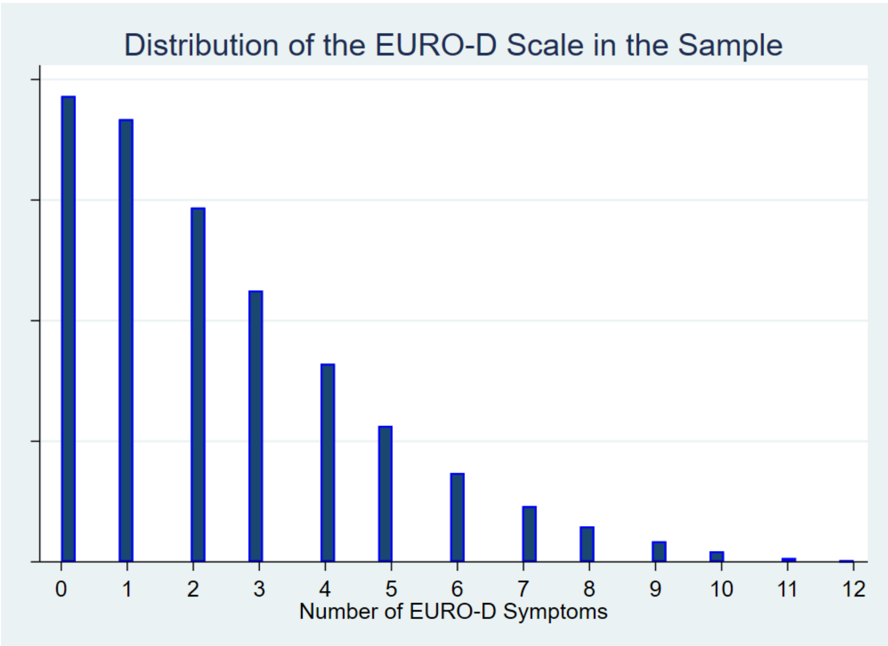

Figure 3.1: Distribution of the EURO-D scale

Table 3.1 present the distribution of the dependent variable. We can see that around a quarter of respondents are depressed at the time of interview.

Table 3.1: Distribution of the dependent variable

Depression	Frequency	Percentage
0	254 440	73.60
1	91 288	26.40

3.4 Independent variables

The goal of this subsection is to introduce the independent variables chosen for my analysis. The selection was based on data availability, theoretical and economic rationale, and empirical evidence from existing research, as discussed in Chapter 2. Each variable's distribution will be presented and discussed, along with its expected economic effect on the dependent variable.

Respondents' age at the time of the interview is included as an independent variable. The age distribution is shown in Figure 3.2. Age is expected to impact the probability of depression as it relates to many important life aspects. Although factors like physical health decline, retirement, and decreased leisure funds are accounted for by other variables in the regression, age is still expected to influence the reduction in day-to-day activities and the loneliness from losing family and friends. Therefore, advanced age is expected to be a significant risk factor for elderly depression. Age squared will be included in the regression to account for the likely non-linear effect of age. The average age of the respondents is 67.55 years, with a median age of 66.8 years. The maximum age of a respondent is 105.7 years.

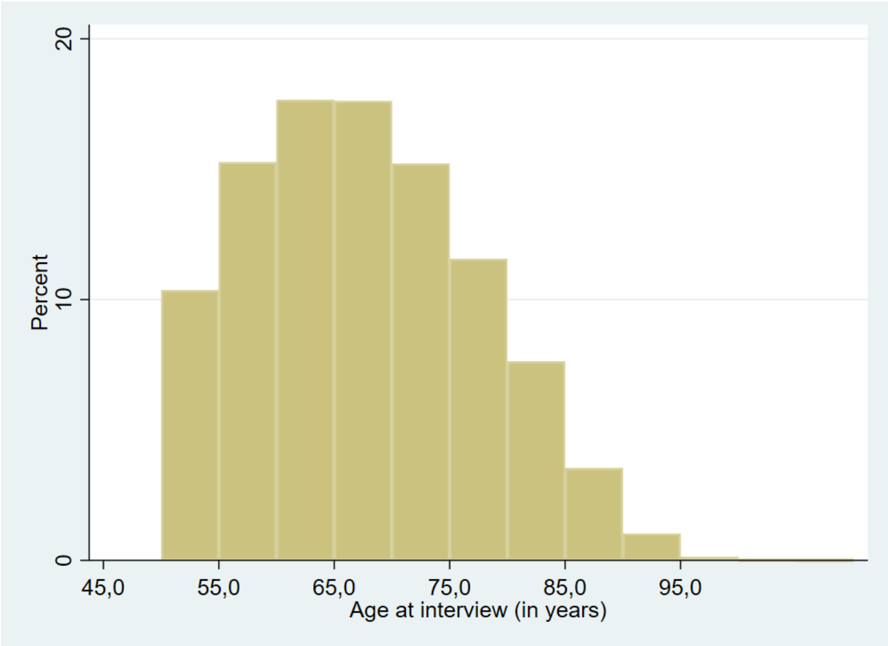

Figure 3.2: Histogram of Age at interview

Education of the respondent is represented in the model by a categorical variable with levels of: "none or primary", "secondary", "tertiary". The variable was created from the more detailed ISCED-97 categories. The distribution of a simple categorical education variable is shown in table 3.2. Education is expected to serve as a protective factor against elderly depression by enhancing cognitive reserve and problem-solving skills, which can delay cognitive decline and provide resilience against depression. Additionally, educated individuals typically have stronger social networks and greater community involvement, providing emotional support and reducing feelings of loneliness.

Table 3.2: Distribution of education in the sample

Education category	**Frequency**	**Percentage**
none or primary	72 993	21.11
secondary	196 026	56.70
tertiary	76 709	22.19

In figure 3.3 we can observe the distribution of the binary depressed variable across the countries in the sample. This variation across countries motivates the use of country-specific dummies in the regression. The inclusion of country-specific dummy variables will enhance the results as it will capture some of the country-level heterogeneity that is expected to be present. A total of 28 dummy variables will be used corresponding to countries in figure 3.3. Even though the countries share a continent and many are part of the EU, they still differ significantly in social support systems, healthcare policies, and retirement benefits, all of which can heavily affect the mental health of the elderly. [1]

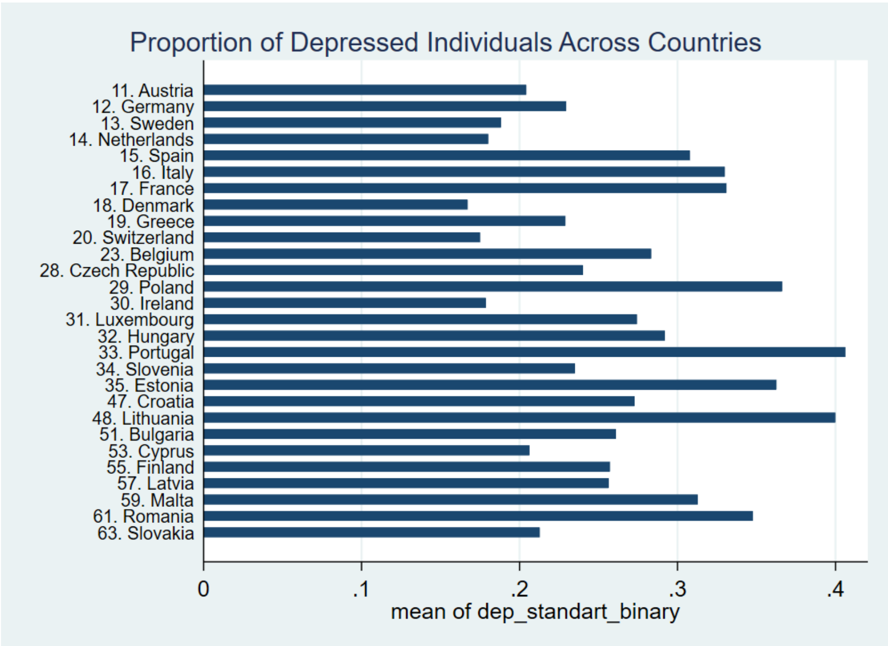

Figure 3.3: Proportion of depressed individuals across countries

Household size is expected to affect elderly depression, although the direction of the effect is difficult to predict. On one hand, larger household sizes can increase economies of scale - reduce spending per member, and provide more opportunities for support and decreased loneliness. On the other hand, controlling for wealth and income, a larger household size means more people to support with the same resources. I will use the log transformation of household size in the regression as I suspect strong diminishing marginal effects and to reduce skewness. Figure 3.4

[1] Different methods of controlling for country-specific differences were considered. For example, sorting the countries into different groups; however, finding the correct methodology for grouping the respective countries with regard to depression is beyond the scope of this thesis.

shows the distribution of household size, revealing that the majority of households have two or less members.

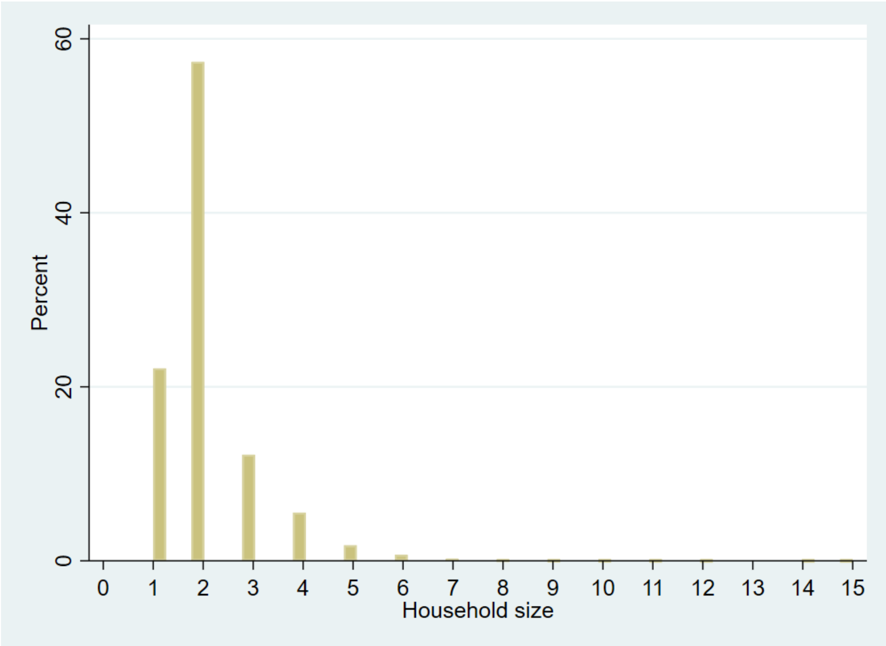

Figure 3.4: Distribution of household size

Table 3.3 shows the distribution of gender in the sample, with nearly 56% of respondents being female. This is likely due to the longer life expectancy of females. Based on the literature, females are expected to have a higher probability of elderly depression. Even though we control for many variables related to health, financial status, and sociodemographic characteristics, being female is still expected to be a risk factor for elderly depression due to nuanced effects that cannot be captured by objective variables.

Table 3.3: Distribution of gender

Gender	**Frequency**	**Percentage**
male	152 688	44.16
female	193 040	55.84

Marital status is strongly supported in the literature as a significant driver of elderly depression (Van de Velde *et al.* 2010; Schmitz 2021; Schaan 2013). Significant differences are expected between individuals still living with their lifelong spouse and those who have lost their partner. Interaction terms between marital status and gender will be included to identify the most vulnerable groups of elderly individuals, for example Van de Velde *et al.* (2010) identified widowed man as the most vulnerable elderly. The distribution of marital status in the sample is shown in table 3.4.

Table 3.4: Distribution of marital status in the sample

Marital status	**Frequency**	**Percentage**
Married, living with spouse	236 160	68.31
Registered partnership	5 217	1.51
Married, separated from spouse	4 006	1.16
Never married	19 095	5.52
Divorced	29 299	8.47
Widowed	51 951	15.03

A categorical variable representing the number of children respondents have is also expected to affect depression among the elderly. Having children is generally considered a protective factor against depression, as more children can imply stronger family support and reduced depression. Table 3.5 presents the distribution of this variable.

Table 3.5: Distribution of number of children category

Number of children category	**Frequency**	**Percentage**
0	32 431	9.38
1	62 766	18.15
2	145 653	42.13
3+	104 878	30.34

The next variable of interest is a binary indicator of whether the household received any help from family outside the household, friends, or neighbors. Help in this context includes personal care (e.g., help with dressing, bathing, eating, getting out of bed, using the toilet), practical household assistance, and help with paperwork, such as settling financial or legal matters. The distribution of this variable in the sample is shown in table 3.6. This variable serves as a proxy for receiving social support, allowing exploration of the role of external support systems in the context of elderly depression.

Table 3.6: Distribution of number of children category

Did household receive help?	Frequency	Percentage
no	70 233	20.31
yes	275 495	79.69

Four variables related to respondents' health are included in the model. Depression itself is a health variable, but various health-related variables helps to capture all confounding factors. This ensures that the observed relationships between other variables and depression are not biased. Better health is expected to have a protective effect against depression.

Self-perceived health of a respondent is expected to be the strongest among the health variables, as it captures nuances that objective health measures might miss. The distribution of this variable is shown in table 3.7.

Table 3.7: Distribution of self perceived health in the sample

Self perceived health	Frequency	Percentage
Excellent	25 095	7.26
Very good	60 965	17.63
Good	131 324	37.98
Fair	95 683	27.68
Poor	32 661	9.45

More visits to a doctor in the past twelve months, as measured by a categorical variable, are suspected to indicate greater health issues and, consequently, a higher probability of depression.The distribution of doctor visits in the sample is presented in 3.8.

Table 3.8: Distribution of doctor visits in the sample

Doctor visits	Frequency	Percentage
never or once	74,949	21.68
twice or thrice	74,531	21.56
4-10 times	135,749	39.26
10+	60,499	17.50

The binary variable "overnight stay" indicates whether respondents have stayed overnight in a medical, surgical, psychiatric, or any other specialized hospital during the past twelve months. The economic rationale and expected effect are similar to those for doctor visits. The distribution of this variable is shown in 3.9.

Table 3.9: Distribution of overnight stay in the sample

Overnight stay	**Frequency**	**Percentage**
Yes	49,441	14.30
No	296,287	85.70

The number of chronic diseases the respondent suffers from is also included in the model. Due to changes in the list of diseases asked about in different waves, only the simplified variable from EasySHARE is used, which includes diseases consistently asked about across all waves. The chronic diseases counted include heart attack, high blood pressure or hypertension, high blood cholesterol, stroke or cerebral vascular disease, diabetes or high blood sugar, chronic lung disease, cancer or malignant tumor, stomach or duodenal ulcer, peptic ulcer, Parkinson's disease, cataracts, and hip or femoral fracture. The distribution of respondents' chronic diseases is shown in Table 3.10. Because strong diminishing marginal effects are suspected and because the distribution is so uneven, several transformations for this variable will be considered.

Table 3.10: Distribution of chronic diseases in the sample

Chronic diseases	**Frequency**	**Percentage**
0	122 486	35.43
1	106 391	30.77
2	66 418	19.21
3	32 553	9.42
4	12 428	3.59
5	4 056	1.17
6	1 089	0.31
7	251	0.07
8	50	0.01
9	5	0.00
10	1	0.00

The variable "job situation" is an important categorical variable in my analysis, generated from the question "In general, how would you describe your current situation?" The possible responses are: retired, employed or self-employed, unemployed, permanently sick or disabled, and homemaker.

I expect that disabled elderly will be at the greatest risk of depression. The response "unemployed" relates to respondents aged 50-65, as older respondents are usually retired. Therefore, those who identify as unemployed are expected to be at a greater risk of depression because being unemployed during productive years, when one needs to support oneself and possibly other household members financially, can significantly impact mental health.

An interesting aspect will be the estimate for the "retired" category, as it will capture the effect of retirement itself, indicating whether the benefits of free time and pension income outweigh the loss of activity and social networks typically associated with work. The distribution of job situations is presented in table 3.10.

Table 3.11: Distribution of job situation in the sample

Job situation	**Frequency**	**Percentage**
retired	209 970	60.73
employed or self-employed	86 045	24.89
unemployed	9, 22	2.61
permanently sick or disabled	10 386	3.00
homemaker	30 305	8.77

Housing situation captures the living arrangement of a respondent, indicating whether the respondent is a homeowner, a member of a cooperative, a tenant or subtenant, or living rent-free in a property not owned by them. The distribution of this variable is shown in table 3.12.

Table 3.12: Distribution of housing situation in the sample

Housing situation	**Frequency**	**Percentage**
Owner	264 934	76.63
Member of a cooperative	8 527	2.47
Tenant	50 344	14.56
Subtenant	1 852	0.54
Rent free	20 071	5.81

Subjective well-being is measured by a set of dummy variables indicating how well the individual's household can make ends meet: 'with great difficulty', 'with some difficulty', 'fairly easily', and 'easily'. The benefit of using this variable lies in its ability to provide nuanced information about respondents' financial situations, which fully objective variables like household wealth and income might miss. It is expected that feeling financially secure will serve as a protective factor against elderly depression. The distribution of this variable is shown in table 3.13.

Table 3.13: Distribution of making ends meet in the sample

Making ends meet	**Frequency**	**Percentage**
With great difficulty	35 637	10.31
With some difficulty	90 751	26.25
Fairly easily	108 449	31.37
Easily	110 891	32.07

Household net worth is the sum of total household net financial assets and household real assets. Net financial assets include all bank accounts, bonds, stocks, mutual funds, long-term investments, and liabilities. Real assets comprise the value of the owned main residence, mortgage on the main residence, secondary homes, owned businesses, and cars. Higher wealth is expected to serve as a protective factor against elderly depression. The mean household net worth is 260 609 euros, while the median is 150 675 euros, indicating a right-skewed distribution. The distribution of log-transformed household wealth is shown in Figure 3.5.

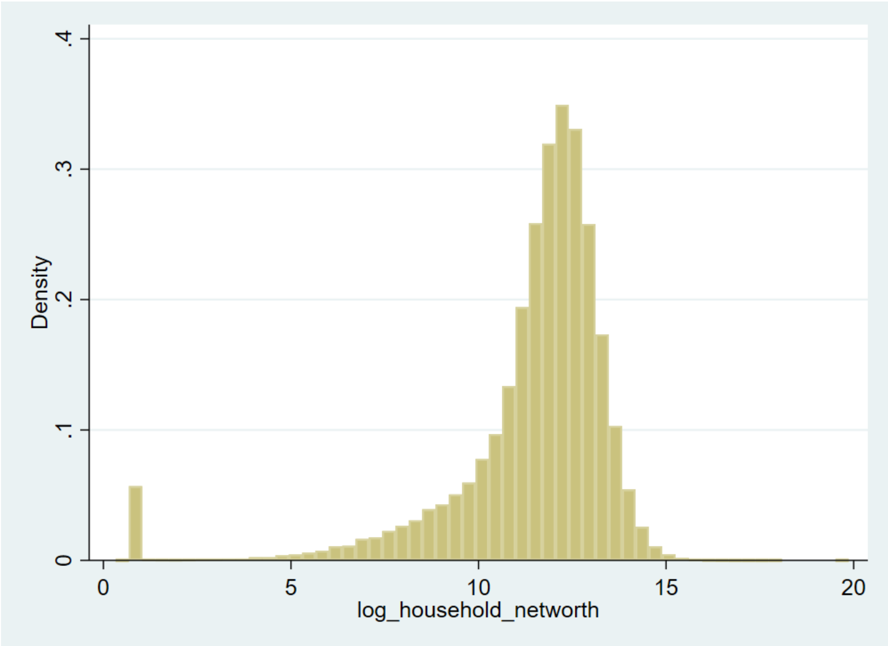

Figure 3.5: Histogram of log transformed household networth

High income is generally expected to be a protective factor against elderly depression. However, my primary interest is comparing the effects of income and household wealth. The mean household gross yearly income among respondents is 30,780 euros, while the median is 23,295 euros, indicating a similar right-skewed distribution as net worth. Similar to wealth, a log-transformed distribution of income is shown in Figure 3.6. The final transformations of the wealth and income variables will be thoroughly discussed in the results chapter.

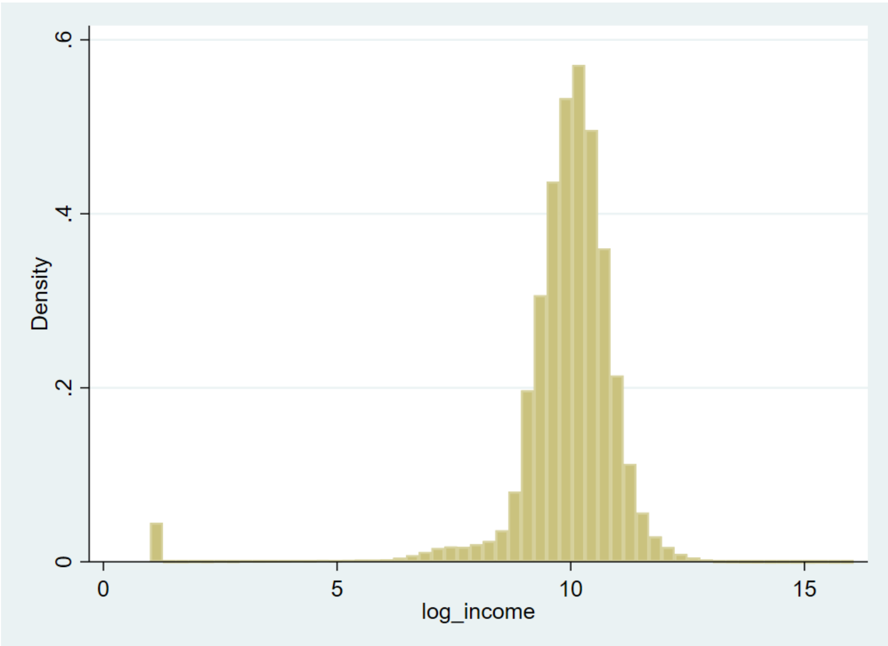

Figure 3.6: Histogram of log transformed household income

Chapter 4

Methodology

This chapter introduces the methodology of panel data logit models. First the static fixed effects logit model is introduced in Section 4.1. In Section 4.2, the features of the static random effects panel data model are described relative to the common features introduced earlier in the fixed effects model. In Section 4.3, the dynamic random effects model is described, and its advantages over the static random effects model are justified. Using multiple specifications allows us to assess the sensitivity of estimates to different modeling assumptions.

The static fixed effects and random effects models address unobserved heterogeneity in different ways. The fixed effects model controls for unobserved heterogeneity by allowing for individual-specific intercepts, effectively differencing out time-invariant characteristics, ensuring that any bias due to unobserved, constant factors is mitigated. On the other hand, the random effects model assumes that the unobserved individual-specific effects are random and uncorrelated with the explanatory variables. This assumption allows for the inclusion of time-invariant variables in the analysis and provides more efficient estimates compared to fixed effects model if the assumption holds true.

Unlike the static model, the dynamic random effects logit model includes a lag of the dependent variable, allowing it to examine the dependence of respondents' current state of depression on their past states of depression. Additionally, the dynamic model accounts for the initial condition using the Wooldridge method, addressing potential biases from the initial observation.

The dependent variable in this study is a binary variable indicating whether the respondent is depressed at the time of the interview, modeled as an unobserved latent variable denoted as y_{it}^*. In this case, the latent variable y_{it}^* is unobserved; instead, the number of symptoms from the Euro-d scale is observed. The binary outcome y_{it}^* is derived from the Euro-d scale such that:

$$y_{it}^* = \begin{cases} 1 & \text{if count of symptoms} \geq 4 \\ 0 & \text{otherwise} \end{cases}$$

This definition of the dependent variable is consistent across all presented models.

4.1 Static fixed effects logit

The static fixed effects logit of a latent dependent variable can be written as:

$$y_{it}^* = \alpha_i + \beta' x_{it} + \epsilon_{it} \qquad (i = 1, \dots, N; t = 1, \dots, T) \tag{4.1}$$

In Equation 4.1, x_{it} are the observed variables expected to affect depression among the elderly, ϵ_{it} is the individual and time-specific error term, assumed to be independently and identically distributed among observations and following a logistic distribution. Error term ϵ_{it} is also assumed to be independent of the observed variables x_{it}. The fixed effects model has no formal assumptions on unobserved heterogeneity parameter α_i. Instead, parameter α_i captures all time-invariant individual-specific effects, that vary across individuals but remains constant over time. These effects could be correlated with the regressors x_{it}.

If the assumptions about the error term hold, the probability of an elderly individual i being depressed in time period t, conditional on the regressors and individual-specific fixed effects, is given by the following expression:

$$P_{it} = P(y_{it} = 1 \mid x_{it}, \alpha_i) = \Lambda(\beta' x_{it} + \alpha_i) \tag{4.2}$$

where $\Lambda(z)$ denotes the logistic cumulative distribution function:

$$\Lambda(z) = \frac{1}{1+e^{-z}} \tag{4.3}$$

For a logistic regression model with the linear predictor $\beta' x_{it} + \alpha_i$, the probability can be written as:

$$P_{it} = \frac{1}{1+e^{-(\beta' x_{it}+\alpha_i)}} \tag{4.4}$$

The fixed effects logit model is estimated using conditional maximum likelihood, which conditions out the individual-specific effects α_i as described by (Chamberlain 1980). This method effectively controls for all time-invariant individual-specific characteristics, allowing for consistent estimation of the effects of the time-varying covariates.

The model is fitted via mentioned conditional maximum likelihood in STATA (StataCorp 2023a). More details about the formulas and particular methods used can be observed in (StataCorp 2023b).

4.2 Static random effects logit

Compared to Section 4.1 the static random effects logit imposes several restrictions on Parameter α_i and can be written as:

$$y^*_{it} = \alpha_i + \beta' x_{it} + \epsilon_{it} \qquad (i = 1, \ldots, N; t = 1, \ldots, T) \tag{4.5}$$

In Equation 4.5 similarly to fixed effects model, x_{it} are the observed variables expected to affect depression among the elderly, ϵ_{it} is the individual and time-specific error term, assumed to be independently and identically distributed among observations and following a logistic distribution. Error term ϵ_{it} is assumed to be independent of the observed variables x_{it}. Compared to the fixed effects model the random effect model poses several restrictions on unobserved heterogeneity parameter α_i. Parameter α_i is assumed to be independently and identically distributed following a normal distribution with mean 0 and variance σ^2_α, and assumed to be independent of x_{it} and ϵ_{it}.

Under these assumptions, the probability of an elderly individual i being depressed in time period t can be obtained by similar expression as in Section 4.1 by following Equation 4.2, Equation 4.3 and Equation 4.4.

In random effects models, unobserved heterogeneity α_i is treated as a random variable drawn from a distribution, usually with mean zero and variance σ_u^2. If α_i is uncorrelated with the independent variables, random effects provides more efficient estimates. In fixed effects models, unobserved heterogeneity α_i is treated as correlated with the independent variables, making fixed effects more consistent when random effects assumptions do not hold. The Hausman test is used to decide between fixed effects and random effects, which is further discussed in Section 5.2.

The model is fitted via maximum likelihood in STATA (StataCorp 2023a). More details about the formulas and particular methods used can be observed in (StataCorp 2023b).

4.3 Dynamic random effects logit

The dynamic random effects logit model extends the static specification by including the previous state of depression $y_{i,t-1}$ into the equation. The dynamic random effects logit model can be written as:

$$y_{it}^* = \alpha_i + \beta' x_{it} + \gamma y_{i,t-1} + \epsilon_{it} \qquad (i = 1, \ldots, N; t = 2, \ldots, T) \tag{4.6}$$

Here, x_{it} are the observed variables suspected to affect depression among the elderly, and $y_{i,t-1}$ is the indicator of depression in the previous period, capturing the persistence of depression over time. Parameter α_i is the unobserved individual-specific effect. Error term ϵ_{it} is assumed to be independent of the observed variables x_{it} and assumed to be independently and identically distributed among observations and following a logistic distribution.

In the dynamic model, it is crucial to address the initial condition problem, considering the correlation between the dependent variable in the first wave y_{i1} and the unobserved heterogeneity α_i. Failure to account for this correlation may lead to inconsistent estimation. This is because the initial value of the dependent variable is likely influenced by the same unobserved factors that affect subsequent values. Ignoring this relationship can bias the estimates of the dynamic parameters, as the initial condition is not truly exogenous. To handle the initial condition problem, we will adopt the Wooldridge method (Wooldridge 2005).

In this approach, we treat y_{i1} as a given variable and introduce a new parameter λ to account for the correlation between the unobserved individual-specific time-invariant effect, denoted as α_i, and y_{i1}. The unobserved individual effect α_i is modeled as:

$$\alpha_i = \tilde{\alpha}_i + \lambda y_{i1} \tag{4.7}$$

where $\tilde{\alpha}_i$ is the random effect that is uncorrelated with the initial condition y_{i1}. The parameter $\tilde{\alpha}_i$ follows the same assumptions as the random effect in the static model. Parameter $\tilde{\alpha}_i$ is assumed to be independently and identically distributed following a normal distribution with mean 0 and variance $\sigma^2_{\tilde{\alpha}}$, and assumed to be independent of x_{it} and error term ϵ_{it}.

The dynamic specification incorporates the previous state of depression ($y_{i,t-1}$), capturing the persistence of depression over time and providing a more realistic representation of the data. This allows for the assessment of how past depression influences current depression, which is crucial for understanding the dynamics of depression among the elderly.

If the assumptions about the error term hold, the probability of an elderly individual i being depressed in time period t, conditional on the regressors, previous depression state, and individual-specific random effects, is given by the following expression:

$$P_{it} = P(y_{it} = 1 \mid x_{it}, y_{i,t-1}, \alpha_i) = \Lambda(\beta' x_{it} + \gamma y_{i,t-1} + \alpha_i) \tag{4.8}$$

where $\Lambda(z)$ denotes the logistic cumulative distribution function:

$$\Lambda(z) = \frac{1}{1 + e^{-z}} \tag{4.9}$$

For a logistic regression model with the linear predictor $\beta' x_{it} + \gamma y_{i,t-1} + \alpha_i$, the probability can be written as:

$$P_{it} = \frac{1}{1 + e^{-(\beta' x_{it} + \gamma y_{i,t-1} + \alpha_i)}} \tag{4.10}$$

The dynamic random effects logit model is estimated using standard maximum likelihood, which incorporates the individual-specific effects α_i directly into the likelihood function. This method allows for the consistent estimation of the effects of the time-varying covariates and addresses the initial condition problem using the Wooldridge method (Wooldridge 2005).

The model is fitted via maximum likelihood in STATA (StataCorp 2023a). More details about the formulas and particular methods used can be observed in (StataCorp 2023b).

Chapter 5

Results

This chapter presents the results of the analyses. Firstly, the results of static random and fixed effects models will be presented, followed by the differences between them and the Hausman test results. Then, the dynamic specification and its value added over static models will be discussed.

All models share the same pool of explanatory variables, with exceptions due to model specificities, such as the addition of initial conditions and lagged dependent variables for the dynamic random effects logit model or the exclusion of time-invariant variables in the fixed effects model.

Selected results of the static models are in Table 5.1 and selected results of the dynamic model are in Table 5.2. The complete estimation results containing all estimates can be found in the appendix A.2 and A.3. The choice of which estimates to present in this section was based on their importance to the goals of this thesis and their statistical significance.

5.1 Static models

Table 5.1 presents the estimates of the static random effects logit and static fixed effects logit models. Baseline categories are included for the categorical variables. In the context of my dependent variable (depression), positive coefficients indicate factors that increase the log-odds of depression, while negative coefficients indicate factors that decrease the log-odds of depression. I will primarily focus on the estimates from the random effects model but will comment on the differences with the fixed effects model when relevant.

Table 5.1: Random-effects and Fixed-effects Logit regression Results

Variable	RE Estimates	RE SE	FE Estimates	FE SE
age_squared	0.0015***	0.0001	0.0020***	0.0001
age	-0.2062***	0.0086	-0.4392***	0.0334
Education				
None or primary	0 (base)		0 (base)	
Secondary	-0.1707***	0.0196	-0.2702	0.2846
Tertiary	-0.1872***	0.0246	0.7361	0.4643
Wave specific dummies				
wave_1	0 (base)		0 (base)	
wave_2	-0.1892***	0.0270	0.1937**	0.0781
wave_4	0.0837***	0.0252	1.1901***	0.2052
wave_5	0.0190	0.0250	1.4725***	0.2652
wave_6	0.0423	0.0252	1.8327***	0.3255
wave_7	0.0032	0.0349	2.1840***	0.3882
wave_8	0.0257	0.0271	2.5869***	0.4662
wave_9	0.1441***	0.0265	3.0893***	0.5314
Logarithm of household size	0.1493***	0.0214	0.2067***	0.0405
Partner or spouse in household				
Yes	0 (base)		0 (base)	
No	0.2715***	0.0327	0.3505***	0.0568
Gender				
Male	0 (base)		0 (base)	
Female	1.0034***	0.0178	(omitted)	(omitted)
Marital status and gender interactions				
Married, living with spouse	0 (base)		0 (base)	
Married, separated from spouse	0.2345**	0.0926	0.2847	0.2398
Divorced	0.1769***	0.0464	-0.3388**	0.1547
Widowed	0.3671***	0.0469	0.5231***	0.0978
Female × Married, living with spouse	0 (base)		0 (base)	
Female × Never married	-0.2929***	0.0597	-0.5928	0.3911
Female × Divorced	-0.2032***	0.0510	0.1198	0.2000
Female × Widowed	-0.3934***	0.0434	-0.4660***	0.0956
Number of children				

Continued on next page

Table 5.1: Random-effects and Fixed-effects Logit regression Results

Variable	RE Estimates	RE SE	FE Estimates	FE SE
0	0 (base)		0 (base)	
1	-0.0192	0.0283	0.1113	0.0734
2	-0.1289***	0.0268	0.0471	0.0743
3+	-0.0940***	0.0278	0.0487	0.0792
Outside help recieved				
Yes	0 (base)		0 (base)	
No	-0.4089***	0.0140	-0.2879***	0.0178
Self-percieved health				
Excellent	0 (base)		0 (base)	
Very good	0.2231***	0.0329	0.1255***	0.0428
Good	0.8427***	0.0312	0.5329***	0.0423
Fair	1.7923***	0.0325	1.1586***	0.0444
Poor	3.0717***	0.0369	2.0057***	0.0506
Doctor visits in last year				
Never or once	0 (base)		0 (base)	
Twice or thrice	0.0652***	0.0187	0.0025	0.0240
4-10 times	0.2645***	0.0175	0.1294***	0.0234
10+	0.5685***	0.0209	0.3625***	0.0283
Overnight hospital stay in last year				
Yes	0 (base)		0 (base)	
No	-0.2668***	0.0156	-0.2294***	0.0194
Number of chronic diseases				
None	0 (base)		0 (base)	
1	0.0948***	0.0153	0.1318***	0.0206
2+	0.2883***	0.0164	0.2890***	0.0238
Job Situation				
Retired	0 (base)		0 (base)	
Unemployed	0.3111***	0.0372	0.2801***	0.0524
Permanently sick or disabled	0.4120***	0.0337	0.2011***	0.0483
Housing situation				
Owner	0 (base)		0 (base)	
Member of a cooperative	0.1902***	0.0435	0.1895***	0.0733
Tenant	0.0321	0.0239	0.1250***	0.0478
Subtenant	0.1162	0.0766	0.2164**	0.1054

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Table 5.1: Random-effects and Fixed-effects Logit regression Results

Variable	RE Estimates	RE SE	FE Estimates	FE SE
Rent Free	0.0284	0.0282	0.1538***	0.0405
How complicated is it to make ends meet				
Great difficulty	0 (base)		0 (base)	
Some difficutlty	-0.5098***	0.0197	-0.2871***	0.0261
Fairly easily	-0.8287***	0.0215	-0.4452***	0.0295
Easily	-0.9249***	0.0237	-0.4618***	0.0328
Household networth category				
Very low	0 (base)		0 (base)	
Low	-0.0968***	0.0207	-0.0018	0.0281
Middle	-0.1554***	0.0229	-0.0156	0.0316
High	-0.1555***	0.0245	0.0056	0.0341
Very high	-0.0963***	0.0266	0.0912**	0.0380
Household income category				
Very low	0 (base)		0 (base)	
Low	0.0015	0.0177	0.0294	0.0230
Middle	0.0603***	0.0196	0.0618**	0.0256
High	0.0726***	0.0213	0.0503*	0.0282
Very high	0.0797***	0.0234	0.0590*	0.0314
Country specific estimates				
Austria	0 (base)		0 (base)	
Germany	0.1373***	0.0406	(omitted)	(omitted)
Sweden	0.3231***	0.0455	(omitted)	(omitted)
Netherlands	0.1021**	0.0472	(omitted)	(omitted)
Spain	0.4924***	0.0430	(omitted)	(omitted)
Italy	0.6795***	0.0420	(omitted)	(omitted)
France	0.8712***	0.0407	(omitted)	(omitted)
Denmark	0.1680***	0.0467	(omitted)	(omitted)
Greece	0.0714	0.0467	(omitted)	(omitted)
Switzerland	0.2801***	0.0485	(omitted)	(omitted)
Belgium	0.7015***	0.0396	(omitted)	(omitted)
Czech Republic	-0.0521	0.0418	(omitted)	(omitted)
Poland	0.5735***	0.0461	(omitted)	(omitted)
Ireland	0.2430	0.1251	(empty)	(empty)
Luxembourg	0.6769***	0.0653	(omitted)	(omitted)

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Table 5.1: Random-effects and Fixed-effects Logit regression Results

Variable	**RE Estimates**	**RE SE**	**FE Estimates**	**FE SE**
Hungary	-0.0025	0.0580	(omitted)	(omitted)
Portugal	0.7010***	0.0622	(omitted)	(omitted)
Slovenia	0.0710	0.0456	(omitted)	(omitted)
Estonia	0.3854***	0.0414	(omitted)	(omitted)
Croatia	0.0841	0.0522	(omitted)	(omitted)
Lithuania	0.8856***	0.0726	(omitted)	(omitted)
Bulgaria	-0.1934**	0.0972	(omitted)	(omitted)
Cyprus	-0.3444***	0.1126	(omitted)	(omitted)
Finland	0.5353***	0.0731	(omitted)	(omitted)
Latvia	-0.4379***	0.0765	(omitted)	(omitted)
Malta	0.9462***	0.0917	(omitted)	(omitted)
Romania	0.3910***	0.0758	(omitted)	(omitted)
Slovakia	0.2800***	0.0947	(omitted)	(omitted)
_cons	4.2488***	0.3129		
/lnsig2u	0.7070***	0.0158		
sigma_u	1.4240***	0.0113		
rho	0.3813***	0.0037		
Number of observations	345 728		123 199	
Degrees of freedom	84		56	

Note: *** p<0.01, ** p<0.05, * p<0.1

The estimates for age and its squared value are both statistically significant, suggesting a U-shaped relationship between age and depression. Initially, as age increases, the likelihood of depression decreases, but after a certain point, further increases in age are associated with an increasing likelihood of depression.

In the random effects model, this breaking point is at age 70. At age 70, most individuals have retired and lost their societal roles and responsibilities, leading to a potential lack of purpose and an increased risk of depression. Secondly, after age 70, the shrinking of social circles and loss of lifelong friends could significantly contribute to rising depression rates. The failure to keep up with modern means of communication and entertainment could also contribute to the rise of depression rate. Age of 70 could be the breakpoint where the supposed financial stability and free time gained through retirement are outweighed by the aforementioned negatives.

The fixed effects specification suggests a much steeper initial decline in depression likelihood compared to the random effects model. Although technically U-shaped, the effect is more accurately described as L-shaped, as the break point occurs at the unrealistic age of 110, with the probability dropping rapidly between ages 50 and 70. I attribute the difference between the random and fixed effects models to the fact that the fixed effects model omits many time-invariant variables, which may result in the model absorbing some of the influences of these omitted variables.

The effect of education is statistically significant, with higher education acting as a protective factor against elderly depression, this finding matches the current sentiment in the literature (Chang-Quan *et al.* 2010b; Yaka *et al.* 2014; Bjelland *et al.* 2008). Other methods of accounting for education were tested in previous regressions, like more detailed categorical variable or years of education. More detailed categorical variables, indicated that the subsequent education (compared to none/primary) has a substantial effect, while further education offers little to no additional benefit. Likewise, years of education did not bring any significant additional explanatory power.

Regarding the fixed effects, it is apparent that the estimates lack statistical significance. This is because only a small portion of the dataset experienced changes in this category between waves, effectively making it a time-invariant variable. Waves of the interview suggest a significant positive effect of COVID periods on depression. The wave collected in years 2021 and 2022 serves as a risk factor for depression as suspected by OECD and European Commision (2022). Similarly, years of economic downturn increase the probability of depression, estimate for wave 4 which was collected mainly in 2011, when the economy was still suffering from the European sovereign debt crisis, which started in 2009 is statistically significant and poses as a risk factor for depression. Years of economic prosperity - wave 2, collected in years 2006 and 2007 on the other hand suggests a significant protective effect against depression. Based on these results, it is evident that COVID-19, with its increased social isolation and more complicated access to healthcare, negatively affected depression among the elderly.

Household size significantly increase elderly depression. However, since we control for household total wealth and household total income, the main explanation for this observed result is that the household must care for additional inhabitants using the same resources. Similarly, if a respondent lives without a spouse or partner, they are likely in a household with one fewer inhabitant compared to a similar respondent who lives with a spouse or partner.

The variable may also capture protective effects such as economies of scale or the availability of in-house social support and help. However, these positive factors are outweighed by the financial stress that an increased household size brings. Several ways to including household size in the model were tested, including linear and categorical transformation. The log transformation provided the best fit because it captures the strong diminishing marginal effect of household size on depression risk, indicating that the impact of additional household members decreases as the household size increases.

Sharing a household with a partner either with or without marriage serves as a protective factor against depression. These findings are consistent with Prince *et al.* (1999a); Yaka *et al.* (2014); Zhang & Li (2011). This estimate complements the variables gender and marital status.

The estimates regarding gender and marital status indicate that women face a much higher risk of depression than men, consistent with Cole & Dendukuri (2003); Djernes (2006); Schmitz & Brandt (2019). Both the RE and FE models suggest that that being widowed or divorced negatively affects only males as the interaction term of marital status and women mitigates the negative effects for women, this was also presented by Van de Velde *et al.* (2010). However, the magnitude of these effects is negligible compared to the gender estimate.

Interestingly, the estimate for 'married, living separated from spouse' is not fully explained by the 'living with a romantic partner' variable, suggesting that respondents living with a long-term spouse face a lower risk of depression compared to those who, although living with a romantic partner, are separated from their spouse. similarly, a divorced respondent that lives with a partner that is not his spouse faces significantly higher risk of depression compared to a respondent that is married and living with his spouse. Overall, the most vulnerable groups among the elderly include women living without a partner, women in general, and widowed men living without a partner.

Having two or more children serves as a small protective factor against elderly depression, which is in line with the findings of Buber & Engelhardt (2008). This likely indicates that having a larger family corresponds to a stronger social network and creates more opportunities for positive social interactions, which positively affect the respondent's mental health. Other variables related to children or transformations of this variable were considered, but the selected categorical approach was the most statistically sensible. Similar to household size, the categorical estimates suggested a heavy decline in marginal effect, making a linear approach suboptimal. Additionally, a variable indicating whether one of the children lives less than a kilometer from the respondent was not statistically significant when controlling for the number of children.

The estimation results for "Outside help received" suggest that respondents living in households that received any form of outside help in the last year are at greater risk of depression. Elderly individuals who do not receive outside help may have better mental health because they stay more physically and mentally active, feel more independent and self-sufficient, and avoid feelings of inadequacy or stigma that can come with needing help. Self-sufficiency and active engagement contribute to higher self-esteem and reduced depression and anxiety.

The estimates for all health variables align with expectations and are consistent between the FE and RE models. Being healthy, feeling healthy, not suffering from chronic diseases, and not requiring overnight hospital stays are all significant protective factors against elderly depression. The strongest driver is the subjective measure of health—self-perceived health. This is because self-perceived health contains not only physical health but also the individual's subjective assessment of their overall well-being, which is closely linked to their mental state. Additionally, self-perceived health captures the nuanced details of various health issues and their effects on the respondent better than objective data captured by other variables. The number of chronic diseases and doctor visits were modeled as categorical variables to account for the non-linear relationship and potential extreme values.

Being unemployed and not retired is a risk factor for depression. For those aged 50-65 in the sample, unemployment means loss of income, potential stress on financial stability, and diminished self-esteem, all of which could increase the risk of depression, this result is in line with work of Yaka *et al.* (2014); Sidik *et al.* (2004). Being permanently sick or disabled also acts as a risk factor compared to being retired. Despite accounting for many health variables, this variable still holds significant statistical and economic importance, likely due to the social isolation and loss of independence that impact mental well-being.

Owning a house is a significant protective factor against depression, as it implies better financial stability and less financial stress from not paying rent. However, an interesting observation can be made when comparing the RE and FE specification. In the RE model, none of the housing categories are statistically significant, whereas in the FE model, all categories are significant. To understand this phenomenon, it is important to examine the household net worth estimates. In the RE model, household net worth is statistically significant, while it is not in the FE model. Since household net worth in SHARE is generated by net property and building values, it is likely that this effect was captured by different variables in the respective models.

The measure of subjective financial well-being is by far the most significant driver of depression among the financial variables. Omitting this variable leads to an increase in the size and significance of the wealth and income estimates (mainly wealth), but decreases the overall fit of the model. This suggests that the subjective measure captures financial stress that objective measures alone may miss.

Household net worth acts as a protective factor against elderly depression as suggest by Semyonov *et al.* (2013). The results confirm the expectation that there is a "limit" of wealth beyond which the probability of depression does not decrease any further. Interestingly, the wealthiest 20% are actually less protected compared to the "top" 40-80% wealth households. The wealthiest 20% face more depression than those in the 40-80th percentile due to higher social isolation and potential existential concerns about the meaningfulness of their wealth, contrasting with those in the middle range who might benefit from a balance of financial stability and more grounded social connections. Omitting the income variable did not change the impact of the wealth estimates, but omitting the subjective measure of financial well-being increased the impact of this variable, meaning it absorbs some of its power.

Household income categories act as a very small risk factor for households in the 40-100th percentile of income. This is probably because people with sufficient income respond with the best answers in the subjective measure and face stress connected to "maintaining" their income as their age progresses and earning opportunities decrease further. If wealth and the subjective measure are omitted, the income estimates absorb part of those estimates, resulting in similar results as for wealth — a solid protective measure with a clear ceiling beyond which increases do not decrease the probability of depression.

To conclude wealth acts as a better protective factor against depression than income when accounting for both and the subjective measure of financial well-being. The caveat of possible multicollinearity of these variables will be mentioned in the Chapter 6, but this does not change the fact that wealth is the better predictor.

Country estimates suggest increased probability of depression in economically strong northern countries with limited access to sunlight, or the higher depression rates in economically less developed countries, such as those from the EU 2004 enlargement—a more detailed analysis is beyond the scope of this thesis.

5.2 Hausman test

The FE and RE models were compared using the Hausman test. The Hausman test compares the estimates of the consistent fixed effects estimator and the more efficient random effects estimator. The null hypothesis is that both models are consistent, but the random effects estimator is also efficient. Under the alternative hypothesis, only the fixed effects estimator is consistent.

With 55 degrees of freedom, the chi-squared statistic of 3029.29 is reached in the test. We reject the null hypothesis (Prob $>$ chi2 $=$ 0.00). This indicates that the random effects estimates are considered inconsistent, and the fixed effects estimates should be deemed more suitable for assessing causality.

Although the random effects estimates are inconclusive in terms of causality, they still hold value. They provide important information about the effects of time-invariant variables like education or country. Additionally, the RE estimates serve as a robustness check for the FE results. Since both estimators delivered comparable results when accounting for unobserved heterogeneity in different ways, the results can be considered more robust (de Bresser & van Soest 2015).

5.3 Dynamic model

Table 5.2 presents the estimates of the dynamic random effects logit model. The setup is the same as in the previous section: positive values imply a risk factor that increases the log-odds of depression, while negative values imply a protective factor that reduces odds of depression. Since there are no major differences in the direction of impact between the static and dynamic estimates, I will not go through the dynamic estimates individually but will focus on the most interesting relative differences.

Table 5.2: Random-effects Logistic Regression Results

Variable	Coefficient	Std. Error
Initial condition		
not depressed	0 (base)	
depressed	0.8324***	0.0260
Lagged value		
not depressed	0 (base)	
depressed	1.0069***	0.0223
age_squared	0.0011***	0.0001
age	-0.1433***	0.0137
Education		
None or primary	0 (base)	
Secondary	-0.0463	0.0250
Tertiary	-0.0344	0.0314
Wave specific dummies		
wave_2	0 (base)	
wave_5	0.1754***	0.0308
wave_6	0.1499***	0.0306
wave_7	0.2206***	0.0389
wave_8	0.2107***	0.0445
wave_9	0.4141***	0.0331

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Table 5.2: Random-effects Logistic Regression Results

Variable	**Coefficient**	**Std. Error**
Logarithm of household size	0.1121***	0.0307
Partner or spouse in household		
Yes	0 (base)	
No	0.2067***	0.0457
Gender		
Male	0 (base)	
Female	0.6741***	0.0234
Marital status and gender interactions		
Married, living with spouse	0 (base)	
Married, separated from spouse	-0.1121	0.1326
Divorced	0.0190	0.0622
Widowed	0.1918***	0.0622
Female × Married, living with spouse	0 (base)	
Female × Never married	-0.2583***	0.0779
Female × Divorced	-0.1151	0.0662
Female × Widowed	-0.3183***	0.0563
Number of children		
0	0 (base)	
1	-0.0176	0.0378
2	-0.0570	0.0357
3+	-0.0398	0.0367
Outside help recieved		
Yes	0 (base)	
No	-0.3136***	0.0202
Self-percieved health		
Excellent	0 (base)	
Very good	0.2056***	0.0515
Good	0.7191***	0.0483
Fair	1.5219***	0.0501
Poor	2.6001***	0.0567
Doctor visits in last year		
Never or once	0 (base)	
Twice or thrice	0.0741**	0.0286
4-10 times	0.2216***	0.0262

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Table 5.2: Random-effects Logistic Regression Results

Variable	Coefficient	Std. Error
10+	0.4334***	0.0308
Overnight hospital stay in last year		
Yes	0 (base)	
No	-0.2715***	0.0223
Number of chronic diseases		
None	0 (base)	
1	0.0410	0.0221
2+	0.1104***	0.0230
Job Situation		
Retired	0 (base)	
Unemployed	0.1724***	0.0625
Permanently sick or disabled	0.2494***	0.0515
Housing situation		
Owner	0 (base)	
Member of a cooperative	0.1674***	0.0569
Tenant	-0.0182	0.0335
Subtenant	0.1315	0.1117
Rent free	-0.0159	0.0401
How complicated is it to make ends meet		
Great difficulty	0 (base)	
Some difficutlty	-0.3865***	0.0307
Fairly easily	-0.6333***	0.0325
Easily	-0.7150***	0.0350
Household networth category		
Very low	0 (base)	
Low	-0.0332	0.0308
Middle	-0.1102***	0.0339
High	-0.1144***	0.0360
Very high	-0.0531	0.0386
Household income category		
Very low	0 (base)	
Low	0.0382	0.0255
Middle	0.0702**	0.0288
High	0.1162***	0.0317

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Table 5.2: Random-effects Logistic Regression Results

Variable	**Coefficient**	**Std. Error**
Very high	0.1004***	0.0360
Country specific estimates		
Austria	0 (base)	
Germany	0.0430	0.0500
Sweden	0.1800***	0.0545
Netherlands	-0.0571	0.0635
Spain	0.1994***	0.0531
Italy	0.4956***	0.0509
France	0.5767***	0.0483
Denmark	0.1107**	0.0553
Greece	-0.5378***	0.0620
Switzerland	0.1131**	0.0556
Belgium	0.4507***	0.0475
Czech Republic	-0.1096**	0.0505
Poland	0.1177	0.0673
Luxembourg	0.4517***	0.0869
Hungary	-0.3650***	0.1260
Slovenia	-0.1295**	0.0582
Estonia	-0.0148	0.0496
Croatia	-0.1975**	0.0900
Lithuania	0.3976***	0.0946
Bulgaria	-0.3869***	0.1368
Cyprus	-0.2602	0.1838
Finland	0.3605***	0.1136
Latvia	-0.8981***	0.1164
Malta	0.6746***	0.1251
Romania	-0.3413***	0.1062
Slovakia	-0.0544	0.1249
_cons	1.7131***	0.5050
/lnsig2u	-0.2576	0.0518
sigma_u	0.8791	0.0228
rho	0.1902	0.0080
Number of observations	141 668	

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Table 5.2: Random-effects Logistic Regression Results

Variable	**Coefficient**	**Std. Error**
Degrees of freedom	82	

Note: *** p<0.01, ** p<0.05, * p<0.1

Explanatory power represented by the parameter ρ suggests that the dynamic model explains more of the variance in unobserved heterogeneity than the static model. In the static model, 38.1% of the variance was unexplained. In the dynamic model, only 19% of the variance is unexplained.

The initial condition is captured by the parameter λ as mention in Equation 4.7. The rationale is that λ should capture the endogeneity of the initial condition, which affects all subsequent values of y_{it} for $t \geq 1$. Controlling for this effect is crucial in obtaining an unbiased $\tilde{\alpha}_i$, which is not influenced by y_{it}. In our particular case, the estimate of the initial condition has strong economic and statistical significance, suggesting that the results would be biased without this treatment. The estimate allows us to account for individual characteristics and experiences that occurred prior to the SHARE dataset and are not captured by it.

The lagged value of depression is statistically and economically significant, indicating that state dependence is one of the important drivers of elderly depression. Economically, this highlights the need for early intervention and continuous mental health or systematic support, as previous depressive states have a strong and lasting impact on individuals' mental health. This result can be best rationalized by considering that the elderly have limited opportunities for drastic life changes, making it difficult to significantly improve their situation and alleviate depression.

Regarding the differences between the estimates of static and dynamic RE logit specifications, some variables lost their statistical significance after accounting for state dependence, namely education and number of children. The effect of most independent variables generally diminishes as they no longer absorb the positive effect of omitted state dependence. Interestingly, the estimate for the COVID wave becomes even stronger in the dynamic specification, further confirming the hypothesis that COVID-19 negatively affected depression among the elderly. The estimate for being female decreases in strength in the dynamic model, suggesting that the effect of state dependence may be more pronounced in women.

Due to missing observations, the random effects model had to omit some wave and country specific dummies. Specifically, by definition of dynamic RE model, we dropped the first wave for each respondent and all observations where the respondent did not participate in previous waves. Consequently, there are some missing estimates in the dynamic model compared to the static model, notably for waves 1 and 4 [1]. Additionally, some countries are missing because they were never part of the data collection in two subsequent waves. For example, Portugal participated in waves 4, 6, and 9, so the lagged variable could not be constructed.

[1] wave 3 was dropped as mentioned in the data chapter

Chapter 6

Discussion

This chapter discusses research findings in the context of empirical literature, acknowledges limitations of this research and suggests possible remedies and evenues for future research. The thesis applies Fixed effects and random effects logit models to estimate determinants of depression in the sample of 138 345 elderly Europeans from 28 countries and 8 time periods between the years 2004 and 2022. Dynamic model was used to look into state dependence - how past depressive states affect the probability of suffering from depression in current time period.

The results suggest that women are more prone to depression than men, which supports the findings of Cole & Dendukuri (2003); Djernes (2006); Schmitz & Brandt (2019) the effect is significant even after accounting for various factors such as health, wealth, education, age, state dependence, and marital status. Gender differences in the way adverse life outcomes are reflected in depressive symptoms, could contribute to this disparity (Gutiérrez-Lobos *et al.* 2000). The additional caregiving responsibilities that predominantly fall on women could also account for this gap, as higher levels of informal caregiving are associated with depressive symptoms Langa *et al.* (2004). Biological factors may also play a significant role in explaining the gender gap, such as hormonal differences or the fact that women bear most of the biological burden of reproduction (Hopcroft & Bradley 2007).

Individuals not sharing a household with a romantic partner are significantly more prone to depression. This confirms the findings of Prince *et al.* (1999a); Yaka *et al.* (2014); Zhang & Li (2011), suggesting that daily activities, healthcare, and financial responsibilities can be shared between partners, making it easier for individuals to handle the challenges of aging. Our results suggest that widowhood and being divorced or single affect men worse than women, which aligns with the findings of Van de Velde *et al.* (2010). This can be best explained by the findings of Schaan (2013); Langa *et al.* (2004), who suggest that caregiving individuals face a smaller risk of depression after losing their partner—a role more often held by females in elderly couples. According to our results, the COVID-19 period is a significant risk factor for elderly depression, with its impact surpassing that of economic cycle fluctuations, which is inline with OECD and European Commision (2022) statement that prevalence of depressive symptoms rose sharply during the pandemic. The effects of the COVID period on elderly depression were caused by increased isolation, limited healthcare access, and the heightened threat of death, all of which are particularly significant to the elderly population. These factors have exacerbated feelings of loneliness, anxiety, and vulnerability, contributing to a substantial rise in depression rates among older adults during the pandemic. The probability of depression decreases during economic upturns, such as in the years 2006 and 2007, while it increases during periods affected by economic downturns, such as the sovereign debt crisis that began in 2009.

Adverse physical health outcomes are strongly connected to depression. Our results align with current literature, indicating that the number of chronic diseases and self-perceived health are significant predictors of depression. When both factors are compared, the number of chronic diseases shows weaker economic significance (Chang-Quan *et al.* 2010a; Beekman *et al.* 1995; Cole & Dendukuri 2003; Yaka *et al.* 2014). Policies should focus on physical health of individuals. Prioritize the prevention of chronic diseases and adverse health outcomes through regular health screenings, preventive care programs, and promotion of healthy lifestyle. Ensuring access to quality healthcare services for the elderly is needed to fight depression.

Employment status before retirement is a significant factor in elderly depression, those results are in line with findings of Yaka *et al.* (2014) or Sidik *et al.* (2004). The loss of income in advanced age can disrupt preparation of retirement savings leading to anxiety about the future. The feeling of inadequacy from being unable to fulfill societal and personal expectations as a provider, can contribute to depression. Addressing age discrimination in the workplace and hiring processes is essential. Policymakers should consider subsidizing the hiring of senior workers and providing retraining programs for older individuals to reduce unemployment-related depression.

Promoting homeownership among younger populations can create protective factors against depression in later years by providing sense of security. By establishing a stable living situation early, individuals can build equity and avoid the uncertainty of rent increases or rental contracts. Policies should encourage homeownership through affordable housing programs, financial education, and incentives for first-time buyers to help individuals build a solid foundation for their future well-being.

Wealth is found to be a protective factor against depression, supporting the findings of Semyonov *et al.* (2013). The wealthy experience fewer stressful events than the poor, and also have more resources to cope with stressful events when they occur (Gallo & Matthews 2003). Financial stability provides access to high-quality healthcare and ensures that elderly individuals can afford medications, treatments, and regular check-ups, promoting overall health and well-being. Sufficient financial resources also enable participation in social and recreational activities that foster social connections and prevent elderly depression. The measure of subjective well-being showed the biggest impact on depression, Omitting this variable leads to an increase in the size and significance of the wealth and income estimates (mainly wealth), but decreases the overall fit of the model. This suggests that the subjective measure captures financial stress that objective measures alone may miss, though it introduces potential endogeneity issues.

The statistical significance of our country-specific dummy variables confirms that differences in healthcare systems, social safety nets, cultural factors, economic conditions, and geographic factors are significant drivers of elderly depression, as highlighted by Copeland *et al.* (1999); Horackova *et al.* (2019). Our results could be improved by accounting for a dummy variable for groups of countries with similar characteristics. Although designing a correct methodology to group countries by geographic properties that could affect depression is beyond the scope of this thesis, a methodology for country grouping on SHARE data serves as a motivation for further research. A paper focusing on cross-country differences in elderly depression could develop several methods for grouping countries and test them against each other using goodness of fit measures.

The thesis suffers from some limitations which serve as a motivation for further research. Endogeneity poses a potential issue in this study due to the inclusion of subjective measures of wealth and health and other health variables, which may introduce reverse causality. For instance, individuals may visit doctors frequently because they are depressed, or they may be depressed because they visit doctors so often. Subjective measures, while capturing nuances that objective measures might miss, are particularly susceptible to endogeneity.

Despite this, the results remain relevant and align with existing literature and theoretical expectations. To address endogeneity in future research, instrumental variables or Arellano-Bond estimators can be employed. These methods help control for reverse causality and could provide results more suitable for assessing the causal relationship between subjective measures and depression.

The study may suffer from survivorship bias, as it only includes individuals who have survived to be part of the survey waves. If depressed individuals face much higher mortality compared to their non-depressed counterparts (or specific subsets, such as depressed men or poor depressed respondents), there would be fewer respondents reporting, potentially leading to significant underestimation of these effects. Future studies should consider methods to account for survivorship bias, perhaps by incorporating data on mortality and using statistical techniques to adjust for this bias.

Multicollinearity is a concern in this study due to the high covariance between the extreme values of respondents' wealth, income, and subjective measures of financial status. For example, respondents who reported struggle to make ends meet and were in the lowest income category likely also had the lowest wealth. The correlation matrix reveals moderate positive correlations between household category, income category and household networth category, the correlation coefficients are around 0.36 for all three pairs, which in the context of dummy variables suggests noteworthy relationship. Multicollinearity can inflate standard errors, making the estimates less reliable. Future research could address this problem by focusing on distinct combinations of these variables, which could be designed through principal component analysis or by identifying patterns among the variables. This approach was beyond the scope of this thesis.

The thesis makes a significant contribution to empirical literature by accounting for state dependence, which is often overlooked in previous studies. We find strong evidence for significance of state dependence, confirming it as one of the most significant predictors of depression among the elderly (Cole *et al.* 1999; Beekman *et al.* 1995; Djernes 2006). By accounting for many other factors, we provide precise estimates of the effect. The differences between the estimates of static and dynamic random effects logit specifications highlight the importance of state dependence in this context. Some variables, such as education and the number of children, lost their statistical significance after accounting for state dependence. Additionally, other independent variables have a diminished effect when the impact of omitted state dependence is properly addressed, resulting in less biased estimates.

Besides the thesis contributes to the empirical literature by the treatment of outliers - mostly categorical variables were used, to strengthen the robustness of results. This approach mitigates the impact of outliers as they either fall into the smallest or greatest category. To further test the robustness of the results, the specifications were additionally estimated on a sample that had no imputed values and relied only on values actually reported by respondents. The results were consistent with the estimates presented in Chapter 5. The imputed dataset was still used for the better sample size of non-imputed variables, leading to more reliable results.

Chapter 7

Conclusion

This thesis examined the determinants of elderly depression, using data from the Survey of Health, Ageing and Retirement in Europe (SHARE) collected between 2004 and 2022, which included 138,345 respondents from 28 countries. The analysis employed fixed and random effects models to test relationships identified in current literature as drivers of elderly depression. Results were consistent across samples and model specifications.

Wealth was established as a protective factor against depression, which aligns with the general consensus of current literature (Semyonov *et al.* 2013). However, we identified wealth to be a stronger predictor of depression than income, a point not fully agreed upon in existing research.

We find strong evidence for the significance of state dependence, confirming it as one of the most significant predictors of depression among the elderly. The comparison of static and dynamic models highlights the importance of accounting for this variable, as seen by better goodness of fit and changes in the magnitude and statistical significance of other variables in the dynamic model.

By highlighting the importance of accounting for the initial conditional value, we contribute to empirical research. The initial value of the dependent variable is likely influenced by unobserved factors that also affect subsequent values, failing to account for this correlation may lead to inconsistent estimation. Using the Wooldridge method (Wooldridge 2005), we address this issue and demonstrate that the initial condition is significant in our research. Ignoring it would result in biased estimates, as it allows us to account for individual characteristics and experiences not captured by the SHARE dataset.

We contribute to COVID empirical research finding out that COVID periods significantly increased the probability of depression among the elderly. The effect was stronger than economic cycle fluctuations. Specifically, we found out that during economic up turn, depression decreases as in the years 2006 and 2007, whereas during recession, depression significantly increases as in years 2010 and 2011 but by no means as strongly as during COVID years in 2021 and 2022.

Age was found to have a U-shaped effect on depression, where the odds of depression decrease when individuals are 50-70 years old and then start to rise.

Better than primary education was found to be a protective factor. Similarly, having more than one child, sharing a household with a romantic partner, owning one's own home, and not being unemployed before retirement are all protective factors.

Being a woman is associated with a greater risk of elderly depression even after accounting for many other determinants. Interestingly, being divorced or widowed affects males much more adversely than women.

Better physical health outcomes are strongly associated with lower depression odds, suggesting that preventing chronic diseases, promoting a healthy lifestyle, and regular health screenings are important.

Country specific dummy variables were of high statistical significance, suggesting that differences in economies, set-up of health and social support systems, cultural and geographic differences are strongly affecting elderly depression.

We acknowledge potential shortcomings in the methodology, such as multicollinearity and endogeneity, however remedies are beyond this study's scope. Future research could improve results by grouping countries with similar characteristics and testing methodologies using goodness of fit measures. Endogeneity, due to subjective measures of wealth and health introducing reverse causality, can be addressed using instrumental variables or Arellano-Bond estimators to provide more accurate causal assessments. Multicollinearity, due to high covariance between wealth, income, and subjective financial status, inflates standard errors and reduces reliability. Future studies could mitigate this by employing principal component analysis or identifying patterns among variables.

Besides emphasizing the importance of state dependence in social science research, the thesis contributes to the literature through its approach to outlier treatment. Because most variables showed a non-linear relationship to the dependent variable, transformation to categorical variables was often used. This method improved the robustness and reliability of the results, as extreme values were absorbed by the categories.

The findings of this thesis underscore the significant impact of state dependence on elderly depression, highlighting the necessity for continuous and systematic support for those already affected. Policymakers should develop programs that facilitate socialization opportunities for the elderly, such as community centers, social clubs, and organized activities. Targeted support programs are essential for higher-risk groups, such as elderly women and widowed or divorced men, including accessible psychiatric care, support groups, and community engagement initiatives.

Policies should also focus on physical health by prioritizing the prevention of chronic diseases through regular health screenings, preventive care programs, and promoting healthy lifestyles. Ensuring access to quality healthcare services is crucial for addressing mental health issues in this demographic. Additionally, addressing age discrimination in the workplace and hiring processes is essential, with policymakers considering subsidizing the hiring of senior workers and providing retraining programs for older individuals to reduce unemployment-related depression.

Promoting homeownership among younger populations can create protective factors against depression in later years. Policies should encourage homeownership through affordable housing programs, financial education, and incentives for first-time buyers. These policy implications should be implemented to ensure that current and future elderly populations in Europe can experience a dignified elderhood.

Appendix A

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This paper uses data from SHARE Waves 1, 2, 3, 4, 5, 6, 7, 8 and 9 (DOIs: 10.6103/SHARE.w1.900, 10.6103/SHARE.w2.900, 10.6103/SHARE.w3.900, 10.6103/SHARE.w4.900, 10.6103/SHARE.w5.900, 10.6103/SHARE.w6.900, 10.6103/SHARE.w7.900, 10.6103/SHARE.w8.900, 10.6103/SHARE.w8ca.900, 10.6103/SHARE.w9.900, 10.6103/SHARE.w9ca900) see B rsch-Supan et al. (2013) for methodological details.(1) The SHARE data collection has been funded by the European Commission, DG RTD through FP5 (QLK6-CT-2001-00360), FP6 (SHARE-I3: RII-CT-2006-062193, COMPARE: CIT5-CT-2005-028857, SHARELIFE: CIT4-CT-2006-028812), FP7 (SHARE-PREP: GA N 211909, SHARE-LEAP: GA N 227822, SHARE M4: GA N 261982, DASISH: GA N 283646) and Horizon 2020 (SHARE-DEV3: GA N 676536, SHARE-COHESION: GA N 870628, SERISS: GA N 654221, SSHOC: GA N 823782, SHARE-COVID19: GA N 101015924) and by DG Employment, Social Affairs & Inclusion through VS 2015/0195, VS 2016/0135, VS

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This paper uses data from the generated easySHARE data set (DOI: 10.6103/SHARE.easy.900), see Gruber et al. (2014) for methodological details. The easySHARE release 8.8.0 is based on SHARE Waves 1, 2, 3, 4, 5, 6, 7, 8 and 9 (DOIs: 10.6103/SHARE.w1.900, 10.6103/SHARE.w2.900, 10.6103/SHARE.w3.900, 10.6103/SHARE.w4.900, 10.6103/SHARE.w5.900, 10.6103/SHARE.w6.900, 10.6103/SHARE.w7.900, 10.6103/SHARE.w8.900, 10.6103/SHARE.w9.900).

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Appendix A

Appendix

A.1 Euro-d questions

1. Have you been sad (depressed, miserable, in low spirits, blue) recently?
2. How do you see your future?
3. Have you ever felt that you would rather be dead?
4. Do you tend to blame yourself or feel guilty about anything?
5. Have you had trouble sleeping recently?
6. What is your interest in things?
7. Have you been irritable recently?
8. What has your appetite been like?
9. Have you had too little energy recently?
10. How is your concentration?
11. What have you enjoyed doing recently?
12. Have you cried recently?

A.2 Dynamic estimates

Table A.1: Random-effects Logistic Regression Results

Variable	Coefficient	Std. Error
Initial condition		
not depressed	0 (base)	
depressed	0.8324***	0.0260
Lagged value		
not depressed	0 (base)	
depressed	1.0069***	0.0223
age_squared	0.0011***	0.0001
age	-0.1433***	0.0137
Education		
None or primary	0 (base)	
Secondary	-0.0463	0.0250
Tertiary	-0.0344	0.0314
Wave specific dummies		
wave_2	0 (base)	
wave_5	0.1754***	0.0308
wave_6	0.1499***	0.0306
wave_7	0.2206***	0.0389
wave_8	0.2107***	0.0445
wave_9	0.4141***	0.0331
Logarithm of household size	0.1121***	0.0307
Partner or spouse in household		
Yes	0 (base)	
No	0.2067***	0.0457
Gender		
Male	0 (base)	
Female	0.6741***	0.0234
Marital status and gender inderactions		
Married, living with spouse	0 (base)	
Registered partnership	0.0294	0.1164
Married, separated from spouse	-0.1121	0.1326
Never married	-0.0013	0.0698
Divorced	0.0190	0.0622

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Table A.1: Random-effects Logistic Regression Results (continued)

Variable	Coefficient	Std. Error
Widowed	0.1918***	0.0622
Female × Married, living with spouse	0 (base)	
Female × Registered partnership	0.0191	0.1551
Female × Married, separated from spouse	0.1053	0.1676
Female × Never married	-0.2583***	0.0779
Female × Divorced	-0.1151	0.0662
Female × Widowed	-0.3183***	0.0563
Number of children		
0	0 (base)	
1	-0.0176	0.0378
2	-0.0570	0.0357
3+	-0.0398	0.0367
Outside help recieved		
Yes	0 (base)	
No	-0.3136***	0.0202
Self-percieved health		
Excellent	0 (base)	
Very good	0.2056***	0.0515
Good	0.7191***	0.0483
Fair	1.5219***	0.0501
Poor	2.6001***	0.0567
Doctor visits in last year		
Never or once	0 (base)	
Twice or thrice	0.0741**	0.0286
4-10 times	0.2216***	0.0262
10+	0.4334***	0.0308
Overnight hospital stay in last year		
Yes	0 (base)	
No	-0.2715***	0.0223
Number of chronic diseases		
None	0 (base)	
1	0.0410	0.0221
2+	0.1104***	0.0230
Job Situation		

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Table A.1: Random-effects Logistic Regression Results (continued)

Variable	**Coefficient**	**Std. Error**
Retired	0 (base)	
Employed or self-employed	0.0781**	0.0316
Unemployed	0.1724***	0.0625
Permanently sick or disabled	0.2494***	0.0515
Homemaker	0.0366	0.0335
Housing situation		
Owner	0 (base)	
Member of a cooperative	0.1674***	0.0569
Tenant	-0.0182	0.0335
Subtenant	0.1315	0.1117
Rent free	-0.0159	0.0401
How complicated is it to make ends meet		
Great difficulty	0 (base)	
Some difficutlty	-0.3865***	0.0307
Fairly easily	-0.6333***	0.0325
Easily	-0.7150***	0.0350
Household networth category		
Very low	0 (base)	
Low	-0.0332	0.0308
Middle	-0.1102***	0.0339
High	-0.1144***	0.0360
Very high	-0.0531	0.0386
Household income category		
Very low	0 (base)	
Low	0.0382	0.0255
Middle	0.0702**	0.0288
High	0.1162***	0.0317
Very high	0.1004***	0.0360
Country specific estimates		
ustria	0 (base)	
Germany	0.0430	0.0500
Sweden	0.1800***	0.0545
Netherlands	-0.0571	0.0635
Spain	0.1994***	0.0531

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Table A.1: Random-effects Logistic Regression Results (continued)

Variable	Coefficient	Std. Error
Italy	0.4956***	0.0509
France	0.5767***	0.0483
Denmark	0.1107**	0.0553
Greece	-0.5378***	0.0620
Switzerland	0.1131**	0.0556
Belgium	0.4507***	0.0475
Czech Republic	-0.1096**	0.0505
Poland	0.1177	0.0673
Luxembourg	0.4517***	0.0869
Hungary	-0.3650***	0.1260
Slovenia	-0.1295**	0.0582
Estonia	-0.0148	0.0496
Croatia	-0.1975**	0.0900
Lithuania	0.3976***	0.0946
Bulgaria	-0.3869***	0.1368
Cyprus	-0.2602	0.1838
Finland	0.3605***	0.1136
Latvia	-0.8981***	0.1164
Malta	0.6746***	0.1251
Romania	-0.3413***	0.1062
Slovakia	-0.0544	0.1249
_cons	1.7131***	0.5050
/lnsig2u	-0.2576	0.0518
sigma_u	0.8791	0.0228
rho	0.1902	0.0080

Note: *** p<0.01, ** p<0.05, * p<0.1

A.3 Static estimates

Table A.2: Comparison of Random-effects and Fixed-effects Logistic Regression Results

Variable	**RE Estimates**	**RE SE**	**FE Estimates**	**FE SE**
age_squared	0.0015***	0.0001	0.0020***	0.0001
age	-0.2062***	0.0086	-0.4392***	0.0334
Education				
None or primary	0 (base)		0 (base)	
Secondary	-0.1707***	0.0196	-0.2702	0.2846
Tertiary	-0.1872***	0.0246	0.7361	0.4643
Wave specific dummies				
wave_1	0 (base)		0 (base)	
wave_2	-0.1892***	0.0270	0.1937**	0.0781
wave_4	0.0837***	0.0252	1.1901***	0.2052
wave_5	0.0190	0.0250	1.4725***	0.2652
wave_6	0.0423	0.0252	1.8327***	0.3255
wave_7	0.0032	0.0349	2.1840***	0.3882
wave_8	0.0257	0.0271	2.5869***	0.4662
wave_9	0.1441***	0.0265	3.0893***	0.5314
Logarithm of household size	0.1493***	0.0214	0.2067***	0.0405
Partner or spouse in household				
Yes	0 (base)		0 (base)	
No	0.2715***	0.0327	0.3505***	0.0568
Gender				
Male	0 (base)		0 (base)	
Female	1.0034***	0.0178	(omitted)	(omitted)
Marital status and gender inderactions				
Married, living with spouse	0 (base)		0 (base)	
Registered partnership	-0.0205	0.0831	0.0616	0.2549
Married, separated from spouse	0.2345**	0.0926	0.2847	0.2398
Never married	0.0260	0.0522	0.1050	0.2994
Divorced	0.1769***	0.0464	-0.3388**	0.1547
Widowed	0.3671***	0.0469	0.5231***	0.0978
Female × Married, living with spouse	0 (base)		0 (base)	
Female × Registered partnership	0.1610	0.1106	0.1279	0.3495
Female × Married, separated from spouse	-0.1576	0.1202	-0.1829	0.3165
Female × Never married	-0.2929***	0.0597	-0.5928	0.3911

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Table A.2: Comparison of Random-effects and Fixed-effects Logistic Regression Results (continued)

Variable	**RE Estimates**	**RE SE**	**FE Estimates**	**FE SE**
Female × Divorced	-0.2032***	0.0510	0.1198	0.2000
Female × Widowed	-0.3934***	0.0434	-0.4660***	0.0956
Number of children				
0	0 (base)		0 (base)	
1	-0.0192	0.0283	0.1113	0.0734
2	-0.1289***	0.0268	0.0471	0.0743
3+	-0.0940***	0.0278	0.0487	0.0792
Outside help recieved				
Yes	0 (base)		0 (base)	
No	-0.4089***	0.0140	-0.2879***	0.0178
Self-percieved health				
Excellent	0 (base)		0 (base)	
Very good	0.2231***	0.0329	0.1255***	0.0428
Good	0.8427***	0.0312	0.5329***	0.0423
Fair	1.7923***	0.0325	1.1586***	0.0444
Poor	3.0717***	0.0369	2.0057***	0.0506
Doctor visits in last year				
Never or once	0 (base)		0 (base)	
Twice or thrice	0.0652***	0.0187	0.0025	0.0240
4-10 times	0.2645***	0.0175	0.1294***	0.0234
10+	0.5685***	0.0209	0.3625***	0.0283
Overnight hospital stay in last year				
Yes	0 (base)		0 (base)	
No	-0.2668***	0.0156	-0.2294***	0.0194
Number of chronic diseases				
None	0 (base)		0 (base)	
1	0.0948***	0.0153	0.1318***	0.0206
2+	0.2883***	0.0164	0.2890***	0.0238
Job Situation				
Retired	0 (base)		0 (base)	
Employed or self-employed	0.0224	0.0212	0.1071***	0.0305
Unemployed	0.3111***	0.0372	0.2801***	0.0524
Permanently sick or disabled	0.4120***	0.0337	0.2011***	0.0483

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Table A.2: Comparison of Random-effects and Fixed-effects Logistic Regression Results (continued)

Variable	**RE Estimates**	**RE SE**	**FE Estimates**	**FE SE**
Homemaker	0.0461*	0.0240	0.0104	0.0401
Housing situation				
Owner	0 (base)		0 (base)	
Member of a cooperative	0.1902***	0.0435	0.1895***	0.0733
Tenant	0.0321	0.0239	0.1250***	0.0478
Subtenant	0.1162	0.0766	0.2164**	0.1054
Rent Free	0.0284	0.0282	0.1538***	0.0405
How complicated is it to make ends meet				
Great difficulty	0 (base)		0 (base)	
Some difficutlty	-0.5098***	0.0197	-0.2871***	0.0261
Fairly easily	-0.8287***	0.0215	-0.4452***	0.0295
Easily	-0.9249***	0.0237	-0.4618***	0.0328
Household networth category				
Very low	0 (base)		0 (base)	
Low	-0.0968***	0.0207	-0.0018	0.0281
Middle	-0.1554***	0.0229	-0.0156	0.0316
High	-0.1555***	0.0245	0.0056	0.0341
Very high	-0.0963***	0.0266	0.0912**	0.0380
Household income category				
Very low	0 (base)		0 (base)	
Low	0.0015	0.0177	0.0294	0.0230
Middle	0.0603***	0.0196	0.0618**	0.0256
High	0.0726***	0.0213	0.0503*	0.0282
Very high	0.0797***	0.0234	0.0590*	0.0314
Country specific estimates				
Germany	0.1373***	0.0406	(omitted)	(omitted)
Sweden	0.3231***	0.0455	(omitted)	(omitted)
Netherlands	0.1021**	0.0472	(omitted)	(omitted)
Spain	0.4924***	0.0430	(omitted)	(omitted)
Italy	0.6795***	0.0420	(omitted)	(omitted)
France	0.8712***	0.0407	(omitted)	(omitted)
Denmark	0.1680***	0.0467	(omitted)	(omitted)
Greece	0.0714	0.0467	(omitted)	(omitted)

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Table A.2: Comparison of Random-effects and Fixed-effects Logistic Regression Results (continued)

Variable	**RE Estimates**	**RE SE**	**FE Estimates**	**FE SE**
Switzerland	0.2801***	0.0485	(omitted)	(omitted)
Belgium	0.7015***	0.0396	(omitted)	(omitted)
Czech Republic	-0.0521	0.0418	(omitted)	(omitted)
Poland	0.5735***	0.0461	(omitted)	(omitted)
Ireland	0.2430	0.1251	(empty)	(empty)
Luxembourg	0.6769***	0.0653	(omitted)	(omitted)
Hungary	-0.0025	0.0580	(omitted)	(omitted)
Portugal	0.7010***	0.0622	(omitted)	(omitted)
Slovenia	0.0710	0.0456	(omitted)	(omitted)
Estonia	0.3854***	0.0414	(omitted)	(omitted)
Croatia	0.0841	0.0522	(omitted)	(omitted)
Lithuania	0.8856***	0.0726	(omitted)	(omitted)
Bulgaria	-0.1934**	0.0972	(omitted)	(omitted)
Cyprus	-0.3444***	0.1126	(omitted)	(omitted)
Finland	0.5353***	0.0731	(omitted)	(omitted)
Latvia	-0.4379***	0.0765	(omitted)	(omitted)
Malta	0.9462***	0.0917	(omitted)	(omitted)
Romania	0.3910***	0.0758	(omitted)	(omitted)
Slovakia	0.2800***	0.0947	(omitted)	(omitted)
_cons	4.2488***	0.3129		
/lnsig2u	0.7070***	0.0158		
sigma_u	1.4240***	0.0113		
rho	0.3813***	0.0037		

Note: *** p<0.01, ** p<0.05, * p<0.1