Exploring the Impact of Retirement on Mental Health Among the European Elderly Population

Farnaz Khoshkhoo

Student Number: 2088421

MASTER OF SCIENCE IN ECONOMETRICS AND MATHEMATICAL ECONOMICS

SCHOOL OF ECONOMICS AND MANAGEMENT

TILBURG UNIVERSITY

Supervised by: Prof. Dr. Arthur van Soest

August 2023

Contents

Abstract

An increase in life expectancy, coupled with declining birth and mortality rates, has brought about profound demographic shifts in many OECD countries. The phenomenon of population aging has emerged as a significant economic challenge for pension systems. Substantial efforts have been dedicated to reforming these systems, promoting later retirement, and ensuring the enduring sustainability of pension programs. Nevertheless, concerns regarding the potential consequences of these reforms on individuals' mental well-being necessitate a comprehensive examination. This study aims to investigates the mental health impact of retirement among thirteen European countries using the most updated data sets from easySHARE.

The analysis employs panel FE and RE Poisson models, utilizing the statutory retirement age as an instrumental variable in FE-IV model to address endogeneity issues in the retirement decision. The findings reveal retirement's significant protective effect on mental well-being, leading to an average reduction of 25 % in depressive symptoms. The bootstrap analysis reinforces this result.

Gender disparities in retirement's protective impact on mental health are evident, with males experiencing a more pronounced protective effect (33% reduction in number of depressive symptoms) than females (22%). Additionally, the study identifies that retirement leads to a substantial decrease in the prevalence of depressive symptoms by 30% among married retirees compared to married employees. To mitigate potential bias, the study refines the sample by excluding unemployed, permanently sick, disabled, and homemakers from the definition of retirement. The results highlight a significant negative association between transition from work to retirement and the number of depressive symptoms when, focusing solely on employed and retired individuals.

1 Introduction

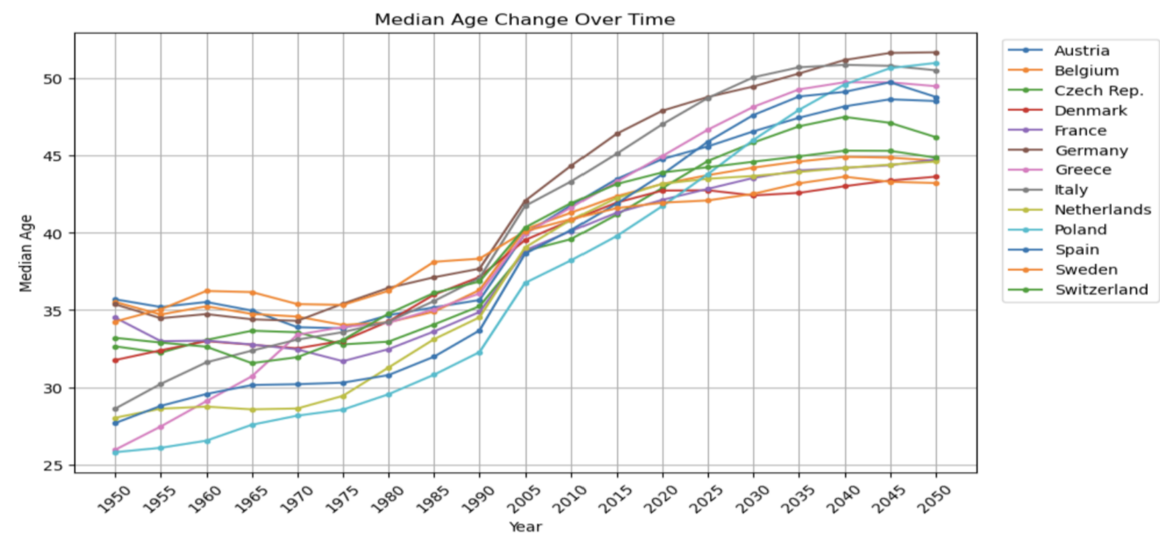
In developed nations, an increase in life expectancy, coupled with declining birth and mortality rates, has brought about profound demographic shifts, notably contributing to the increased number of retirees. (OECD, 2021). This shift is resulting in a higher proportion of individuals in the retirement age bracket compared to those in the working-age group (Mosca & Barrett, 2014). Illustrated in Graph 1 is the trajectory of median age over nearly seven decades, alongside predictions for future trends. It's worth noting that the median age of the populations in those mentioned countries in the graph, ranged between 40 and 50 in the year 2020.

The ongoing demographic transition poses considerable challenges to ensuring the sustainability of pension systems (OECD, 2021). As more people retire and depend on pensions, there's a mounting financial strain on pension funds. To deal with this phenomenal many countries have restructured their pension systems by encouraging later retirement (OECD, 2021). While extending the retirement age is pivotal for the viability of pension systems (Picchio & Van Ours, 2020), concerns arise about the repercussions on individuals who must work longer. It's imperative to thoroughly consider the consequences of these policy adjustments to gauge their efficacy (Heller-Sahlgren, 2017). Notably, the influence of retirement on mental well-being is a critical aspect that demands attention.

The onset of retirement coincides with a series of significant life changes, encompassing change in leisure time, income sources and social connections. These shifts are expected to impact the overall health and well-being of retirees (Behncke, 2011). Gaining a precise understanding of how retirement affects mental well-being is essential for crafting effective strategies and policies.

This study's objective is to examine how people's mental states change after they retire, focusing on individuals above fifty years old. By scrutinizing the relationship between retirement and mental health, this study seeks to offer valuable insights into the complex dynamics during this life phase.

Graph 1-The Median Age Among Some European Countries



Source: OECD, 2021.

Following the introduction of the study variables, chapter 2 presents a comprehensive literature review. The literature review aims to provide an overview of existing research on the correlation between age, gender, marital status, education, and income with mental health. It explores how these factors influence mental health outcomes among elderly individuals and set the stage for understanding the specific impact of retirement on mental well-being. Finally, the literature review delves into the specific topic of interest: the relationship between retirement and mental health.

Chapter 3 establishes a clear definition of the retirement variable and introduces the EURO-D scale for assessing mental health. Control variables, descriptive statistics, and potential confounding factors are discussed. Chapter 4 focuses on count data and the Poisson regression model. It explains the Count model for panel data and explores different models, including Fixed and Random Effects Static Poisson models, Dynamic models, and the Quasi-Fixed Effects model. Chapter 5 presents the study's results, providing a comprehensive analysis and discussion of the findings. And finally, chapter 6 concludes the finding of the study and explores avenues for future research.

2 Literature Review

Exploring the relationship between retirement and mental well-being has gained significant research attention recently. However, when attempting to summarize these studies, drawing definitive conclusions from the gathered data poses challenges. While some studies suggest a positive effect, others propose either no discernible influence or even a negative outcome.

A comprehensive literature review will be provided in this section. To start, we will offer an overview of the existing research concerning the connections between age, gender, marital status, education, and income with mental health. Subsequently, we will present the body of literature that examines the impact of retirement on mental well-being. This literature can be categorized into three groups: studies solely investigating the correlation between retirement and mental health without considering instrumental variables (IV), studies employing an IV approach, and finally, an examination of comprehensive overview studies.

2.1 How Does Age Affect Mental Health?

Blanchflower and Oswald (2008) embarked on an investigation into life satisfaction across diverse regions such as Europe, the United States, Asia, and Latin America. Their study revealed a distinctive U-shaped relationship between age and well-being. Interestingly, this pattern showcased the lowest point during middle age, while both younger and older individuals exhibited higher levels of comfort. This intriguing U-shaped connection was reaffirmed by findings from the Gallup World Poll survey, spanning over 160 nations, which reported the least level of well-being at ages ranged from 45 to 54 (Steptoe et al., 2015).

However, it is important to note that this pattern may not apply to very old age individuals, typically encompassing those aged 70 years and above (Westerhof & Keyes, 2010). Individuals in this age group often grapple with various challenging life circumstances, such as a decline in social connection, reduced income, and an array of health issues. Consequently, they frequently report diminished life satisfaction (Allen, 2008). The confluence of these unfavorable factors collectively contributes to a decline in mental well-being among very old individual (Wang et al., 2016).

2.2 How Does Gender Affect Mental Health?

Gender significantly shapes the landscape of mental health, yet it's important to recognize that it's not about one gender experiencing worse mental health than the other; rather, it's about distinct types of mental challenges being encountered by men and women (Rosenfield & Smith, 2009).

The World Health Organization (WHO) underscores that certain conditions like depression and anxiety exhibit a higher prevalence among women (WHO, 2013; Sonnenberg et al., 2020). Females are nearly twice as likely as males to develop depression in their lifetime (WHO, 2013; Ceo et al., 2011). Conversely, men display a higher occurrence of externalizing disorders like substance misuse and antisocial behavior (Srivastava & Anand, 2020).

In summary, women tend to manifest affective disorders like anxiety and depression when confronted with stressors, whereas men are inclined towards behavioral disorders, including substance abuse and traits linked to antisocial personality in response to similar challenges.

2.3 How Does Marital Status or Parental Status Affect Mental Health?

Evidence derived from scholarly investigations underscores that being married or living in a domestic partnership can lead to heightened life satisfaction and is linked to improved mental health (Becker et al., 2019). The observed health and survival benefits among those who are married are likely in part due to several protective factors inherent to having a spouse. Partners frequently offer companionship and emotional reinforcement, all of which contribute to a wholesome lifestyle (Kravdal et al., 2023). Moreover, potential economic advantages are associated with shared resources within marriage.

Additionally, in terms of parental status, the presence of children can influence their parents' experiences through an array of social mechanisms and life phases, giving rise to both favorable and adverse effects. The relationship between having children and life satisfaction seems ambiguous trajectories in literature (Mastekaasa, 1994; Becker et al., 2019). Nonetheless, there is convincing proof suggesting that the connection between parenthood and one's well-being becomes progressively more positive as parents become older. It seems that as parent become older the social support of children become more important (Margolis & Myrskylä, 2011).

2.4 How Do Education and Income Affect Mental Health?

Mental health is not uniformly spread throughout different socio-economic tiers. To put it differently, people react diversely to stress-inducing situations based on their socio-economic backgrounds. Socio-economic background pertains to an individual's societal and economic standing, encompassing factors like income, education, occupation, and social status. A consistent body of evidence underscores that as one's socio-economic status declines, the likelihood of experiencing significant psychiatric disorders increases (Steele et al., 2007).

Furthermore, a higher educational attainment is intricately tied to a decreased risk of encountering mental disorders (Allen et al., 2014). Insights gleaned from surveys conducted within community-based studies highlight that individual with more extensive educational backgrounds tend to utilize specialized mental health services more frequently. This consistent access to such services equips them with effective tools to navigate stress, thereby elevating their mental well-being (Starkes et al., 2005).

Moreover, a superior income level is linked to a diminished vulnerability to poor mental health (Sareen et al., 2011). Individuals with lower incomes could grapple with a host of stressors that exert detrimental effects on their mental well-being, including financial instability, limited access to healthcare, inadequate housing, and restricted availability of nourishing food options.

2.5 How Does Retirement Affect Mental Health?

Retirement marks the transition from an individual's active work phase to a new chapter beyond their professional career. While retirement can offer improved mental well-being by reducing work-related stress and fostering opportunities for fresh social connections, it's not without its challenges. These include feelings of social isolation due to the loss of interaction with former colleagues (Kolodziej & García-Gómez, 2019). Moreover, retirement often brings about reduced income and spending, which can potentially impact mental health negatively.

In this section, we delve into the body of research exploring the relationship between retirement and mental well-being, categorizing it into three key areas: studies exclusively examining the correlation between retirement and mental health, studies applying an instrumental variable (IV) methodology, and comprehensive overview studies that offer a panoramic analysis of existing research. By structuring the literature in this manner, our aim is to provide a comprehensive overview of the research landscape on retirement and mental health, facilitating a deeper and nuanced understanding of the subject.

Association between Retirement and Mental Health

Vo et al. (2015) employed logistic regression to investigate how retirement affects mental well-being. The findings indicated that retired individuals, regardless of gender, tend to have poorer mental health than those who remain employed.

Employing first-difference estimation models, Mosca and Barrett (2014) discovered that enforced retirement correlated significantly with negative mental health outcomes and depression, whereas voluntary retirement displayed no noteworthy impact. On a more positive note, Oksanen et al. (2011) demonstrated that retirement had a favorable impact on mental health. Similarly, Westerlund et al. (2009) presented evidence suggesting an enhancement in mental well-being associated with retirement. Jokela et al. (2010) inferred that health status experienced improvements following both mandatory and voluntary retirement.

Studying the relationship between retirement and mental well-being using correlation analysis produces results marked by a degree of variability. However, the complexity arises from the fact that these studies face limitations due to the non-random nature of retirement, making it difficult to definitively establish a direct cause-and-effect relationship between retirement and mental health outcomes.

Assessing Retirement's Influence on Mental Well-being Using IV Methods

In pursuit of more robust evaluations of retirement's influence on mental health, contemporary investigations have taken up the gauntlet of endogeneity by adopting diverse methodological strategies. Particularly noteworthy are the incorporation of Instrumental Variables (IV) methods. These methodology factor in the substantial economic incentives that arise upon eligibility for state pension benefits, accounting for the contention that reaching these age thresholds should only influence mental health through retirement, once the gradual effects of age are factored in. By employing this technique, researchers are better positioned to disentangle the specific impact of retirement on mental well-being, while simultaneously controlling for potential confounding variables. Subsequently, this discourse delves into multi-country and single-country studies that used IV approaches for their investigations.

Coe and Zamarro (2011), utilizing SHARE data, finding no noteworthy influence of retirement on depression. Belloni et al. (2016) delved into this subject by utilizing the SHARE dataset and applying the FE-IV approach, with a specific focus on economic downturns. Their findings indicated that, overall, retirement did not have a significant effect on mental health. However, a noteworthy exception surfaced during economic crises: male blue-collar workers experienced an increase in depressive symptoms, and in such situations, retirement seemed to provide a protective effect.

Heller-Sahlgren (2017) embarked on a study using SHARE dataset. Their methodology encompassed the FE-IV technique, exploiting specific retirement age thresholds delineated by state pension regulations. Additionally, they embraced the Regression Discontinuity Design (RDD) to mitigate potential biases in retirement decisions. The findings unveiled that an immediate link between retirement and mental health wasn't discernible in the short term. Nevertheless, over the long term, retirement manifested a detrimental effect on mental well-being. This adverse trajectory became conspicuous several years post-retirement and remained consistent across genders, educational levels, and occupations.

Kolodziej and García-Gómez (2019) ventured into the domain with a distributional regression approach coupled with IV estimation, drawing on the SHARE dataset. Their investigation unveiled a departure from the traditional narrative by concluding that retirement exhibits a protective impact. Their study also highlighted an uneven distribution of retirement benefits, particularly favoring individuals who were susceptible to depression.

Numerous inquiries examined the situation in England, like Behncke (2011), adopting an IV methodology, ascertained that retirement exerted negligible impact on workers' mental health. Fé and Hollingsworth (2016), suggested minimal influence of retirement on retirees' mental health in both short and long terms, using RDD approach. In contrast, Carrino et al. (2020) spotlighted that deferring retirement engendered augmented mental health challenges, especially among women of lower socio-economic strata. Delving into the matter, Martinez-Jimenez et al. (2021) found retirement, on average, led to a diminution in mental well-being, with variations observed based on gender and occupational status.

Eibich (2015) utilized RDD methods rooted in age-associated financial incentives within the German pension structure. Eibich revealed distinct shifts in the age-retirement pattern at 60 and 65, underscored by financial incentives. Eibich discerned that retirement positively impacted the mental health of workers, particularly those with higher educational attainment. This subset experienced diminished work-related stress, extended sleep duration, and an augmented active lifestyle post-retirement. Notably, there was no notable effect on the mental health of workers with lower educational attainment.

In 2020, Picchio and Van Ours undertook an inquiry that employed RDD on Dutch data to explore retirement's consequences. Their findings illuminated differential impacts based on gender and marital status. Specifically, partnered men experienced an enhancement in mental well-being post-retirement, while single workers and women exhibited minimal effects, irrespective of marital status.

Overview Studies

Van der Heide et al. (2013) conducted an overview study and their findings unveiled a predominant trend in longitudinal investigations, showcasing a beneficial impact on mental well-being post-retirement. However, it is noteworthy that approximately a quarter of these studies revealed a lack of substantial effect. In a separate scrutiny, Nishimura et al. (2018) surveyed eight studies, highlighting the pivotal role played by estimation methodologies and the countries under examination in influencing the diversity of outcomes.

In the study conducted by Pilipiec et al. (2020), an assessment encompassing ninetheen distinct research investigations was carried out. Their findings revealed a certain degree of ambiguity and lack of clarity concerning the consequences of the later retirement on overall well-being.

In the study by Van Ours (2022), a spectrum of empirical findings came to the fore. On an average scale, retirement exhibited the potential to increase mental well-being, although this effect depends on individual attributes, occupational strata, and the context of retirement, whether it is by choice or obligation. Furthermore, the impact on mental health might not manifest immediately but could unfold over time, underscoring the importance of considering the duration of retirement. If workers are compelled to stop work due to mandatory retirement, it can yield adverse health outcomes such as depression or anxiety. Conversely, voluntary retirement might lead to a positive impact on mental health as the transition is a matter of choice.

Filomena and Picchio (2023) embarked on a comprehensive analysis. The study combed through 85 articles published between 2000 and 2021. The findings indicated that the influence of retirement on health outcomes was minimal and seldom yielded significant effects. Utilizing model averaging techniques, the researchers delved into potential sources of variation and concluded that differences in the way that health was defined or different scheme of retirement played a significant role in producing the diverse effects observed. Particularly noteworthy was their determination that mandatory or involuntary retirement was linked to adverse health consequences.

In contrast to prior research endeavors employing diverse methodologies, this study distinguishes itself by employing Poisson regression panel data analysis across eight waves of EasySHARE data. This exceptionally rich dataset confers the unique advantage of scrutinizing individual transformations over time through panel data, thereby facilitating a more exhaustive and intricate exploration of the influence of retirement on mental well-being.

3 Data and Descriptive Statistics

Introduction

This study is centered on investigating the potential influence of retirement on mental health through the analysis of data from the easySHARE, which is an adopted from the SHARE data set[1]. SHARE collects a wide range of information related to aging, including health, well-being, work, family, income, wealth, and social support (SHARE, 2022). The survey started in 2004 and spans 28 European countries. EasySHARE is a subset of SHARE data, containing the same number of observations but fewer variables. The most recent data collection, the 8th wave, took place in 2019-2020 (EasySHARE, 2022).

Our study made use of all eight easySHARE data sets, excluding the third wave which lacked mental health information. Thirteen European countries were included: Austria, Belgium, Denmark, France, Germany, Italy, Greece, Netherlands, Spain, Sweden, Switzerland, Czech Republic, and Poland. These countries were chosen because they participated in at least five waves, which was the highest attendance among the countries. Our focus was on individuals aged 50 years and above. The observations (not individuals) with incomplete survey records were excluded to ensure data quality, resulting in a final sample of 216,180 observations. Across all 13 countries, the number of observations is roughly equal, with each country contributing a similar number of participants. Notably, Belgium had the highest number of respondents, making up 11% of the total sample (Table 5).

Depression levels were assessed using the Eurod index, a tool consisting of twelve questions designed to gauge the presence of various signs of depression, each question assessing one depressive symptoms. This index quantifies the presence of depressive symptoms on a scale from zero up to 12. This index has been verified for enabling cross-country comparisons of depression rates and risks (EasySHARE, 2022).

To analyze how retirement impacts mental health, it's crucial to define retirement clearly, as this definition significantly influences outcomes. Previous studies have generally identified individuals as retired if they reported being retired or if they considered themselves permanently absent from the workforce due to reasons such as illness, disability, unemployment, or being a homemaker, and

1. Survey of Health, Ageing, and Retirement

hadn't engaged in paid work in the previous month ((Bonsang et al., 2012); (Coe & Zamarro, 2011); (García-Gómez & Kolodziej, 2019); (Mazzonna & Peracchi, 2012). This study adhered to the same retirement definition as previous research. Having this consistency lets us compare our findings to similar studies, helping us understand better how retirement affects mental health across different groups and situations. In Table 1, we included additional factors like Gender, Age, Marital Status, Education Level, Parental Status, Income, Wealth, and Country of origin to compare and control the results alongside retirement status.

Descriptive Statistics

Table 1 provides an overview of the demographic information pertaining to the survey participants. This study focuses exclusively on individuals who are 50 years of age or older. To better understand the data, we categorized the age into four groups, 50-59, 60-69, 70-79, and 80 or more years. The majority of observations (35.7%) are from the age group of 60-69 with an average mental health score, of 2.1. While this score is 3 for the age group 80 years or older, surpassing the overall average. The mean age of the sample is progressively rising across waves, starting at 64 in the initial wave and reaching 71 by the eighth wave, (Table 2). The mean age of respondents across various countries falls within a relatively close range of 65 to 69 years, (Table 5).

Females make up 55% of the observations, with the average number of depressive symptoms at 2.7, while males account for 45%, with the average number of depressive symptoms at 1.8. Based on the factors that have been considered in the Mental Health index, on average women displayed more depressive symptoms. In terms of marital status, most of the observations, 69%, are in the 'Married and Living with a Spouse' group. This group of observations showed fewer symptoms, 2.1 on average. Divorced and Widowed reported higher numbers of depressive symptoms (2.5 and 3 respectively) than Married individuals or those who have Never been Married.

The sample's years of education range from 0 to 35, with an average of 10.8. The Education variable is categorized into four groups, Very Low-Level Education with less than 5 years of education, Low-Level with 6 to 12 years, Intermediate-Level with 13 to 16 years, and High-Level Education with more than 17 years. The average number of depressive symptoms for these categories are 2.9, 2.4, 2.02, and 1.88, respectively. This implies a clear inverse relationship between educational attainment and the average number of depressive symptoms; as educational levels increase; the occurrence of depressive symptoms decreases.

Table 1- Descriptive Statistics of Pooled Data

Variable	Attribute	Fraction %	Eurod (Mean)
Age	50-59	25.5	2.2
	60- 69	35.7	2.1
	70- 79	26.1	2.4
	80 and more	12.6	3.0
Gender	Female	55	2.7
	Male	45	1.8
Marital Status	Married and living together with a spouse	69	2.1
	Married, living separated from a spouse	2.55	2.3
	Never married	5.34	2.4
	Divorced	8.4	2.5
	Widowed	14.68	3.0
Education Level	Very Low Level: 0-5 Years	12.03	2.9
	Low Level: 6-12 Years	54.07	2.4
	Intermediate Level: 13-16 Years	24	2.0
	High Level: 17-35 Years	9.9	1.9
Employment Status	Retired	58	2.3
	Employed or Self-employed	25.13	1.8
	Unemployed	2.56	2.8
	Permanently sick or disabled	2.99	4.0
	Homemaker	11.30	2.9
Parental Status	Not having children	9.7	2.4
	Having at least one Child	90.3	2.3
Household Income	0-15,000	26.8	2.8
	15,001- 30,000	34.5	2.3
	30,001- 45,000	18.3	2.0
	+45,000	20.3	1.8
Household net Wealth	Zero or less	4.3	3.4
	0-50,000	21.0	2.7
	50,001- 500,000	59.4	2.2
	+500,000	15.2	1.9
Wave 1		8.15	2.2
Wave 2		14.2	2.3
Wave 4		17.4	2.4
Wave 5		21.8	2.3
Wave 6		20.6	2.3
Wave 7		5.6	2.4
Wave 8		12.0	2.3

Table 2- Variable Descriptions across Waves

	variable	Average	Standard Deviation	Minimum	Maximum
Wave 1	Age	64	9.6	50	102
	Retired	0.72	0.4	0	1
	Euro-D	2.2	2.1	0	12
	Income	35,566	41,549	0	1,474,265
	Years of Education	10.2	4.3	0	25
	Parental Status	0.89	0.3	0	1
	Female	0.54	0.49	0	1
	Marital status	0.7	0.4	0	1
	Wealth	244,053	749,230	-549,223	70,300,000
Wave 2	Age	65	9.8	50	102
	Retired	0.72	0.44	0	1
	Euro-D	2.28	2.2	0	12
	Income	29,697	31,697	0	1,370,702
	Years of Education	10.47	4.27	0	30
	Parental Status	0.9	0.3	0	1
	Female	0.54	0.49	0	1
	Marital status	0.71	0.45	0	1
	Wealth	247,897	385,473	-3,111,776	11,500,000
Wave 4	Age	66	9.8	50	104
	Retired	0.73	0.44	0	1
	Euro-D	2.41	2.24	0	12
	Income	36,306	37,734	0	740,799
	Years of Education	10.62	4.43	0	30
	Parental Status	0.9	0.3	0	1
	Female	0.55	0.49	0	1
	Marital status	0.68	0.46	0	1
	Wealth	300,398	680,590	-718,856	27,000,000
Wave 5	Age	66	9.7	50	102
	Retired	0.72	0.45	0	1
	Euro-D	2.3	2.2	0	12
	Income	35,696	53,802	0	4,375,536
	Years of Education	11.1	4.47	0	35
	Parental Status	0.9	0.3	0	1
	Female	0.54	0.49	0	1
	Marital status	0.7	0.45	0	1
	Wealth	467,280	13,500,000	-422,016	1,460,000,000

(continued) Table 2- Variable Descriptions across Waves

	Variable	Average	Standard Deviation	Minimum	Maximum
Wave 6	Age	67	9.7	50	102
	Retired	0.74	0.43	0	1
	Euro-D	2.36	2.24	0	12
	Income	29,432	29,075	0	784,828
	Years of Education	10.98	4.47	0	35
	Parental Status	0.9	0.3	0	1
	Female	0.55	0.49	0	1
	Marital status	0.68	0.46	0	1
	Wealth	289,868	496,352	-449,789	53,800,000
Wave 7	Age	72	8.3	50	101
	Retired	0.89	0.3	0	1
	Euro-D	2.41	2.3	0	12
	Income	26,008	36,596	0	2,059,925
	Years of Education	10.78	4.3 8	0	30
	Parental Status	0.91	0.28	0	1
	Female	0.57	0.49	0	1
	Marital status	0.66	0.47	0	1
	Wealth	280,705	461,894	-8,253,175	11,100,000
Wave 8	Age	71	8.9	50	101
	Retired	0.82	0.38	0	1
	Euro-D	2.3	2.2	0	12
	Income	29,533	30,508	0	1,046,229
	Years of Education	11.33	4.4	0	25
	Parental Status	0.91	0.28	0	1
	Female	0.56	0.49	0	1
	Marital status	0.67	0.47	0	1
	Wealth	329,415	622,715	-1,138,827	21,300,000
Overall	Age	67	9.8	50	104
	Retired	0.74	0.43	0	1
	Euro-D	2.33	2.23	0	12
	Income	32,357	39,227	0	4,375,536
	Years of Education	10.85	4.4	0	35
	Parental Status	0.9	0.29	0	1
	Female	0.55	0.49	0	1
	Marital status	0.69	0.46	0	1
	Wealth	325,044	6,353,526	-8,253,175	1,460,000,000

The study also investigated the relationship between current job situations and mental health. Most of the respondents in the sample, 58%, reported being Retired, while almost 25% were Employed or self-employed with the lowest average number of depressive symptoms, 1.8. Unemployed, Permanently Sick or Disabled, and Homemakers comprised 16.8% of respondents and had the highest average number of depressive symptoms, notably, the Permanently Sick or Disabled group had a Eurod scale score of 4, signifying particularly elevated symptoms.

Individuals in the Employed or Self-employed category were also surveyed about their job satisfaction using the statement: "*Considering everything, I am content with my job*." The available options for responders were: Strongly Agree, Agree, Disagree, and Strongly Disagree. The findings presented in Table 3, reveal that individuals who strongly agreed with the statement reported the lowest average depressive symptoms compared to other respondents, among either part-time or full-time employers.

Table3 – Eurod Value and Satisfaction with the main Job, by Full-time or Part-time job

Job situation	Strongly agree	Agree	Disagree	Strongly disagree	Total
Full-time	1.6	2	2.8	3.3	1.9
Part-time	1.9	2.1	2.8	3.7	2.2

As it was mentioned the ‘Eurod’ index quantifies the mental health which is constructed with twelve questions each assess one depressive symptom, with higher frequency at 0 or 1 depressive symptom (Histogram 1). Table 4 presents all twelve questions that were asked from respondents to construct the Eurod index. In all questions, female respondents got higher scores on average than males. The variation in responses between different genders is notable in certain statements. For instance, in Euro1, respondents were asked, "In the last month, have you been sad or depressed." It is worth noting that 46% of women responded affirmatively to this question, whereas only 28% of men responded affirmatively.

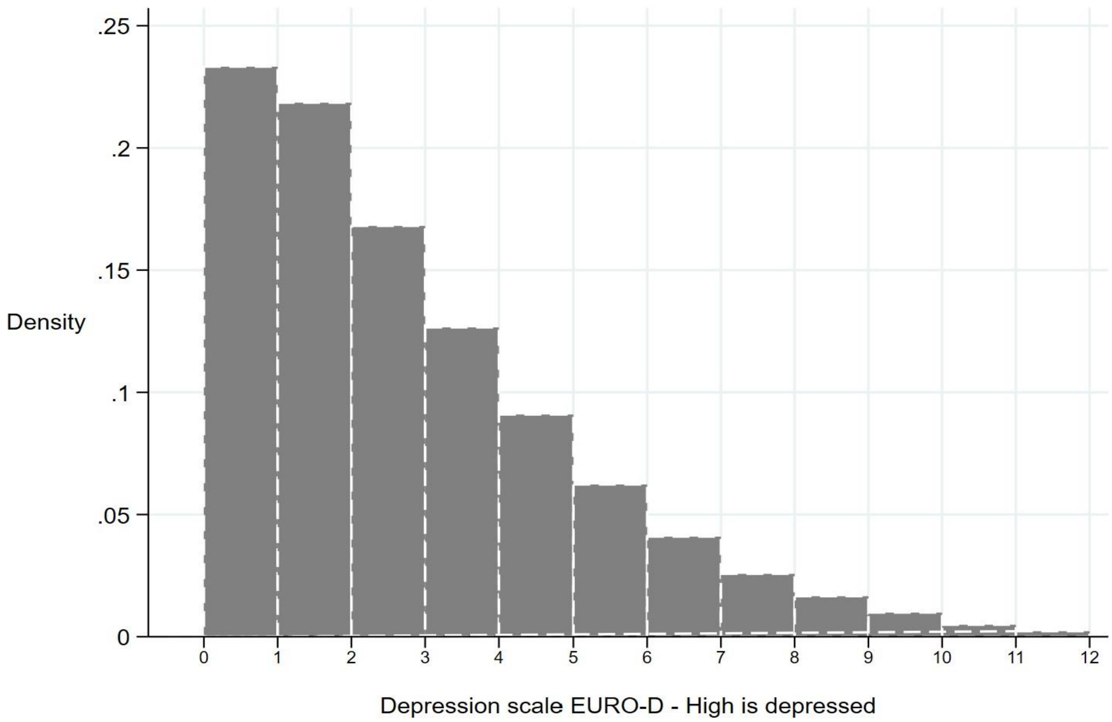
Table 4- Average Affirmative Responses to Eurod 12 Questions among different Genders

Eurod	Question	Female %	Male %
Euro1	whether the respondent has been sad or depressed in the last month.	46	28
Euro2	Whether the respondent has hopes for the future.	15	14
Euro3	Whether in the last month, the respondent felt that s/he would rather be dead.	8	4
Euro4	whether the respondent tends to blame her/himself or feel guilty about anything.	9	5
Euro5	Whether the respondent has trouble sleeping recently	40	24
Euro6	Whether the respondent feels any change (loss) in general interest in things	9	7
Euro7	Whether the respondent has been irritable recently	27	25
Euro8	Whether the respondent feels any change (diminution) in appetite	10	6
Euro9	whether a respondent had too little energy to do the things she/he wanted to do in the last month.	38	28
Euro10	whether a respondent has difficulties with concentrating on a television program, film, radio program, or reading	19	16
Euro11	What have you enjoyed doing recently? (Mentioned versus failed to mention)	12	12
Euro12	whether the respondent has cried at all in the last month	34	12

In the group of countries examined, Table 5, the Eurod index exhibited average values spanning from 1.7, representing the lowest, to 3.3, signifying the highest. Notably, Denmark had the lowest average value, while Poland had the highest average value for the Eurod index.

Income is one of the variables that seem to carry information about mental health among older individuals. The summary statistics for 'Household Net Income' in Table 2 reveal key insights. The dataset indicates an average income of € 32,358 for all waves, along with a high standard deviation of €39,232, suggesting a wide range of income levels among the participants. To gain a clearer perspective on the income variable, we categorized the income variable into four groups: up to €15,000 annually, between €15,001 and €30,000, €30,001 to €45,000, and more than €45,000. Interestingly, as income levels rise, the mean number of depressive symptoms decreases, (Table 1). That implies a negative correlation between income and the prevalence of depressive symptoms, indicating that individuals with higher income levels tend to experience fewer depressive symptoms, on average.

Histogram 1- EURO-D Probability Density



Household net wealth is another control variable in this study. The data is available in SHARE database and was computed as the sum of 'Household net financial assets' and 'Household real assets.' It is essential to note that the household net wealth can take negative values, since it is a net value. As displayed in Table 2, the overall mean value for household net wealth amounts to €325,044 for all waves, with a considerably high standard deviation, indicating significant dispersion of data points around the mean. This suggests a wide range of household net wealth values in the dataset. Interestingly, similar to the income variable, the statistical data presented in Table 1 reveal a noteworthy trend: There exists an inverse correlation between household net wealth and the quantity of reported depressive symptoms.

Table 5- Descriptive Statistics by Country

Countries	Observation	Share in Sample	Income (Mean)	Eurod (Mean)	Wealth (Mean)	Years of Education (Mean)	Age
Austria	13,849	6.4 %	31256	1.98	213849	9	67
Germany	18,232	8.4 %	36663	2.1	246397	12	66
Sweden	16,773	7.7 %	34707	1.9	361661	11	69
Netherlands	11,912	5.5 %	46666	1.9	279315	11	65
Spain	19,269	8.9 %	21210	2.6	269402	8	68
Italy	20,089	9.3 %	23422	2.8	747342	8	67
France	20,029	9.2 %	37921	2.8	4235237	11	67
Denmark	16,198	7.5 %	34487	1.7	403099	13	66
Greece	14,074	6.5 %	17192	1.8	133125	9	67
Switzerland	12,969	6 %	56487	1.8	754581	9	67
Belgium	24,080	11.1 %	47281	2.4	378080	12	66
Poland	8,132	3.7 %	13887	3.3	41099	9	66
Czech Republic	20,574	9.5 %	16164	2.2	79400	12	67

4 Empirical Approach

4.1 Introduction

In the realm of Microeconometrics models, the primary focus lies in the examination of individual decision-making, particularly in relation to discrete outcomes. These outcomes encompass scenarios such as choices to make a purchase (e.g., deciding on insurance coverage), or responses to survey inquiries about self-assessed well-being. Instead of measuring economic outcomes quantitatively, as depicted by Greene (2020), these instances involve a dependent variable indicating whether a specific outcome has occurred.

In the context of our study, the dependent variable, referred to as "Eurod," signifies the count of depressive symptoms observed among participants of the SHARE survey. This count ranges from 0 to 12 and serves as a quantification of events within a specific category, typically taking on non-negative whole-number values. This characterization aligns with what Greene (2020) terms as count data or Event Counts.

Event Counts, as defined by Greene (2020), pertain to the observed outcomes that capture the number of particular events. These count data variables assume values as nonnegative integers, a concept also highlighted by Wooldridge (2002). Typically, such data exhibits a skewed distribution, featuring a concentration of lower counts and a declining frequency as counts increase, (Greene, 2020). Similarly, the Eurod variable showcases a right-skewed distribution, indicating a greater likelihood of smaller counts and a mean of 2.3, accompanied by a Standard Deviation of 2.2 (as presented in Histogram 1 and Table 2).

Due to the inherent non-negativity of the dependent variable, it becomes essential to ensure that E(y|x) remains nonnegative for all x. However, when $\hat{\beta}$ represents the ordinary least squares (OLS) estimator, instances can arise where $X\hat{\beta} < 0$, potentially leading to negative predicted values for the dependent variable (Woodridge,2002). This underscores the importance of appropriately addressing the discrete nonnegative nature of the outcome variable. When dealing with such data, specialized models like Poisson regression or Negative binomial regression come into play. These models adeptly accommodate the distinct and non-negative nature of count data. Specifically, the Poisson regression model establishes itself as a foundational approach for count data analysis (Greene, 2020).

4.2 Assumption and Features of Poisson Regression

The fundamental Poisson regression model posits that each observation y_i (given X) arises from a Poisson distribution characterized by parameter λ_i which has a connection with the predictors. In other words, y given x conforms to a Poisson distribution with parameter λ_i, (Wooldridge, 2002). Where λ presents the rate parameter. The key equation of the model's probability mass function can be formulated as:

$$\Pr(Y = y_i|X_i) = \lambda_i^{y_i} e^{-\lambda_i}/y_i! \qquad i = 0,1,\dots,n$$

The conditional mean calculated as follow: $E[y_i|X_i] = \lambda_i = \exp(X_i'\beta)$. Where β is a $k \times 1$ parameter vector. The exponential of $X_i'\beta$ secures the parameter λ_i would remain nonnegative. Typically, the focus is on changes in this conditional mean due to fluctuations in the regressors. Also, the conditional variance is given by: $Var[y_i|X_i] = \exp(X_i'\beta)$.

The linear relationship between the log of the conditional expected value of y and the regressors weighted by their corresponding coefficients can be written as:

$$lnE(y|X) = ln\lambda_i = \ln(\exp(X_i'\beta)) = X_i'\beta$$

This log-linear representation is the prevalent formulation for λ_i. It stands as a straightforward method for parameter estimation through maximum likelihood techniques. The log-likelihood function is constructed as:

$$\ln L \;\; = \sum_{i=1}^{n}[-\lambda_i + y_i X_i'\beta - \ln y_i!].$$

Differentiating with respect to β yields the Poisson MLE $\hat{\beta}$ as the solution to the first-order conditions:

$$\frac{\partial \ln L}{\partial \beta} = \sum_{i=1}^{n}(y_i - \lambda_i)X_i = 0.$$

The Hessian is:

$$\frac{\partial^2 \ln L}{\partial \beta \partial \beta'} = -\sum_{i=1}^{n} \lambda_i \; X_i X_i' .$$

Given the estimates, the prediction for observation i is $\hat{\lambda}_i = \exp\left(X_i\hat{\beta}\right)$, (Greene, 2020).

Nonetheless, the Poisson model has faced criticism due to its underlying presumption that $ar(y_i|X_i) = E(y_i|X_i)$. This assumption, known as the equidispersion assumption of the Poisson regression model, often proves inadequate in practice, as data rarely adheres to this pattern (Greene, 2020). In our dataset, the conditional variance surpasses the conditional mean, giving rise to a phenomenon termed overdispersion. One primary factor contributing to this amplified variability is unobserved heterogeneity, a common occurrence that introduces supplementary dispersion. Unobserved heterogeneity can be attributed to a multiplicative random variable (Cameron &Trivedi, 2013). We can easily talk about the units used in our dataset. In the Poisson model, there's something called λ_i tells us how many events we expect in a certain amount of time or space. To handle situations where the time or space varies, we can adjust the model by adding an exposure time factor, T_i:

$$Prob(y = y_i|X_i, T_i) = \frac{\exp(-T_i\lambda_i)\,(T_i\lambda_i)^{y_i}}{y_i!}\ , \qquad \lambda_i = \exp\left(X_i^{`}\beta\right), y_i = 0,1, \dots, n$$

If T_i is the same for all i, lnT_i will effectively become part of the model's constant term., (Greene, 2020). In our case, the exposure is the 'last one-month' period for all individuals.

This chapter aims to examine the application of Poisson FE and RE models. Furthermore, we will explore the Hausman Test as a means of determining the appropriate approach to employ. Additionally, we will delve into the metrology of a Dynamic model and a Quasi-Fixed Effects approach.

4.3 Poisson Regression for Panel Date

As previously indicated, this study makes use of a panel dataset sourced from easySHARE. One of the central strengths of panel data lies in its remarkable flexibility, affording researchers the means to model the diverse behavioral variations among individuals (Greene, 2020). Furthermore, it enables a general form of individual heterogeneity. In the context of panel data analysis, the underlying assumption is that data independence prevails across individual units for a given year, while permitting correlations within each individual unit. Put simply, this time-based correlation is generally well-addressed by accounting for individual-specific effects (Cameron & Trivedi, 2013).

The fundamental equation of Poisson regression model is:

$$\Pr(Y = y_{it}|X_{it}, \alpha_i) = \frac{e^{-\mu_{it}} \mu_{it}{}^{y_{it}}}{y_{it}!} \quad (1)$$

$$y_{it} \sim P[\mu_{it} = \alpha_i \lambda_{it}]$$

$$\lambda_{it} = \exp(X'_{it} \beta), \; i = 1, \dots, n, \; t = 1, \dots, T.$$

Incorporating α_i as the individual effect represents a noteworthy departure from the conventional linear model. A substantial distinction arises in the approach by employing multiplicative individual-specific effects rather than additive ones. By adopting the exponential structure for λ_{it}, these multiplicative effects can be comprehended as an adjustment to the intercept, essentially altering the baseline interpretation.

$$E[y_{it} \mid X_{it}, \alpha_i] = \mu_{it}$$

$$= \alpha_i \exp(X'_{it} \beta)$$

$$= \exp(\delta_i + X'_{it} \beta),$$

Where $\delta_i = \ln \alpha_i$ (Cameron &Trivedi, 2013).

The following section begins with Fixed Effects and then Random Effects models. It is important to highlight that for multiplicative effect X_{it} are initially assumed to be strictly exogenous, so:

$$E[y_{it}|X_{i1}, \dots, X_{iT}, \alpha_i] = \alpha_i \lambda_{it}.$$

4.4 Fixed Effects Static Poisson Model for Panel Data

The FE Poisson model is estimated with respect to following assumptions:

1- The individuals $i = 1,2, \dots, n$ are a random sample; n is large, and T can be small,

2- $y_{it}|(x_i, \alpha_i) \sim Poisson(\mu_{it}), \mu_{it} = \alpha_i e^{x'_{it}\beta}$, with $x_i = (x_{i1}, \dots, x_{iT})$,

3- $Given\ x_i, \alpha_i$ the random variables $y_{i1}, \dots, y_{iT}$ are mutually independent.

The Fixed Effects (FE) approaches possess certain advantages, primarily in not necessitating the assumption of orthogonality between the independent variable and heterogeneity. When it comes to estimating FE count data models, we have two avenues to explore: direct estimation through Maximum Likelihood, which might not yield consistent estimates, especially when T is fixed and $n \to \infty$. Alternatively, we can opt for Conditional Maximum Likelihood, which involves analyzing the data conditioned on sufficient statistics for the individual effects (Cameron &Trivedi, 2013).

Maximum Likelihood

In the context of estimating the Fixed Effects (FE) Poisson model for Panel data through maximum likelihood (ML), the underlying assumption is that given λ_{it} and α_i, the variable y_{it} follows a Poisson distribution with the mean value $\mu_{it} = \alpha_i \, \lambda_{it}. Here\ the$, λ_{it} is determined by a specified function involving X_{it} and β , and X_{it} excluding an intercept. In the FE model, no assumptions are imposed regarding unobserved heterogeneity, and the parameters $\alpha_1, \dots, \alpha_n$ remain unknown but must be accounted for during estimations. This model can be easily estimated when working with a small value of n. Particularly, the exponential mean specification can be expressed as $\exp\left(\sum_{j=1}^{n} \delta_j \; d_{jit} + X_{it}'\beta\right)$, where the d_{jit} is an indicator variable that equals one if the it^{th} observation pertains to individual j and equals zero otherwise. In such cases regressing y_{it} on $d_{1it}, d_{2it}, \dots, d_{nit}$ and X_{it} can be performed. However, this approach becomes unwieldy when n significantly surpasses the software's maximum limit for the number of regressors. A noteworthy concern arises around the potential inconsistency of parameter estimates when T is limited and n approaches infinity. This inconsistency is rooted in the escalating number of parameters to estimate $n + \dim(\beta)$, as n approaches infinity, which could offset the advantages of a larger sample size, nT. The individual FE are considered incidental parameters, given that the main focus rests on the slope coefficients. In certain FE panel data models, an abundance of incidental parameters can lead to inconsistency in estimating parameters for both β and α_i. This inconsistency diminishes as T approaches infinity (Cameron &Trivedi, 2013). However, there are few cases where the incidental parameter issue does not arise, and the Poisson model is one such case, (Greene, 2020).

For $[y_{it} | \, X_{it}, \alpha_i \sim Piosson(\alpha_i \, X_{it}' \, \beta)]$, the condtional joint density for i^{th} observation is:

$$\Pr[y_{i1}, \dots, \; y_{iT} | \; X_{i1}, \dots, X_{iT}, \alpha_i, \beta] = \prod_t [\exp\,(-\alpha_i \, \lambda_{it})(\alpha_i \lambda_{it})^{y_{it}} / y_{it}!]$$

Referring to equation (1), we have $\lambda_{it} = \exp(X_{it}' \, \beta)$ then:

$$= \prod_t [\exp\,(-\alpha_i \, e^{X_{it}\beta})(\alpha_i e^{X_{it}\beta})^{y_{it}} / y_{it}!])$$

$$= \exp(-\alpha_i \sum_t \lambda_{it}) \prod_t \alpha_i^{y_{it}} \; \prod_t \lambda_{it}^{y_{it}} \, / \prod_t y_{it} \, !. \qquad (2)$$

The corresponding log-density is:

$$lnPr[y_{i1}, \dots, y_{iT} | \alpha_i, \beta] = \; -\alpha_i \sum_t \lambda_{it} + \ln \alpha_i \sum_t y_{it} + \sum_t y_{it} \, \ln \lambda_{it} - \sum_t ln y_{it} \, !.$$

Differencing with respect to α_i and setting to zero yields:

$$\widehat{\alpha_\iota} = \frac{\sum_t y_{it}}{\sum_t \lambda_{it}} \qquad (3)$$

Substituting this back into equation (2), simplifying and considering all n observation yields the concentrated likelihood function,

$$L_{conc}(\beta) = \prod_i \left[\exp(-\sum_t y_{it}) \prod_t (\frac{\sum_t y_{it}}{\sum_t \lambda_{it}})^{y_{it}} \frac{\prod_t \lambda_{it}^{y_{it}}}{\prod_t y_{it}!} \right] \quad (4)$$

This is the likelihood for n independent observation on a T dimensional multinomial variable with cell probabilities:

$$P_{it} = \frac{\lambda_{it}}{\sum_s \lambda_{is}} = \frac{\exp(X_{it}'\beta)}{\sum_s \exp(X_{is}'\beta)}$$

As shown that for the Poisson FE model there is no incidental parameters problem. Estimates of β that are consistent for fixed T and $n \rightarrow \infty$ can be obtained by maximization of (4), (Cameron &Trivedi, 2013). The consistency of the MLE for β despite the incidental parameters is a special result that holds for the Poisson multiplicative FE models.

Conditional Maximum Likelihood Models

The method pioneered by Andersen (1970), known as the conditional maximum likelihood (CML) approach, conducts statistical analysis taking into account the sufficient statistics for $\alpha_1, \alpha_2 \ldots, \alpha_n$, which, for distributions like the Poisson, involve individual-specific summations represented by $T\bar{y}_i = \sum_{t=1}^{T} y_{it}$. The conditional joint probability density for the i^{th} observation can be expressed as:

$$\Pr[y_{i1}, \ldots, y_{iT} | \sum_{t=1}^{T} y_{it}] = \frac{(\sum_t y_{it})!}{\prod_t y_{it}!} \times \prod_t (\frac{\mu_{it}}{\sum_s \mu_{is}})^{y_{it}} \qquad (5)$$

This is a multinomial distribution, with probabilities $p_{it} = \frac{\mu_{it}}{\sum_t \mu_{it}}, t = 1, \ldots, T$. Models with multiplicative effects set $\mu_{it} = \alpha_i \lambda_{it}$, has advantage that simplification occurs as α_i cancels in the ratio ${}^{\mu_{it}}/_{\sum_t \mu_{is}}$. Then equation (5) becomes:

$$\Pr[y_{i1}, \ldots, y_{iT} | \sum_{t=1}^{T} y_{it}] = \frac{(\sum_t y_{it})!}{\prod_t y_{it}!} \times \prod_t (\frac{\lambda_{it}}{\sum_s \lambda_{is}})^{y_{it}}$$

Because $y_{i1}, \ldots, y_{iT} | \sum_t y_{it}$ is multinomial distribution with probabilities $p_{i1}, \ldots, p_{iT}$, where $p_{it} = {}^{\lambda_{it}}/_{\sum_s \lambda_{is}}$, it follows that y_{i1} had mean $p_{it} \sum_s y_{is}$. This implies that we are essentially estimating the FE α_i by $\sum_s y_{is} / \sum_s \lambda_{is}$.

The conditional MLE of the Poisson FE model $\hat{\beta}_{PFE}$ therefor maximizes the conditional log-likelihood function:

$$L_c(\beta) = \sum_{i=1}^{n}[\ln\left(\sum_{t=1}^{T} y_{it}\right)! - \sum_{t=1}^{T}\ln\left(y_{it}\,!\right) + \sum_{t=1}^{T} y_{it}\left(X_{it}'\beta - \ln\left(\sum_{s=1}^{T}\exp(X_{it}'\beta)\right)\right)]. \quad (6)$$

Note that this is proportional to the natural logarithm of $L_{conc}(\beta)$ given in (4), and therefore here the conditional MLE equals the MLE, (Cameron &Trivedi, 2013).

4.5 Static Random Effects Poisson Models for Panel Data

In the context of panel data analysis, the Fixed Effects (FE) methodology presents an advantage by not requiring the assumption of uncorrelatedness between heterogeneity and the included exogenous variables. Should uncorrelatedness between regressors and heterogeneity hold, the Random Effects (RE) model becomes an appealing alternative, (Greene, 2020).

Our estimation of the RE model is grounded in several key assumptions:

1- The individuals $i = 1,2,\ldots,n$ are a random sample; n is large, and T can be small,
2- $y_{it}|(x_i,\alpha_i) \sim Poisson(\mu_{it}), \mu_{it} = \alpha_i e^{x_{it}^{`}\beta}$, with $x_i = (x_{i1},\ldots,x_{iT})$,
3- $Given\ x_i, \alpha_i$ the random variables $y_{i1},\ldots,y_{iT}$ are mutually independent.
4- α_i independent of x_i
5- $\ln(\alpha_i) \sim N(0,\sigma_\alpha^2)$, the lognormal distribution of α_i.

One potential approach involves specifying the density function $f(\alpha_i)$ of α_i, and then integrating out α_i to derive the joint density of $y_{i1},\ldots,y_{iT}$ conditional on just lambda $\lambda_{i1},\ldots,\lambda_{iT}$. Then:

$$\Pr[y_{i1},\ldots,y_{iT}|X_{i1},\ldots,X_{i1}] = \int_0^\infty [y_{i1},\ldots,y_{iT}|X_{i1},\ldots,X_{i1},\alpha_i] f(\alpha_i)\, d\alpha_i$$

$$= \int_0^\infty \prod_t \Pr[y_{it}|X_{i1},\ldots,X_{i1},\alpha_i]\, f(\alpha_i) d\alpha_i$$

Distinct probability distributions for α_i give rise to varied distributions for $y_{i1},\ldots,y_{iT}$. However, significant attention is drawn to the outcome when $f(\alpha_i)$ adheres to a normal distribution, as achieving results for a singular α_i opens the door for extending these findings to random effects in slope coefficients, (Cameron &Trivedi, 2013).

4.6 The Hausman Test

An unavoidable question arises: which methodological approaches should be employed? It becomes difficult to justify treating individual effects as uncorrelated with other regressors, as the RE model assumes. This can potentially introduce inconsistency in RE estimation due to the presence of correlation between the included variables and the random effect.

To scrutinize the assumption of strict exogeneity in both models, the Hausman test examines the correlation of α_i and the regressors. By assuming to be uncorrelated, validating all the model assumptions of the RE approach. This assertion implies consistency for both the RE and FE estimators, with the RE estimator also being asymptotically efficient (Verbeek, 2017). The alternative hypothesis suggests that α_i and X_{it} are correlated. In this scenario, the model assumptions of the RE approach are invalidated, rendering the RE estimator inconsistent, while the FE estimator remains consistent (Verbeek, 2017), but not efficient. Where the H_0 is:

$$Var(\hat{\beta}_{FE} - \hat{\beta}_{RE}) \approx Var(\hat{\beta}_{FE}) - Var(\hat{\beta}_{RE})$$

The test statistic of the Hausman test is then given by:

$$H = (\hat{\beta}_{FE} - \hat{\beta}_{RE})'(\widehat{var(\hat{\beta}_{FE})} - \widehat{var(\hat{\beta}_{RE})})^{-1}(\hat{\beta}_{FE} - \hat{\beta}_{RE})$$

This test statistic follows an asymptotic χ^2 distribution with K degrees of freedom, where K represents the number of the time-varying regressors (Verbeek, 2017). The null hypothesis is rejected if the test statistic H surpasses the critical threshold $\chi^2_{k_j\,\alpha}$ (Cameron and Trivedi, 2013). Rejecting the H_0 implies a connection between the individual-specific effect and the explanatory variables, hinting at a preference for the fixed-effects specification. However, a limitation of the FE model is its inability to estimate the effects of variables that remain constant or exhibit minimal variation over time. It's plausible that several variables of interest fall into this category. The Quasi-Fixed Effect model address this concern as an extension of the FE specification.

4.7 Quasi-Fixed Effects Poisson Model for Panel Data

Mundlak highlighted reservations regarding the underlying assumption of the RE model, which fails to consider the plausible correlation between α_i (individual-specific effects) and explanatory variables. This concern is substantiated by recognizing that in many scenarios, such correlation holds merit (Hsiao, 2014). Introducing a solution to this, the Quasi-Fixed Effect (QFE) approach emerges. The central premise of the QFE approach involves the consideration that the unobserved heterogeneity, α_i, encompasses the following two components:

$$\alpha_i = \sum_{t=1}^{T} x_{it}'\theta_t + \tilde{\alpha}_i$$

Where $ln\tilde{\alpha}_i \sim N\left(0, \sigma_{\tilde{\alpha}}^2\right)$, independent of x_{it} , $t = 1, \ldots, T$. The θ_t are allowed to be non-zero only for selected time-varying regressor j. Moreover, we will assume that θ_t is the same for all t=1, …, T. Therefore, the equation for α_i can be written as:

$$\alpha_i = \bar{x}_i' \, \delta + \tilde{\alpha}_i \qquad (7)$$

The specification for α_i in the QFE model shows that unobserved heterogeneity and selected covariates are correlated.

Mundlak's approach often stands as a middle ground between fixed and random effects models. A compelling attribute of this strategy lies in its capacity to streamline the execution of the Hausman test. In the given framework, the distinction between the FE and RE models pivots on the presence of a non-zero parameter δ. Thus, by scrutinizing the null hypothesis that δ is equal to zero, it offers an alternative pathway to the two aforementioned methodologies, (Greene, 2020).

Substituting (7) into (2) we get:

$$L_i(\beta, \delta, \sigma_{\tilde{\alpha}}) = \int_0^\infty \prod_t \Pr[y_{it}|X_{i1}, \ldots, X_{i1}, \tilde{\alpha}_i]\, f(\tilde{\alpha}_i) d\tilde{\alpha}_i$$

$$L_i(\beta, \delta, \sigma_{\tilde{\alpha}},) = \int_0^\infty \prod_t [\exp\left(\lambda y_{i1} + \tilde{\alpha}_i\right)(-e^{X_{it}'\beta}). (\lambda y_{i1} + \tilde{\alpha}_i)(e^{X_{it}'\beta})^{y_{it}}/y_{it}!] f(\tilde{\alpha}) d\tilde{\alpha}$$

4.8 Random Effects Dynamic Poisson Model for Panel Data

In scenarios involving panel data analysis, it is frequent to encounter situations where the phenomenon being studied inherently evolves over time. As a consequence, the past values of the dependent variable play a crucial role in influencing the current outcomes. The relationship is described by the equation:

$$\mathrm{E}(y_{it}|y_{i\,t-1}, \ldots, y_{i0}, x_{it}, \alpha_i) = \alpha_i \exp\left(x_{it}'\beta + \ ln\, y^*{}_{i\,t-1}\, \rho\right)$$

Where $y_{it-1}^* = y_{it-1}$ except when the lagged value is zero, in which case it becomes $y_{it-1}^* = c$. To estimate the Dynamic Random Effects model, we introduce the lagged dependent variable as an additional predictor. The coefficient linked to this predictor is referred to as the state dependence parameter, determining the degree to which the current outcome relies on the preceding state.

In the context of the Dynamic Random Effects model, a significant hurdle emerges when confronted with the lagged value of the initial outcome, yi1 (for t = 1, …, T), due to the unavailability of the lagged value or yi0. This challenge is known as the "initial condition problem," a concept extensively discussed by Wooldridge (2002). Overlooking this correlation could lead to estimations that are both unreliable and imprecise. To surmount this barrier, the Wooldridge method offers a strategic approach. This method entails treating yi1 as a predetermined value while accounting for its interplay with the individual-specific effect αi. (Wooldridge, 2005)

The unobserved individual effect is formulated by combining two elements:

$$\alpha_i = \lambda y_{i1} + \tilde{\alpha}_\iota$$

$ln\tilde{\alpha}_i \sim N\left(0, \sigma_{\tilde{\alpha}}^2\right)$, independent of y_{i1} , $x_{it}, t = 1,2, \dots, T$.

$$L_i(\beta, \rho, \sigma_{\tilde{\alpha}}, \lambda) = \int_0^\infty \prod_t [\exp\,(\lambda y_{i1} + \tilde{\alpha}_\iota)(-e^{X'_{it}\beta + \gamma ln y^*{}_{i\,t-1}}).\,(\lambda y_{i1} + \tilde{\alpha}_\iota)(e^{X'_{it}\beta + \gamma ln y^*{}_{i\,t-1}})^{y_{it}} / y_{it}!] f(\tilde{\alpha}) d\tilde{\alpha}$$

5 Results

5.1 Does Retirement Affect Mental Health?

Static Analysis

Table 6 displays the outcomes of the Poisson regressions. The initial column represents the coefficient of the Poisson regression on pooled data. The results unveil a notable and positive association between retirement and the occurrence of depressive symptoms. According to this estimation, retired individuals[2] experience, on average, 19.3% (significant at 0.01% level) more depressive symptoms, compared to those who are employed, while controlling for other variables.

To benefit from the advantages of panel data in dealing with unobserved variables, the FE and RE models are also estimated. The FE Poisson regression model accounts for individual-specific fixed effects, controlling for all time-invariant characteristics. The coefficients reflect the associations between changes in the variables and the changes within individuals over time. The RE Poisson regression model incorporates random effects, capturing unobserved heterogeneity between individuals, assuming individual effects are not related to the observed explanatory variables.

Based on FE and RE estimation (Table 6), the coefficients of interest are still positive and significantly non-zero, indicating that on average retired individuals experience poorer mental health than employed or self-employed individuals, but the magnitude of the coefficients is smaller compared to the pooled estimator. Based on FE Poisson, on average retired individuals experience 2.2% more depressive symptoms, which is much less than the pooled model's estimate, of 19.3%. Also, RE estimation suggests that retired individuals, on average, experience 12.8% more depressive symptoms than those who are employed, keeping other variables constant.

The Hausman Test serves as the compass in our decision-making process between the RE and FE models. Under the null hypothesis, all model assumptions of the RE model are valid and the ML estimator is consistent and asymptotically efficient. In contrast, the FE estimator is not efficient. Here the Hausman test provides a $chi^2(7)$ statistic, equal to 820.05 which means the null hypothesis is rejected. Under the alternative hypothesis, the assumption of the FE model is valid, and the estimator is consistent.

2. Retired individual includes retired, unemployed, sick and permanently disabled, and homemaker vs employed or self-employed individuals.

By allowing the unobserved heterogeneity to be correlated with the time average of selected time-varying regressors rather than assuming zero correlation, the QFE model provides a consistent estimator, in case the zero-correlation assumption between unobserved heterogeneity and regressors is not met. Here we assumed that the unobserved heterogeneity is correlated with the time average of Retirement, Income, Wealth, and Years of Education, age and marital status as time-varying regressors. The results are provided in the last column of Table 6. What is obvious is that coefficient of interest is again positive in the QFE model, 0.018 with significancy at 1% level, indicating retirement increases the average count of depressive symptoms by 1.8%, keeping other variables constant. The results also showed that the retirement has smaller effect on mental health based on QFE model relative to FE models. Besides, our findings indicated that there exists a significant correlation between the unobserved heterogeneity and the time average of the time-varying regressors at 1% level.

By addressing the possibility of correlated unobserved heterogeneity and regressors, the QFE model could provide a more precise understanding of the effect's robustness. Both QFE and FE models require careful consideration of assumptions. The FE models assume time-invariant unobserved heterogeneity and no correlation with regressors, while QFE models relax the zero-correlation assumption.

However, QFE model seems to be a superior estimator compared to the Fixed Effects (FE) model. Its ability to account for potential correlations between unobserved heterogeneity and time-varying regressors enhances the reliability of estimating retirement's impact on mental health.

Dynamic Random Effects Model

Dynamic Random Effects is another approach which incorporates lagged dependent variables as explanatory variables. It accounts for the potential state dependence and dynamics in the relationship between the independent and dependent variables. The result of the Dynamic RE model is also shown in Table 6. To deal with the initial value issue, the Woodridge approach had been used. The lagged Eurod`s coefficient is positive and significantly non-zero. This implies that past levels of depressive symptoms significantly and positively impact the current levels; or in other words there is persistence or a tendency for depressive symptoms to persist over time. Based on the RE model, the coefficient of interest is still positive indicating a positive correlation between retirement and the number of depressive symptoms.

In this section, we employed five different approaches. Pooled Poisson regression fails to account for unobserved factors, the coefficient obtained would be inconsistent. To address the influence of unobserved factors, we employed RE and FE models. However, the RE model imposes overly restrictive assumptions on the regressors and unobserved factors, which are seldom met in practice. The results obtained from the Hausman Test and the QFE model indicate that the assumption of zero correlation is not valid, rendering the RE estimator inconsistent. Based on the underlying assumption, the FE model is more realistic, and capable in accounting for time-invariant unobserved factors in comparison with RE estimator.

As a summary, according to the findings presented in Table 6, the coefficient of interest demonstrates statistical significance across all models and consistently exhibits a positive effect. This implies that individuals who have retired tend to experience a higher number of depressive symptoms compared to those who have not retired yet. This discovery aligns with the perspective that retirement detrimentally affects health. This perspective contends that retirement can bring about emotional or mental challenges stemming from feelings of isolation, obsolescence, or a sense of aging (Bradford, 1979).

However, an additional obstacle necessitates attention. While the consensus acknowledges the potential influence of retirement on health outcomes, prevailing studies have also established a causal link in the opposite direction: individuals with poorer health tend to opt for retirement (Coile, 2003). So, when people retire and their mental health goes down, it might not be retirement itself causing it. It could be because of the reasons they retired. To tackle this issue, we'll use the Statutory Retirement Age as a tool in the next section.

Fixed Effects Instrument Variable Estimation of the Static Model

In this section, we delve into the FE-IV estimation using the statutory retirement age as an instrumental variable for retirement. For an instrument to be deemed effective, it must satisfy specific criteria related to retirement. Primarily, it should exhibit a clear link or association with retirement. Furthermore, it must possess validity, signifying its independence from mental health-related factors (Heller-Sahlgren, 2017). Importantly, it should not exert a direct influence on the dependent variable.

We adopt a two-stage regression approach to estimate the FE-IV Poisson regression model to account for endogeneity and mitigate unobserved heterogeneity. The initial stage involves estimating a Fixed Effects model wherein the endogenous variable is regressed on the instrumental variable and other endogenous regressors. In the subsequent step, the FE Poisson regression model is estimated using the forecasted values from the first stage as instruments for the endogenous variable.

Here is the procedure taken from Wooldridge (2019):

1- Estimate the reduced form for y_{it2}, the endogenous variable (in our case Retirement), by Fixed Effects and obtain the FE residuals;

$$y_{it2} = Z_{it}\Pi_2 + X'_{it}\beta + \alpha_i + u_{it2}$$

$$\widehat{\ddot{u}}_{it2} = \ddot{y}_{it2} - \ddot{Z}_{it}\widehat{\Pi}_2$$

$$\ddot{y}_{it2} = y_{it2} - T^{-1}\sum_{r=1}^{T} y_{ir2}$$

The instrumental variable should also exhibit a correlation with the endogenous explanatory variable, which is indicated when Π_2 become statistically significance in the first stage regression. The results suggest that the instrument is relevant and strong by giving a positive coefficient of 0.15, which is significant at 1%. The coefficients clearly demonstrate that reaching the state pension age threshold significantly enhances the probability of retirement.

2- Use the FE Poisson on the mean function:

$$E\left(y_{it1} \middle| z_{it}, y_{it2}, X_{it}, \widehat{\ddot{u}}_{it2}, \alpha_i\right) = \alpha_i \exp\left(X'_{it}\beta + \widehat{\ddot{u}}_{it}\rho\right)$$

Then using the robust Wald test of H_0: $\rho = 0$, (Wooldridge, 2019).

Based on our estimation, the H_0 of the Wald test is rejected which indicates that ρ, the coefficient of predicted residuals is significantly different from zero. The value of ρ is 0.28 and it is significant at 1% level, with the confidence interval [0.19, 0.36], representing that the presence of the Instrumental variable is necessary in the model to properly address the endogeneity problem. Table 7 illustrates the results from the first and second stages of the FE-IV Poisson model.

By acknowledging the issue of endogeneity in the retirement decision and based on FE-IV estimation, we uncover a noteworthy finding: retirement no longer worsens mental health issues;

instead, it demonstrates a significant protective effect on mental well-being. Specifically, retired individuals experience an average reduction of 25% in depressive symptoms (keeping other variables constant). This estimated mean effect coefficients has become more pronounced and negative. The bootstrap was also conducted (Table 7). The magnitude of the coefficients did not change and the negative sign of the retirement coefficient in the FE-IV model remained consistent. Drawing from the outcomes of this study, one can deduce that, on average, retirement leads to a reduction in the manifestation of depressive symptoms in individuals and contributes to improved mental well-being among retirees.

The change in results observed before and after using the instrumental variable can be explained that the IV addresses issues of endogeneity or reverse causality properly. By introducing an instrumental variable, such as the statutory retirement age, we were able to isolate the exogenous variation in retirement that is not influenced by mental health factors. This variation allows us to establish a causal relationship between retirement and mental health by utilizing a source of variation that affects retirement but is unrelated to mental health directly. It appears that the IV effectively capture the genuine causal impact of retirement on mental health by exploiting the fluctuations in retirement that is driven by the instrumental variable.

To provide a more comprehensive analysis and delve into the specifics of mental health, we conducted Binary logit FE-IV estimation 12 times, using the same explanatory variables, but with each iteration focusing on one specific Eurod value, from Eurod's 12 components (Table 8). The coefficients predominantly exhibit a negative value, indicating the fact that retirement enhances mental health. However, it's important to note that not all coefficients are significantly different from zero. Specifically, let's examine the effects of retirement on different Eurod values:

Eurod 7 assesses irritability. Our results indicate that retirement lowers the likelihood of experiencing irritation, holding other variables constant. The estimated coefficient stands at -0.8, with a corresponding marginal effect[3] of -0.19 for the transition from being employed to retired in relation to the mean value of the dependent variable. Euro 11 component measures 'Failure to mention enjoyable activities' versus 'Mentioning any enjoyable activities.' Being retired increases

3. $m.e.(x_{ij}) = \frac{\partial}{\partial x_{it,j}} \Pr(y_{it} = 1|x_{it}, \alpha_i) = \Pr((y_{it} = 1|x_{it}, \alpha_i)[1 - Pr(y_{it} = 1|x_{it}, \alpha_i)](-0.8)$= (0.38) (0.62) (-0.8) = -0.19

the probability of mentioning at least one enjoyable activity, keeping other variables constant. Additionally, retirement was found to have a protective impact on fatigue, concentration and showing interest.

By examining these specific Eurod values, we gain a better understanding of the relationship between retirement and mental health. Retirement appears to have a generally beneficial effect on various aspects of mental well-being, such as maintaining interest, reducing irritability, increasing engagement in enjoyable activities, and alleviating fatigue and concentration issues.

Running separate regressions helps identifying specific depressive symptoms which are more strongly affected by retirement. Considering individual component questions provides a comprehensive understanding of how retirement affects various dimensions of mental health including vulnerable symptoms like fatigue or difficulty with concentration. The results also validate the findings from the FE-IV model, by showing similar protective effects of retirement on some depressive symptoms or no significant effect with some other symptoms (but still showing a negative correlation), adding robustness to the conclusion. Additionally, these separate regression findings suggest area for further investigation focusing on symptoms with higher and significant correlation with retirement.

Table 6- Effect of Retirement on Mental Health, Poisson Regression Estimation

	Pooled regression	FE Poisson	RE Poisson	Dynamic RE	Quasi- FE
Retired	0.193 (0.007) **	0.022 (0.008) **	0.128 (0.006) **	0.06 (0.016) **	0.018 (0.008) *
Age	-0.09(0.002) **	-0.1 (0.004) **	- 0.1 (0.003) **	-0.06 (0.006) **	-0.1 (0.003) **
Age Square	0.0007(0.000) **	0.001 (0.000) **	0.001 (0.000) **	0.005(0.000) **	0.0008 (0.000) **
Married	-0.09(0.005) **	- 0.15 (0.01) **	- 0.12 (0.006) **	-0.015 (0.011)	-0.16 (0.000) **
Parental status	-0.014(0.007) *	0.02 (0.02)	- 0.013 (0.009)	- 0.03 (0.017)	- 0.01 (.009)
wealth	-0.035(0.001) **	-.005 (0.002) **	- 0.025 (0.001) **	-0.018(0.003) **	-0.005 (0.001) **
Income	-0.022(0.002) **	-0.006 (0.002) *	- 0.015 (0.002) **	-0.013 (0.005) **	-0.005 (0.002) *
Female	0.32(0.003) **		0.32(0.006) **	0.18 (0.011) **	0.31 (0.006) **
Low-level Education-dummy	-0.157(0.005) **		-0.16 (0.01) **	-0.05(0.018) **	- 0.06 (0.014) **
Medium-level Education_ dummy	-0.23(0.006) **		-0.24 (0.011) **	-0.09(0.021) **	-0.05(0.021) *
High-level Education_ dummy	-0.23(0.007) **		-0.26 (0.013) **	-0.09(0.026) **	0.03 (0.028)
Austria	-0.51 (0.009) **		-0.52 (0.018) **	-0.09 (0.027) **	-0.5 (0.018) **
Germany	-0.29(0.009) **		-0.31(0.017) **	-0.02 (0.022)	-0.25 (0.017) **
Sweden	-0.4 (0.009) **		-0.42 (0.018) **	-0.11 (0.02) **	-0.34 (0.018) **
Netherlands	-0.43(0.009) **		-0.45 (0.018) **	-0.16 (0.023) **	-0.4 (0.018) **
Spain	-0.18(0.008) **		-0.26 (0.017) **	0.006 (0.023)	-0.21 (0.017) **
Italy	-0.13(0.008) **		-0.1a7 (0.017) **	0.09 (0.022) **	-0.12 (0.017) **
France	-0.06(0.009) **		-0.09 (0.017) **	0.06 (0.02) **	-0.03 (0.017) **
Denmark	-0.45(0.009) **		-0.48 (0.018) **	-0.13(0.024) **	-0.4 (0.018) **
Greece	-0.4 (0.009) **		-0.41 (0.018) **	-0.32(0.022) **	-0.37 (0.018) **
Switzerland	-0.46 (0.009) **		-0.5 (0.019) **	-0.2 (0.03) **	-0.4 (0.02) **
Belgium	-0.16 (0.008) **		-0.17 (0.016) **	0	-0.1 (0.017) **
Czech Republic	-0.36 (0.008) **		-0.36 (0.016) **	0	-0.33 (0.017) **
LAG-Eurod	-		-	0.09 (0.002) **	-
Eurod Initial value	-		-	0.10 (0.002) **	-
Mean (Retired)	-		-	-	0.26 (0.012) **
Mean (Income)	-		-	-	-0.02 (0.005) **
Mean (Wealth)	-		-	-	-0.04(0.003) **
Mean (Married)					0.07 (0.013) **
Mean (age)					-0.01 (0.000) **
Mean (Education)	-		-	-	-0.02 (0.002) **

Note: The dependent variable is represented by the Eurod scale, which measures the count of depressive symptoms. Retired individuals are defined as those without paid employment, including retirees, the unemployed, homemakers, the permanently sick, and the disabled, in contrast to those who are employed or self-employed. Standard errors are enclosed in parentheses. The Very-Low-level Education dummy serves as the reference group. Eurod Initial value represents the initial value of the dependent variable in the Woodridge dynamic RE approach, *(** p<0.01, *p<0.05)*.

Table 7- Effect of Retirement on Mental Health, FE-IV Estimation

	1st stage FE-Poisson	2nd stage FE-Poisson	Boosted (2nd stage)
Retired		-0.25 (0.05) **	-0.25 (0.05) **
IV	0.15 (0.002) **	-	-
Age	0.12 (0.001) **	-0.07 (0.008) **	- 0.07 (0.007) **
Age Square	-0.0008 (0.000) **	0.0006 (0.000) **	0.0006 (0.000) **
Married	0.023 (0.004) **	- 0.14 (0.013) **	- 0.14 (0.014) **
Parental Status	0.012 (0.007)	0.02 (0.02)	0.02 (0.03)
Income	-0.002 (0.000) **	- 0.006 (0.003) **	-0.006 (0.002) **
wealth	-0.0007 (0.000)	- 0.005 (0.0018) **	-0.005 (0.0017) **
Re		0.28 (0.05) **	0.28 (0.05) **

Note: The dependent variable is represented by the Eurod scale, which measures the count of depressive symptoms. Retired individuals are defined as those without paid employment, including retirees, the unemployed, homemakers, the permanently sick, and the disabled, in contrast to those who are employed or self-employed. "Re" stands for the residuals from the first stage of estimation. Standard errors are enclosed in parentheses. It's important to highlight that the IV variable in the first stage estimation is significantly non-zero (** $p<0.01$).

Table 8- Static Binary FE-IV Logit Model Estimations- Analysis by Depressive Symptoms

Dependent variable	Retired	Standard Error
1- In the last month, have you been das or Depressed?	-0.16	0.16
2- What are your hopes for the future? (Mentioned or not)	-0.2	0.24
3- In the last month, have you felt you would rather be dead?	-0.6 *	0.4
4- Do you tend to blame yourself or feel guilty about anything?	-0.1	0.3
5- Have you had trouble in sleeping?	0.1	0.17
6- In the last month what is your interest in things? (1: Less interest,0: No change)	-1.17 **	0.3
7- Have you been irritable recently?	-0.8**	0.17
8- What has your appetite been like? (Changed or not)	-0.6 *	0.31
9- In the last month have you had too little energy to do things you wanted to do?	-0.95**	0.17
10- How is your concentration? (Having difficulty or not)	-0.92**	0.22
11-What have you enjoyed recently? (1: Fails to mention any enjoyable activity)	-0.5**	0.23
12- In the last month have you cried at all?	0.06	0.2

Note: The 12 Eurod index components serve as the dependent variables. Retired individuals are defined as those without paid employment, including retirees, the unemployed, homemakers, the permanently sick, and the disabled, in contrast to those who are employed or self-employed. Standard errors are enclosed in parentheses. ** $p<0.01$. *< 0.1

5.2 Does Social support Affect Mental Health?

Evidence suggests the importance of social support for the well-being of elderly individuals (Litwin & Shiovitz-Ezra, 2011). It's logical to assume that the existence of social support in later life plays a crucial role in influencing a person's overall quality of life during retirement (García-Gómez et al., 2019). To measure social support, we use marital status and parental status As discussed in the literature review, living without a partner may elevate the risk of depression among older adults, but the causal relationship between having children and mental health, specifically in relation to depressive episodes, remains uncertain.

The FE-IV findings suggest that (Table 7) on average married individuals experience 14 % fewer depressive symptoms than non-married individuals (Including: living separated, divorced, widowed, never married), considering other variables constant. The coefficient is negative and statistically non-zero. Being married is associated with a decrease in depressive symptoms and this finding is consistent among all approaches that were conducted in this study. The explanatory variable 'Parental status' is a dummy variable assigning 1 for individuals who have at least one child or more and assigning 0 if an individual has no child. Based on the FE-IV model having children has a negative impact on the mental health of elderly people. However, the coefficient was not always statistically significant.

5.3 Do Wealth and Income Affect Mental Health?

The coefficients for wealth and income, obtained through the FE-IV approach show a negative relationship between both wealth and income and the outcome variable (Table 7). Indicating that a one percent increase in income is associated with 0.006% decrease in the expected number of depressive symptoms holding other variables constant. And also, one percent increase in wealth decreases the expected number of depressive symptoms by 0.005%, keeping other variables constant. These coefficients are statistically significant and different from zero, suggesting that changes in wealth and income have a meaningful impact on the outcome variable. Importantly, these results were consistent across other approaches used in the analysis, further reinforcing the findings. Overall, this indicates that individuals with higher income and higher wealth levels, experience fewer depressive symptoms compared to individuals with lower levels of income or wealth.

5.4 Does the Retirement Effect differ by Gender?

With respect to the retirement`s supportive effect on mental health, it should be mention that this effect may not be uniform across individuals. Gender disparities exist in the protective impact of retirement. There are variations in how individuals of different genders respond to retirement. The findings presented in Table 9 demonstrate this discrepancy. Specifically, the results reveal that the average protective effect is more pronounced among males than among females. Retirement results in a 22% reduction in the occurrence of depressive symptoms among females and a 33% decrease among males. Nevertheless, it's important to note that the distinction between these two coefficients is not statistically significant[4].

5.5 Does the Retirement Effect differ by Marital Status?

Apparently, the marital status of individuals plays a role in their experience of retirement-related changes. Descriptive statistics indicate that married individuals tend to report fewer depressive symptoms compared to those who are divorced or widowed. In light of these findings, we conducted FE-IV models separately for married individuals and divorced or widowed individuals. Based on the findings the relationship between retirement and the number of depressive symptoms appears to differ based on marital status. Our findings indicates that (Table 10) there is a negative and significant relation between retirement and the number of depressive symptoms among married individuals. The results suggest retiring is associated with a significant reduction in depressive symptoms (30%) among married individuals, indicating better mental health after retirement. Additionally, for divorced or widowed individuals, the FE-IV model indicates a retirement negatively affects number of depressive symptoms, however, the coefficient (-0.09) is not significant (i.e., not significantly different from zero). Despite the lack of statistical significance, the direction of the correlation is noteworthy as it suggests that among divorced and widowed individuals, retiring may still be associated with a reduction in depressive symptoms, meaning they could experience better mental health after retiring.

4 . $z = \frac{\hat{\beta}_{Female} - \hat{\beta}_{Male}}{\sqrt{var(\hat{\beta}_{Female}) + var(\hat{\beta}_{Male})}} = |\frac{-0.22-(-0.33)}{\sqrt{(0.08)^2+(0.063)^2}}| = 1.07$

Table 9- Effect of Retirement on Mental health, FE-IV Poisson Model- Analysis by Gender

	Female		Male	
	First stage	Second stage	First stage	Second stage
Retired		-0.22 (0.063) **		-0.33(0.08) **
IV	0.15(0.003) **		0.15(0.003) **	
Age	0.1 (0.001) **	-0.06 (0.009) **	0.15(0.002) **	-0.06(0.015) **
Age Square	-0.0006(0.000) **	0.0005(0.000) **	-0.0009(0.000) **	0.0006(0.000) **
Married	0.018(0.005) **	-0.16(0.015) **	0.012(0.007)	-0.15 (0.02) **
Parental Status	0.001(0.009)	0.02(0.03)	0.023(0.01) *	0.02 (0.04)
Income	-0.005(0.001) **	-0.007(0.003) *	0.0006(0.001)	-0.005 (0.004)
wealth	0.0004(0.000)	-0.003(0.002)	-0.002 (0.001) **	-0.01 (0.003) **
RE		0.24 (0.06) **		0.36 (0.08) **

Note: The dependent variable is represented by the Eurod scale, which measures the count of depressive symptoms. Retired individuals are defined as those without paid employment, including retirees, the unemployed, homemakers, the permanently sick, and the disabled, in contrast to those who are employed or self-employed. "Re" stands for the residuals from the first stage of estimation. Standard errors are enclosed in parentheses, (*<0.05,** p<0.01).*

Table 10- Effect of Retirement on Mental Health, FE-IV Estimations- Analysis by Marital status

	Married		Divorced or widowed	
	1st Stage	2nd Stage	1st Stage	2nd Stage
Retired		-0.3 (0.06) ***		-0.09 (0.1)
IV	0.14 (0.002) ***		0.16 (0.005) ***	
Age	0.13 (0.002) ***	-0.09 (0.01) ***	0.1 (0.002) ***	-0.09 (0.015) ***
Age Square	-0.0008 (0.000) ***	0.0008 (0.000) ***	-0.00006 (0.000) ***	0.0007(0.000) ***
Parental status	0.009 (0.01)	0.05 (0.03) *	-0.007 (0.01)	-0.04 (0.04)
Income	-0.003 (0.001) ***	-0.002 (0.003)	-0.002 (0.001)	-0.009 (0.005) *
wealth	0.0002 (0.000)	-0.005 (0.002)	-0.001 (0.001)	-0.007 (0.003) **
Re		0.3 (0.058) ***		0.16 (0.1)

Please Note: The dependent variable is represented by the Eurod scale, which measures the count of depressive symptoms. Retired individuals are defined as those without paid employment, including retirees, the unemployed, homemakers, the permanently sick, and the disabled, in contrast to those who are employed or self-employed. "Re" stands for the residuals from the first stage of estimation. Standard errors are enclosed in parentheses *(* p<0.1, ** p<0.05, *** p<0.01).*

5.6 Robustness Checks

Assessing the impact of retirement on mental health is a complex task due to the presence of unobserved factors that can influence both the decision to retire and mental health. These factors, vary from person to person and make it difficult to isolate the specific effects of retirement. We utilized the Fixed Effects model and statutory retirement age as IV to address these issues to a great extent. However, it should be mentioned that the definition of the variable of interest in this study categorizes into 'Retired' and 'Not Retired' groups. 'Retired' individuals refer to those who stated to be retired from work, who are not actively participating in the workforce; such as unemployed, permanently sick or disabled, or homemakers. Since our focus is on the transition from work to retirement including unemployed or permanently sick, or disabled individuals in the sample may introduce bias in our estimations. To address this concern, we conducted the FE and RF and FE-IV models using only 'Employed' and 'Retired' individuals, excluding unemployed individuals, homemakers, and those who are permanently sick or disabled. The findings from the FE model reveal (Table 11) a significant negative association between retirement and the number of depressive symptoms. The estimated coefficient for retirement is -0.05, indicating that individuals transitioning from work to retirement experience a decrease in depressive symptoms. This suggests a positive effect of retirement on mental health, focusing solely on employed and retired individuals. By narrowing the scope to this specific group, the model better explains the variations in the dependent variable.

Similarly, the FE-IV models, addressing potential endogeneity issues using statutory retirement age as the instrumental variable, also demonstrate a significant and substantial negative effect of retirement on the number of depressive symptoms. The estimated coefficient for retirement in this model is -0.19, showing that on average, retired individuals experience 19% fewer depressive symptoms compared to their employed counterparts. Notably, the protective effect of retirement observed in the FE-IV model is stronger than in the FE model. The statistical significance of this coefficient further reinforces the evidence supporting retirement's positive impact on mental health.

In summary, the results from both FE and FE-IV show that retirement acts as a protective factor for mental well-being. The effect is even more pronounced when using the FE-IV model.

Table 11- Effect of Retirement on Mental Health, Poisson Regression Estimation, (With a different definition for retirement).

	Pooled regression	FE	FE-IV	RE
Retired	0.08 (0.008) **	-0.05 (0.01) **	-0.19 (0.04) **	0.04 (0.008) **
Age	-0.07 (0.003) **	-0.1 (0.004) **	-0.07 (0.009) **	-0.08 (0.003) **
Age Square	0.0005 (0.0000) **	0.0008 (0.000) **	0.0006 (0.00005) **	0.0006 (0.00002) **
Married	-0.07 (0.007) **	-0.133 (0.012) **	-0.13 (0.015) **	-0.1 (0.006) **
Parental Status	-0.016 (0.005) *	0.0003 (0.022)	0.0007 (0.027)	-0.01 (0.009)
wealth	-0.03 (0.001) **	-0.004 (0.002) **	-0.004 (0.002) *	-0.02 (0.001) **
Income	-0.02 (0.002) **	-0.008 (0.0031) **	-0.008 (0.003) *	-0.016 (0.002) **
Female	0.33 (0.0034) **			0.32 (0.0064) **
Low-level Education-dummy	-0.13 (0.005) **			-0.13 (0.011) **
Medium-level Education_ dummy	-0.2 (0.006) **			-0.2 (0.012) **
High-level Education_ dummy	-0.2 (0.007) **			-0.2 (0.01) **
Austria	-0.5 (0.01) **			-0.5 (0.01) **
Germany	-0.3 (0.009) **			-0.3 (0.01) **
Sweden	-0.41 (0.009) **			-0.43 (0.01) **
Netherlands	-0.46(0.01) **			-0.48 (0.02) **
Spain	-0.24 (0.009) **			-0.29 (0.01) **
Italy	-0.14 (0.009) **			-0.17 (0.01) **
France	-0.06 (0.009) **			-0.07 (0.01) **
Denmark	-0.5 (0.01) **			-0.5 (0.01) **
Greece	-0.40 (0.01) **			-0.41 (0.01) **
Switzerland	-0.47 (0.01) **			-0.5 (0.02) **
Belgium	-0.17 (0.009) **			-0.18 (0.01) **
Czech Republic	-0.36 (0.009) **			-0.35 (0.01) **

Important Note: The Eurod scale, quantifying the count of depressive symptoms, serves as the dependent variable. "Retired" individuals are defined as those who self-identify as retired, while the "Not Retired" group comprises employed or self-employed individuals. Please note that the unemployed, homemakers, permanently sick, and disabled are EXCLUDED from this analysis. Standard Errors are denoted in parentheses. The Very-Low-level Education dummy serves as the reference group. Eurod's Initial value reflects the initial value of the dependent variable considered in the dynamic model of the Woodridge approach. Significance levels are indicated as follows: *p<0.05, ** p<0.01..

6 Conclusion

This study utilized comprehensive data from all 8 waves of easySHARE across thirteen European countries and applied Poisson Fixed and Random Effects regression for panel data. To tackle the potential issue of endogeneity, the country-specific statutory retirement ages as instrumental variables were leveraged. These legally mandated retirement ages undeniably influence retirement decisions but are unrelated to an individual's mental health. They allow us to capitalize on variations in retirement eligibility ages across countries, genders, and over time. The Fixed Effects-Instrumental Variable (FE-IV) estimation unveiled that, on average, retirement exerts a protective influence on mental health.

The study also revealed that being married is associated with significantly fewer depressive symptoms compared to individuals living without a partner. Regarding the influence of wealth and income on mental health, our findings demonstrated a negative relationship, indicating that higher income levels and greater wealth are associated with a reduction in depressive symptoms. These results highlight the importance of financial well-being in shaping mental health outcomes in older ages. However, the study acknowledges that these conclusions remain relatively general, and substantial heterogeneity still exists among individuals. The impact of retirement on mental health is influenced by several factors unique to each person, making it challenging to isolate precise effects.

Furthermore, the analysis took into account variations in the impact of retirement based on gender and marital status, examining both men and women, as well as married versus divorced or widowed individuals. By considering these factors, the study aimed to uncover potential heterogeneity in the effects of retirement on mental health. Findings provide compelling evidence that, on average, retirement leads to improved mental health. However, the protective effect of retirement is more pronounced among males. Moreover, the results highlighted favorable influence of retirement on the mental well-being of married individuals, providing further support for the idea that the protective effect of retirement is not universally distributed.

In an effort to mitigate the complexity arising from effect heterogeneity, the study also focused solely on ‘Employed’ and ‘Retired’ individuals. This targeted approach allowed for a better understanding of the variations in the dependent variable and the specific effects of retirement on mental health. The results advocated findings from FE-IV estimation.

It would be better for future research to explore specific subgroups and consider various factors, such as the type of work prior to retirement or job characteristics to gain deeper insights and enhance comprehensively understanding the potential effects of retirement. For example, some people might discover advantages in retiring, particularly if they've endured taxing or detrimental work environments, whereas others could derive fulfillment from their employment because it is meaningful and stimulating.

The findings of this study, resonate with some of the earlier research, such studies by Kolodziej and García-Gómez (2019), Belloni et al. (2016), Eibich (2015), and Gorry and Slavov (2021), all of which point to the potential for retirement to have positive effects on mental health. Additionally, the recognition of a stronger protective effect of retirement on mental health for males, as well as the role of marital status in influencing responses to retirement, parallels the gender and marital status trends identified in Picchio and Van Ours (2020). The alignment of our results with multiple studies reinforces the argument for a favorable impact of retirement on mental health, especially for specific demographic groups. In summary, this study significantly contributes to the existing knowledge base by utilizing an extensive and updated dataset and following FE-IV Poisson model, offering strong evidence for the positive influence of retirement on mental health, particularly in terms of reducing depressive symptoms. The consistency of these findings with prior studies lends substantial support to our conclusions.

Discussion

In this study, utilizing eight waves of panel data made it possible to observe individuals as they underwent the transition into retirement and explore the fluctuations in their mental health during this critical life phase. This approach provided us with a distinct opportunity to address various endogeneity factors within the panel dataset. Nevertheless, there are still areas where improvements can be made. In this section, we will discuss the limitations of our study and propose potential directions for future research. These limitations primarily arise from the need to either significantly broaden the scope of the thesis or acquire a more specialized dataset specifically tailored for this study.

The choice of statutory retirement age as an instrumental variable appears to be reliable. However, it is important to acknowledge the complexity associated with calculating the exact statutory retirement age due to the presence of various pension schemes and exceptions within each country.

Moreover, the statutory retirement age is typically determined based on age cohorts. Taking into account these subtle issues in calculating retirement age would likely enhance the strength of the instrumental variable, thus improving the validity of our analysis.

An additional important consideration in this kind of studies is the presence of heterogeneity among elderly individuals in their experiences with retirement. While our study accounted for gender and marital status differences, it is crucial to recognize differences among occupations like, whether the job is physically demanding, whether there is a high level of work-related stress, or whether individuals are satisfied with their jobs. These factors have the potential to influence the findings of our study and may contribute to the consistency or divergence of our results. Therefore, it would be valuable for future research to delve further into these aspects and assess their impact on the relationship between retirement and mental health outcomes. This would provide a more comprehensive understanding of how different occupational characteristics shape the retirement experience and its subsequent effects on mental well-being.

7 Appendix

Table 12- Statutory Full Retirement Age for Standard Pension Cross-Country (women)

	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
Austria	65(60)	65(60)	65(60)	65(60)	65(60)	65(60)	65(60)	65(60)	65(60)	65(60)	65(60)	65(60)	65(60)	65(60)	65(60)	65(60)
Belgium	65(64)	65(64)	65(64)	65(64)	65(64)	65	65	65	65	65	65	65	65	65	65	65
Czech Republic	62	62	62	62	62	na	na	na	na	62.67 (61.33)	61.2	63.2(62.3)	63.2	63.2(62.7)	63.5	63.7
Denmark	65-67	65-67	65-67	65-67	65-67	65-67	65	65	65	65	65	65	65	65	65	65.5
France	60	60	60	60	60	60	60	60-62	60-62	61.2	61	61.6 -60		63.3		63.5
Germany	65	65	65	65	65	65	65	65.1	65.2	65	65	65	65	65.5	65.5	65.7
Greece	65(60)	65(60)	65(60)	65(60)	65(60)	65(60)	65(61)	62	62	62	62	62	62	62	62	62
Italy	65(60)	65(60)	65(60)	65(60)	65(60)	65(60)	65(60)	65(60)	66.3	62.5(62)	66.7(65.7)	66.7(65.7)	66.7(65.7)	66.7	67	62
Netherlands	65	65	65	65	65	65	65	65	65.1	65.2	65.3	65.5	65.8	66	66	66.3
Poland	65	65	65	65	65	65(60)	65(60)	65(60)	65	65.25(60.25)		66(61)	65(60.8)	65(60.8)	65(60.8)	65
Spain	65	65	65	65	65	65	65	65	65	65	65	65	65	65	65	65
Sweden	65	65	65	65	65	65	65	65	65	65	65	65	65	65	65	65
Switzerland	65(63)	65(64)	65(64)	65(64)	65(64)	65(64)	65(64)	65(64)	65(64)	65(64)	65(64)	65(64)	65(64)	65(64)	65(64)	65(64)

Source: OECD

8 References

Allen, J. P. (2008). The attachment system in adolescence. In J. Cassidy & P. R. Shaver (Eds.), Handbook of attachment: Theory, research, and clinical applications, 419–435.

Allen, J., Balfour, R., Bell, R., Marmot, M. (2014). Social determinants of mental health. International Review of Psychiatry, 26, 392–407.

Barschkett, M., Geyer, J., Haan, P., & Hammerschmid, A. (2021). The effects of an increase in the retirement age on health – Evidence from administrative data. IZA Discussion Paper No. 14893.

Been, J., Knoef, M., & Van Mourik, C. (2020). The causal effect of retirement on health: A meta-analysis. Tilburg: Netspar Academic Series, 2022-019.

Becker, C., Kirchmaier, I., Trautmann, S.T. (2019). Marriage, Parenthood and Social Network: Subjective Well-Being and Mental Health in Old Age. PLOS ONE, 14(7).

Belloni, M., Meschi, E., Pasini, G. (2016). The effect on mental health of retiring during the economic crisis. Health Economics, 25(S2), 126–140

Behncke, S. (2011). Does retirement trigger ill health? Health Economics, 21(3), 282–300

Blanchflower, D.G., Oswald A.J. (2008). Is well-being U-shaped over the life cycle? Soc Sci Med, 66, 1733–49.

Bonsang E., Adam S., Perelman S. (2012). Does retirement affect cognitive functioning? J Health Econ.31(3):490-501.

Boyd, A., Van de Velde, S., Vilagut, G., de Graaf, R., O'Neill, S., Florescu, S., Alonso, J., & Kovess-Masfety, V. (2015). Gender differences in mental disorders and suicidality in europe: results from a large cross-sectional population-based study. Journal of Affective Disorders, 173, 245–254.

Bradford, L.P. (1979). Can You Survive Your Retirement.

Burns, R.A., Butterworth, P., Crisp, D.A. (2020). Age, sex, and period estimates of Australia's mental health over the last 17 years. Australian & New Zealand Journal of Psychiatry, 54(6) 602–608.

Carrino, L., Glaser, K., & Avendano, M. (2020). Later retirement, job strain, and health: Evidence from the new State Pension age in the United Kingdom. Health Economics, 29(8), 891–912

Cameron, A. C., & Trivedi, P. K. (2013). Regression analysis of count data (2nd ed., Ser. Econometric society monographs, 53). Cambridge University Press.

Ceo,N.B., Lindeboom, M. (2008). Does Retirement Kill You? Evidence from Early Retirement Windows. IZA Discussion Papers, 3817.

Coe, N. B., Zamarro, G. (2011). Retirement effects on health in Europe. Journal of Health Economics, 30(1), 77–86.

Coile, C. (2003). Retirement Incentives and Couples' Retirement Decisions. NBER Working Paper No. w9496.

Chevalier, A., Feinstein, L., (2006). Sheepskin or Prozac: The Causal Effect of Education on Mental Health. IZA Discussion, No.2231.

EasySHARE, (2022). Guide to easySHARE, Release 8.0.0

Eibich, P. (2015). Understanding the effect of retirement on health: Mechanisms and heterogeneity. Journal of Health Economics, 43, 1–12.

Fé, E., & Hollingsworth, B. (2016). Short- and long-run estimates of the local effects of retirement on health. Journal of the Royal Statistical Society Series A, 179(4), 1051–1067

Filomena, M., & Picchio, M. (2023). Retirement and health outcomes in a meta-analytical framework. Journal of Economic Surveys, forthcoming.

Fiori, K. L., Antonucci, T. C., & Cortina, K. S. (2006). Social network typologies and mental health among older adults. The Journals of Gerontology. Series B, Psychological Sciences and Social Sciences, 61(1), 25–32.

Garrouste, C., & Perdrix, E. (2022). Is there a consensus on the health consequences of retirement? A literature review. Journal of Economic Surveys, forthcoming

Gorry, D., & Slavov, S. N. (2021). The effect of retirement on health biomarkers. Economics and Human Biology, 40, 100949

Greene, W. H. (2020). Econometric analysis (Eighth edition, Global). Pearson.

Heller-Sahlgren, G. (2017). Retirement blues. Journal of Health Economics, 54, 66–78.

Hernaes, E., Markussen, S., Piggott, J., Vestad, O. L. (2013). Does retirement age impact mortality? Journal of Health Economics, 32(3), 586–598.

Jokela, M., Ferrie, J., Gimeno, D., Chandola, T., Shipley, M., Head, J., Vahtera, J., Westerlund, H., Marmot, M.G., Kivimäki, M. (2010). From midlife to early old age: health trajectories associated with retirement. Epidemiology, 21 (3), 284–290.

Kiecolt-Glaser, J. K. (2018). Marriage, divorce, and the immune system, American Psychologist 73(9): 1098–1108.

Kiely, K. M., Brady, B., & Byles, J. (2019). Gender, mental health and ageing. Maturitas, 129, 76-84. https://doi.org/10.1016/j.maturitas.2019.09.004

Kolodziej, I.W., García-Gómez, P. (2019). Saved by retirement: Beyond the mean effect on mental health. Social Science & Medicine, 225, 85–97.

Kravdal, Ø., Wörn, J., Reme, B.A. (2023). Mental Health Benefits of Cohabitation and Marriage: A Longitudinal Analysis of Norwegian Register Data. Population Studies, 77(1), pp. 91–110.

Li, W., Ye, X., Zhu, D., & He, P. (2021). The longitudinal association between retirement and depression: A systematic review and meta-analysis. American Journal of Epidemiology, 190(10), 2220-2230

Lindeboom, M., Portrait, F., van den Berg, G.J. (2002). An econometric analysis of the mental-health effects of major events in the life of older individuals. Health Economics, 11(6):505-20.

Litwin, H. (2010). Social networks and well-being: a comparison of older people in Mediterranean and non-Mediterranean countries. The Journals of Gerontology Series B: Psychological Sciences and Social Sciences, 65b(5), 599–608.

Litwin, H., & Shiovitz-Ezra, S. (2011). Social network type and subjective well-being in a national sample of older americans. Gerontologist, 51(3), 379–388.

Manuel, J. I., Martinson, M. L., Bledsoe-Mansori, S. E., & Bellamy, J. L. (2012). The influence of stress and social support on depressive symptoms in mothers with young children. Social Science & Medicine (1982), 75(11), 2013–20.

Margolis, R., Myrskylä, M. (2011). A global perspective on happiness and fertility. Population and Development Review, 37(1), 29–56.

Martinez-Jimenez, M., Hollingsworth, B., & Zucchelli, E. (2021). Health, retirement and economic shocks. IZA Discussion Paper No. 14574

Mastekaasa, A. (1994). Marital status, distress, and well-being: an international comparison. Journal of Comparative Family Studies, 25(2), 183–183.

Mazzonna, F., & Peracchi, F. (2012). Ageing, cognitive abilities and retirement. European Economic Review, 56(4), 691–710.

Mosca, I., Barrett, A. (2014). The Impact of Voluntary and Involuntary Retirement onMental Health: Evidence from Older Irish Adults. IZA Discussion Paper, 8723.

Nishimura, Y., Oikawa, M., & Motegi, H. (2018). What explains the difference in the effect of retirement on health? evidence from global aging data. Journal of Economic Surveys, 32(3), 792–847.

OECD Pension at a Glance. (2021), OECD and G20 INDICARORS.

Oksanen, T., Vahtera, J., Westerlund, H., Pentti, J., Sjösten, N., Virtanen, M., Kawachi, I., Kivimäki, M. (2011). Is retirement beneficial for mental health? Antidepressant use beforeand after retirement. Epidemiology 22 (4), 553–559.

Pabón-Carrasco, M., Ramirez-Baena, L., López Sánchez, R., Rodríguez-Gallego, I., Suleiman-Martos, N., &Gómez-Urquiza, J. L. (2020). Prevalence of depression in retirees: a meta-analysis. Healthcare, 8(3).

Picchio, M., Van Ours, J. C. (2020). Mental health effects of retirement. De Economist, 168(3), 319–352.

Pilipiec, P., Groot,W., & Pavlova,M. (2020). The effect of an increase of the retirement age on the health,well-being, and labor force participation of older workers: a systematic literature review. Journal of Population Ageing, 14, 271-315.

Rohwedder, S., Willis, R. J. (2010). Mental retirement. Journal of Economic Perspectives, 24(1), 119–138.

Rose, L. (2020). Retirement and health: Evidence from England. Journal of Health Economics, 73, 102352.

Rosenfield, S., Smith, D. (2009). Gender and mental health: Do men and women have different amounts or types of problems? in: Scheid, T.L., Brown, T.N. (Eds.), A Handbook for the Study of Mental Health: Social Contexts, Theories, and Systems. 2 ed. Cambridge University Press, p. 256–267.

Sareen, J., Afifi, T.O., McMillan, K.A., Asmundson, G.J. (2011). Relationship between household income and mental disorders: findings from a population-based longitudinal study. Arch Gen Psychiatry. 68(4), 419-27.

Schmitz, H., & Westphal, M. (2021). The dynamic and heterogeneous effects of retirement on cognitive decline,Ruhr Economic Papers, No.918.

SHARE, Survey of Health, Ageing and Retirement in Europe, (2022). Release Guide 8.0.0.

Sonnenberg, C. M., Beekman, A. T. F., Deeg, D. J. H., van Tilburg, W. (2000). Sex differences in late-life depression, Acta Psychiatrica Scandinavica, 101, 286-292.

Srivastava, N., Anand, M. (2020). Understanding Gender and Mental Health, in: Anand, M. (Ed.), Gender and Mental Health, Combining Theory and Practice. Springer, Singapore. chapter 1, 3–17.

Starkes, J. M., Poulin, C. C., & Kisely, S. R. (2005). Unmet need for the treatment of depression in atlantic canada. The Canadian Journal of Psychiatry, 50(10), 580–590.

Steele, L.S, Dewa C.S, Lin E, Lee KL. (2007). Education level, income level and mental health services use in Canada: associations and policy implications. Healthc Policy, 3(1), 96-106.

Steptoe, A., Deaton, A., Stone, A.A. (2015). Subjective wellbeing, health, and ageing. Lancet, 385(9968), 640-648.

Van der Heide, I., van Rijn, R., Robroek, S., Burdorf, A., & Propper, K. (2013). Is retirement good for your health? A systematic review of longitudinal studies. Bmc Public Health, 13(1), 1180

Van Ours, J. C. (2022). How Retirement Affects Mental Health, Cognitive Skills and Mortality; an Overview of Recent Empirical Evidence. De Economist, 170(3), 375–400.

Verbeek, M. (2017). A guide to modern econometrics (Fifth). Wiley Custom.

Vo, K., Forder, P. M., Tavener, M., Rodgers, B., Banks, E., Bauman, A., & Byles, J. E. (2015). Retirement, age, gender and mental health: findings from the 45 and up study. Aging & Mental Health, 19(7), 647–57.

Wang, S., Li, B., Ungvari, G.S., Ng CH., et al. (2016). Poor mental health status and its associations with demographic characteristics and chronic diseases in Chinese elderly. Soc Psychiatry Psychiatr Epidemiol, 51(10):1449-1455.

Weiss, A., King, J.E., Inoue-Murayama, M., Matsuzawa, T., Oswald, A.J. (2012). Evidence for a midlife crisis in great apes consistent with the U-shape in human wellbeing. Proc Natl Acad Sci USA,109, 19949–52.

Westerhof, G. J., Keyes, C. L. M. (2010). Mental illness and mental health: the two continua model across the lifespan. Journal of Adult Development, 17(2), 110–119.

Westerlund, H., Kivimäki, M., Singh-Manoux, A., Melchior, M., Ferrie, J. E., Pentti, J., Jokela, M., Leineweber, C., Goldberg, M., Zins, M., & Vahtera, J. (2009). Self-rated health before and after retirement in france (gazel): a cohort study. Lancet, 374(9705), 1889–96.

Wooldridge, J. M. (2010). Econometric analysis of cross section and panel data (2nd ed.). MIT Press.

Wooldridge, J. M. (2019). Panel Data Econometrics: Theory. Academic Press.

World Health Organization (2013), A report about health.

World Health Organization (2013), A report about health.