The Impact of Health Shocks on Early Retirement: A comparison between Belgium and Germany

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THE IMPACT OF HEALTH SHOCKS ON EARLY RETIREMENT: A COMPARISON BETWEEN BELGIUM AND GERMANY.

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LIST OF ABBREVIATIONS

ATT: Average Treatment Effect on the Treated

bAV: Occupational Pensions in Germany (Betriebliche Altersversorgung)

CIA: Conditional Independence Assumption

GPs: General Practitioners

GRV: Compulsory Pension Insurance in Germany (Gesetzliche Rentenversicherung)

MD: Mahalanobis distance matching

PAFs: Population Attributable Fractions

PSM: Propensity score matching

SAH: Self-assessed health

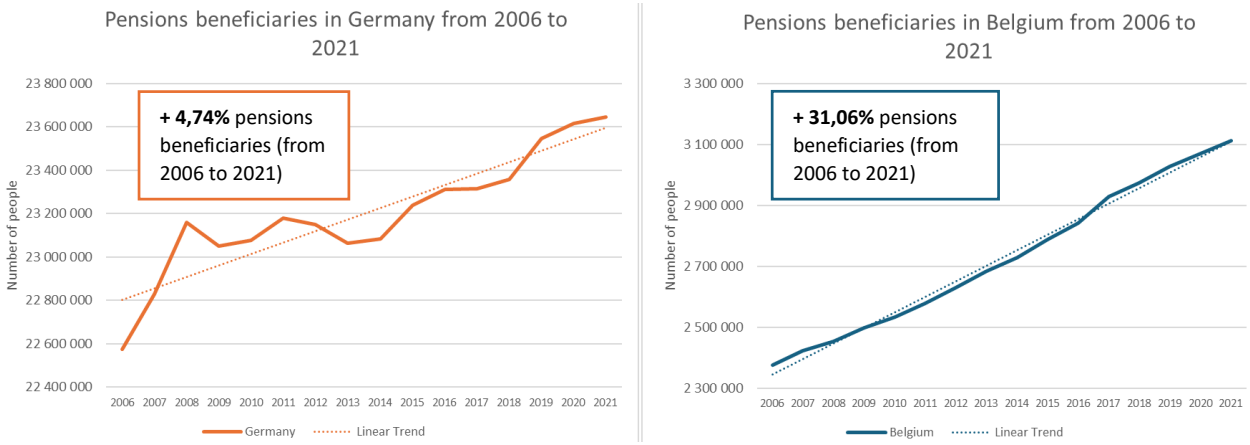
SHARE: Survey of Health, Aging, and Retirement in Europe

1. INTRODUCTION

The global population is increasingly becoming older, with a notable rise in both the number and proportion of elderly individuals. This is the cause of an increase in life expectancy. This rise, coupled with declining birth rates, has led to concerns about the financial impact of an aging population (Marešová et al., 2015). Simultaneously, the population of younger, working-age people is shrinking. In the European Union in 2023, 21.3% of the population is 65 years or older, 19.7% in Belgium, and 22.1% in Germany (Eurostat, 2023). However, by 2050, projections indicate that nearly one-third of the population will be seniors, 65 years and older. This demographic transformation will impact various sectors, including healthcare, social welfare, the labor market, and the broader economy. The increase in the elderly population is expected to increase chronic illnesses and age-related health issues and impose a financial burden on the health system and pension system. Social welfare programs will face mounting pressure, particularly pensions and long-term care services. The diminishing working-age population could lead to labor shortages, potentially necessitating an extension of the retirement age or greater workforce participation among older adults. Addressing these challenges is critical to maintaining societal well-being. Developing effective strategies to support Europe's aging population is imperative (The Lancet Regional Health – Europe, 2023).

Furthermore, as the population grows, the number of pension recipients in Europe also rises sharply. Here are two graphs showing the number of pension beneficiaries (including early retirement pensions) in Belgium and Germany.

Figure 1 - Pensions beneficiaries in Germany and Belgium

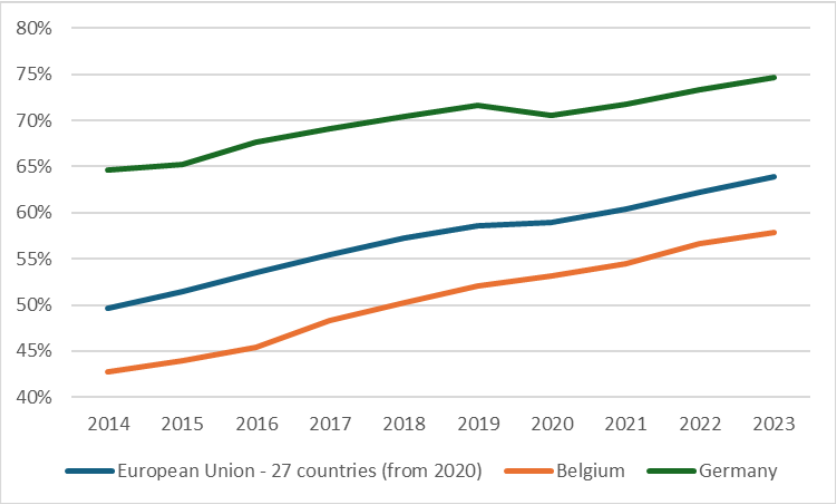


Source: Own computations based on Eurostat data[1]

Figure 1 illustrates an increasing number of pension beneficiaries in Germany and Belgium since 2006. The data consistently supports the idea that the aging population is leading to a growing burden on the social security system due to pensions. Furthermore, while the number of pension recipients is rising, the increase in Germany is much smaller compared to Belgium.

[1] Eurostat. (2024). Pensions beneficiaries at 31st December (Online data code: spr_pns_ben). https://doi.org/10.2908/spr_pns_ben.

Figure 2 - Employment rate of people aged 55 to 64 in Germany and Belgium



Source: Own computations based on Eurostat data[2]

Figure 2 illustrates the percentage of employed individuals aged 55 to 65. Overall, there has been an increase in the percentage of individuals in this age group working in the European Union in recent years. This trend is also noticeable in both Belgium and Germany. However, a more significant proportion of individuals aged 55 to 65 are employed in Germany compared to Belgium. Germany's percentage is above the European average, while Belgium's is below it. The figures show that the percentage of people aged 55 to 65 in employment in the European Union has risen in recent years. This trend can be observed in both Belgium and Germany. These data suggest that Germany is more effectively integrating older workers into the labor market, which could mitigate some of the economic impacts of an aging population.

Given that the increasing aging population is retiring and thus burdening the social security system in Europe, it is essential to understand why individuals choose early retirement. Using data from the Survey of Health, Aging, and Retirement in Europe (SHARE), this study will aim to determine whether a health shock, including both physical (heart attack, stroke, Parkinson's, Alzheimer's, or cancer) and mental illnesses (depression), leads individuals aged 45 to 64 to exit the labor market (early retirement or permanent disability). If such shocks result in early retirement, investing more in healthcare could help a portion of the older active population to remain in the labor market longer.

This analysis focuses on Germany and Belgium. Both countries seem to have similar trends in the increasing number of pension beneficiaries and the employment of individuals aged 55 to 65. However, Belgium has a significantly higher increase in pension beneficiaries than Germany. On the other hand, Germany has a higher employment rate for those aged 55-65 compared to the European average and Belgium. These differences can be attributed to variations in pension and early retirement access conditions. Given the differences between the two countries, it is interesting to see whether the populations of both countries react similarly or differently to a health shock.

This study is structured as follows: Section 2 will include a literature review with conclusions from similar subjects and the German and Belgian retirement legislation. Then, Section 3 will consist of an

[2] Eurostat. (2024). Employment and activity by sex and age - annual data (Online data code: lfsi_emp_a). https://doi.org/10.2908/lfsi_emp_a

explanation of the database and descriptive statistics. Section 4 will develop the econometric method used for the analysis. Next, the analysis results will be discussed in Section 5, along with their implications. Finally, Section 6 will conclude this study, drawing upon the findings of this paper.

2. LITERATURE REVIEW

This literature review will explore the complex interplay between health shocks, early retirement, and pension systems. The review is structured to understand these elements and their interconnections comprehensively.

We define health shocks as these unexpected events that can significantly impact an individual's decision to retire early. Understanding the nature and implications of health shocks sets the stage for our subsequent discussions.

Next, we delve into early retirement, examining the factors influencing an individual's decision to retire before the traditional retirement age. These factors range from personal circumstances to broader economic and policy contexts.

Following this, we focus on pension systems and look at the pension systems in Germany and Belgium. By understanding the structure and function of these systems, we can better grasp how they support or hinder individuals facing health shocks and contemplating early retirement. After outlining the German and Belgian pension systems, we provide a comparative analysis. This comparison highlights key similarities and differences, offering insights into how different policy frameworks can influence retirement decisions.

Finally, we discuss the impact of health shocks on early retirement. We explore how health shocks affect labor market outcomes, examine cross-country differences and policy implications, and consider gender dynamics and long-term effects. This section aims to provide a nuanced understanding of how health shocks intersect with retirement and pension policies.

2.1 Health shock definition

Health shocks, often triggered by severe chronic illnesses recognized by health administrations, are significant events that can dramatically alter an individual's health and well-being. These health shocks, which can manifest as conditions like cancer, heart disease, and diabetes, are not limited to chronic illnesses. Domestic, sports-related, or vehicular accidents are also considered health shocks. These events' sudden and unexpected nature underscores their potential to significantly impact an individual's health and well-being (Duguet & Le Clainche, 2014).

Moreover, self-assessed health (SAH) is a widely employed subjective measure to assess an individual's perceived health. Health shocks can be conceptualized as adverse transitions in self-assessed health, such as a shift from "good" to "poor" health status (Ilmakunnas & Ilmakunnas, 2018). Furthermore, some researchers use medical diagnoses of serious illnesses to identify health shocks, like cancer, heart disease, strokes, etc. These diagnoses provide a more objective measure of health shocks (García Gómez & López Nicolás, 2006).

Most studies examining the relationship between health and employment represent health status by self-reported health indicators. Self-reported assessments may not always provide a complete picture of the severity of a disease. Furthermore, certain studies have underscored limitations in the associations between self-reported health evaluations and aspects of the job market, especially concerning choices related to early retirement. Firstly, scale effects are observed where specific individuals' perceptions of their health do not align with their health status (Lindeboom & Van Doorslaer, 2004). Secondly, self-reported assessments might be influenced by an individual's position in the labor market (García Gómez & López Nicolás, 2006). Thirdly, using proxy variables introduces measurement errors that are not necessarily random. For instance, there could be a justification bias: individuals who reduce their work hours or exit the labor functional limitations to obtain a more accurate health measure free from measurement bias. When a subjective health assessment is used

to explain retirement behavior, the effects of health can often be underestimated rather than overestimated (Jones et al., 2010).

Health problems can significantly impact a person's ability to work, earnings, and decisions about when to retire. They can change a person's interests, ability to work, and the jobs available to them, meaning they might need to change their career and income. There are many different ways to define and measure health problems. Researchers use various methods, from asking people to rate their health to looking at specific illnesses or accidents to understand what a health shock is.

2.2 Early retirement

Retirement is a concept that lacks a clear definition and measurement Disney et al. (2006), Hagan et al. (2008), and Humphrey et al. (2003) pointed out. The distinction between retirement and unemployment becomes blurred, particularly in the context of pension entitlements and shifting social norms, as noted by Humphrey et al. (2003). Individuals may perceive retirement differently, with some associating it solely with pension receipt, while others view it as a permanent exit from the workforce. Moreover, routes into retirement via disability and unemployment further complicate the delineation of labor market status for older workers.

Humphrey et al. (2003) shed light on status redefinition post-state pension age, highlighting a significant decrease in individuals defining themselves as long-term sick or disabled upon reaching this milestone. This shift can be attributed to changes in benefit entitlement, particularly the transition from Incapacity Benefit to pension payments, prompting a reassessment of self-perceived status among older individuals. These implications are crucial as they underscore the societal and individual changes that occur with the transition into retirement.

To analyze the dynamics of self-reported retirement transitions, Hagan et al. (2008) adopted the stock-sampling approach proposed by Jenkins (1995), building upon the Prentice & Gloeckler (1978) model. This discrete-time hazard specification allows us to examine the hazard functions associated with the initial transition to self-reported retirement. By organizing the data to focus on the time at risk of retirement, they simplify the estimation process, employing a complementary log-log specification consistent with an underlying continuous-time proportional hazard model.

In conclusion, the intricacies of retirement dynamics underscore the pressing need for nuanced methodologies to capture the complexity of transitions into retirement. By considering the interplay of pension entitlement, social norms, and individual perceptions, we gain valuable insights into the evolving landscape of retirement decisions among older workers, as elucidated by Jones et al. (2010). This reiteration emphasizes the urgency and importance of further research in this area.

2.2.1 Factors Affecting Early Retirement

As Jones et al. (2010) and McGeary (2009) elucidate, the decision to pursue early retirement is a multifaceted process influenced by various socioeconomic factors. Personal health, private and occupational pension schemes, the employment sector, household income, and the employment status of one's partner emerge as pivotal determinants.

Jones et al.'s research underscores the significant impact of personal health on retirement decisions. Individuals facing diagnoses such as cancer, lung disease, heart disease, stroke, and changes in the Activities of Daily Living (ADL) index are more inclined towards early retirement. This aligns with McGeary's findings, highlighting the differential retirement responses among married and unmarried individuals facing various health conditions.

Moreover, private pension entitlement emerges as a crucial factor influencing retirement timing. Workers with private pension plans exhibit a decreased likelihood of early retirement, potentially

motivated by the desire to augment state pension benefits, as Jones et al. (2010) noted. This suggests that the length of the contribution period to private pensions is a significant determinant of retirement timing, encouraging prolonged workforce participation.

Similarly, occupational pension arrangements play a nuanced role in retirement decisions. While an occupational pension may not significantly influence retirement probabilities, the employment sector significantly shapes retirement intentions. For instance, Jones et al. (2010) highlight a notable increase in retirement probability among men working in the civil and local government sector, contrasting with reduced retirement likelihoods for women in similar roles. This discrepancy may reflect sector-specific retirement arrangements and career preferences, as elucidated by McGeary (2009).

Furthermore, household income and the employment status of one's partner emerge as critical determinants of early retirement decisions. Higher household incomes may delay retirement as individuals seek to maintain their standard of living. Additionally, as emphasized by Jones et al. (2010), the presence of an employed partner reduces the probability of early retirement for men, suggesting a synchronization of retirement decisions within households.

In conclusion, as elucidated by Jones et al. (2010) and McGeary (2009), early retirement decisions are influenced by a complex interplay of personal health, pension entitlements, employment sector, household dynamics, and marital status. Understanding these factors is essential for policymakers and individuals to foster effective retirement planning and workforce management strategies.

A survey involving 92 out of 165 invited General Practitioners (GPs), yielding a response rate of 56%, sheds light on factors influencing early retirement intentions within rural general practice, as elucidated by Pit & Hansen (2014). The data reveal that the average age for intended retirement from direct patient care is 63.5, with 47% planning to retire before reaching 65. GPs harboring intentions for early retirement tend to be younger, work longer hours on average, and experience more work-related sleep disturbances. They feel undervalued and lack the respect and prestige they deserve at work. Additionally, this group exhibits higher levels of burnout and psychological distress, coupled with lower levels of job satisfaction and perceived lifetime best workability. The association between burnout and early retirement intentions is particularly striking. GPs scoring medium or high on the MBI-ee scale have four times higher odds of desiring early retirement than those with low burnout scores (Pit & Hansen, 2014).

Conversely, higher levels of job satisfaction and perceived lifetime best workability correlate with reduced retirement intentions. Moreover, factors such as increased weekly working hours, higher demands in physical and mental work abilities, work-related sleep problems, and psychological distress significantly elevate the likelihood of early retirement intentions. Interestingly, absenteeism does not exhibit a direct relationship with retirement intentions. In contrast, those reporting more than five presenteeism days display higher odds of early retirement desires before adjustments for age and gender. The Population Attributable Fractions (PAFs) further highlight key contributors to early retirement intentions. GPs work over 32 hours a week, experience work-related sleep problems, and exhibit medium to high burnout scores, emerging as the three most influential factors (Pit & Hansen, 2014).

2.3 Pension systems

2.3.1 German pension system

In Germany, individuals participating in compulsory pension insurance are eligible for old-age pensions, considered a reward for their lifelong work. Eligibility requires reaching a certain age and completing a minimum insurance period, typically five years of contributions and substitute periods. All months during which contributions were made or when caring for a child under three count towards

the five-, 15, and 25-year qualifying periods. All pensionable periods, including training and caring for a child under ten, count towards the 35-year qualifying period (European Commission, 2023).

Individuals can opt for a partial pension (one-third, one-half, or two-thirds of the total pension) to reduce work hours without fully retiring. Delaying pension claims beyond the legal retirement age increases the pension by 0.5% per month (6% per year) of the unclaimed amount (European Commission, 2013).

The standard retirement age in Germany will gradually increase to 67 by 2029, starting with those born in 1947. Initially, it increases by one month per cohort from 65 to 66 years, and for those born from January 1, 1959, by two months per cohort until it reaches 67. Individuals born after December 31, 1963, will have a standard retirement age of 67. However, those with 45 years of compulsory contributions can retire at 65 without a reduction in their pension, with no income limits for retirees receiving the average retirement pension (European Commission, 2023).

The early retirement age aligns with the new standard retirement age. However, it remains unchanged for pensions being phased out, such as old-age pensions due to unemployment or part-time work for older workers and old-age pensions for women, which retain a retirement age of 65. Early retirement at a reduced rate is possible from age 63 after 35 years of pension insurance periods. Individuals recognized as severely disabled and having completed a 35-year qualifying period can claim a full-rate pension. For those born on January 1, 1952, the minimum age gradually increases from 63 to 65, while the minimum age for a reduced-rate pension rises from 60 to 62 (European Commission, 2023).

For those born before January 1, 1952, a reduced old-age pension at age 63 can be claimed if they have completed a 15-year qualifying period, paid compulsory contributions for eight of the last ten years before the pension starts, and are either unemployed at the start of the pension, were unemployed for 52 weeks after age 58.5, or worked part-time due to age for at least 24 months before the pension starts. The pension is reduced by 0.3% each month and is drawn before the standard retirement age. Women born before January 1, 1952, can claim an old-age pension at age 60 if they have over ten years of compulsory contributions after age 40. The qualifying period is 15 years. The pension amount primarily depends on the social security contributions made throughout one's insurance life. Periods exempt from contributions or with reduced contributions can also increase the pension (European Commission, 2023).

The German pension system comprises three pillars: compulsory pension insurance (Gesetzliche Rentenversicherung—GRV), occupational pensions (Betriebliche Altersversorgung—bAV), and private pensions (Private Altersvorsorge) (Deutsche Institut für Altersvorsorge, 2023).

The compulsory pension insurance operates on a pay-as-you-go basis, meaning contributions are used immediately to pay current retirees. The contribution rate is 18.6% of gross wages, shared equally between employers and employees. Federal subsidies cover about one-third of the pension insurance's revenue. Generally, all employees are subject to pension insurance, including parents during child-rearing periods, interns, informal caregivers, individuals with disabilities, military and civilian service providers, recipients of maintenance replacement services (like unemployment or sickness benefits), and some part-time students. Self-employed individuals are usually exempt, except for certain professions such as artisans, midwives, coastal sailors, skippers, artists, publicists, and teachers (Deutsche Institut für Altersvorsorge, 2023).

The monthly pension amount is calculated using fee points, access factors, pension values, and pension type factors. Fee points are based on an individual's earnings relative to the average earnings of all insured persons. The access factor adjusts the pension based on the age at which it is claimed. The pension value, reflecting wage developments, currently stands at €37.60 per point. The type factor

varies depending on the nature of the pension, with standard old-age pensions having a factor of 1.0 (Deutsche Institut für Altersvorsorge, 2023).

The occupational pension system allows employers to set up supplementary pensions for their employees, funded through contributions from the employee's gross salary, offering tax and social security benefits. Five primary arrangements include direct promises, pension funds, support funds, and direct insurance. Employees have been entitled to salary conversion for pension financing since 2002 (Deutsche Institut für Altersvorsorge, 2023).

Private pensions consist of voluntary savings that accumulate until retirement to fill the gap left by declining statutory pension levels. Options include retirement insurance, savings plans, securities, and real estate. The investment choice depends on an individual's risk appetite, life situation, and time until retirement (Deutsche Institut für Altersvorsorge, 2023).

In Germany, retirees can work while receiving a pension, but specific rules depend on their age and earnings. For those under the standard retirement age (65-67, depending on birth year), annual earnings are capped at €6,300. Exceeding this limit results in a pension reduction. Upon reaching the standard retirement age, retirees can earn without any restrictions. Pensioners must report their income from employment to ensure correct pension adjustments. Additionally, they can continue contributing to the pension system, potentially increasing their benefits through the Flexi-Pension scheme. It allows a gradual transition to full retirement by combining part-time work with partial pension benefits. Moreover, there is a pension advantage if retirees continue working after reaching the standard retirement age in Germany. Specifically, each month they defer taking their pension, it increases by 0.5%, which amounts to an annual increase of 6% (Deutsche Rentenversicherung, 2024).

The average gross pension in Germany for individuals with at least 35 years of insurance is 1,550 euros. However, there are notable variations across the federal states (Figure A2). For instance, at the end of 2022, North Rhine-Westphalia and Saarland reported the highest average male pensions, at approximately 1,845 euros and 1,840 euros, respectively. This is largely due to the historical prevalence of well-paid mining jobs in these regions, resulting in relatively higher pensions. The disparity between the average pensions for men and women is significantly smaller in eastern Germany compared to the West. In East Berlin, women receive the highest average pension at 1,501 euros, while men receive 1,699 euros. This is primarily because women in the East were less likely to work part-time, leading to smaller income gaps between genders compared to the West. Additionally, with the substantial increase in life expectancy over recent decades, Germans now draw their pensions for much longer than they did 50 years ago. In 2022, the average duration of pension receipt was around 18.8 years for men and approximately 22.2 years for women (Deutsche Rentenversicherung, 2023).

2.3.2 Belgian pension system

In Belgium, anyone who has worked as an employee, self-employed individual, or public sector worker is entitled to a retirement pension at the end of their career. The pension schemes cover two social risks: Old age (retirement pensions) and widowhood (the loss of income suffered by a worker's spouse: survivor pensions). Old age pensions are granted after a person completes an active career and meets the age and career duration requirements or reaches the legal retirement age. The amount is determined based on legal parameters such as career duration, equivalent periods, and earnings. Once initiated, the pension can be adjusted for price changes (automatic indexation) and welfare improvements. Survivor pensions are provided to the surviving spouse after the death of an active or retired partner. The amount is based on the career of the deceased (Pensionstat). 84% of pensioners receive an old-age pension, and only 16% receive a survivor's pension in 2023 (Pensionstat).

The legal retirement age in Belgium is 65 for those retiring on or before January 31, 2025, 66 for those retiring between February 1, 2025, and January 31, 2030, and 67 for those retiring on or after February 1, 2030 (European Commission, 2023).

Early retirement is possible under certain conditions. From January 1, 2019, individuals need to be at least 63 years old and have 42 years of service. Exceptions exist for long careers, allowing retirement at 60 with 44 years of service and 61 with 43 years of service (CSC, 2024).

Belgium has three pension regimes: the employee pension scheme, the self-employed pension scheme, and the civil servant pension scheme. The pension regimes have all different fundings. The Employee Pension Scheme manages retirement pensions for employees who have worked in Belgium under employment contracts and survivor pensions for their dependents after their death. Contractual civil servants also accrue pension rights under this scheme. Pension expenses are charged to the overall management of social security for employees and are funded by employer and employee contributions. Additional resources, such as government subsidies, income from alternative financing, and other allocated revenues, are also directed to the overall management. The self-employed scheme oversees the retirement pensions for self-employed individuals and liberal professions, along with survivor pensions for their dependents after their death. Pension expenses are charged to the overall social security management for the self-employed and are financed through contributions. Additional resources, including government subsidies, income from alternative financing, and other allocated revenues, also support the overall management. The civil servant pension scheme handles retirement pensions for appointed civil servants and other legally equivalent agents, as well as survivor pensions for their dependents after their death. Judges, police officers, military personnel, teachers, local and provincial civil servants, and specific public enterprise employees are entitled to a pension under this scheme, provided they are appointed permanently. Personal contributions partly cover pension expenses but are mainly funded through various state financing systems (Public Treasury, Parastatal Pool, Solidarity Pension Fund for Provincial and Local Administrations) (Pensionstat, 2024). Figure A3 in the appendix shows a graph showing the repartition of the number of pensioners by age group and regime type. Figure A4 gives the average pension amount per regime type.

Belgium has three pension pillars in addition to the three pension schemes. The first pillar consists of legal pensions, which include retirement and survivor pensions within various systems (CSC, 2024).

The second pillar encompasses pension schemes related to the professional situation. This includes group insurance or pension funds offered by the employer (company pension plans) or the sector in which people work (sectoral supplementary pension plans). It also includes individual pension commitments for employees or business owners and dormant pension plans from previous employers or sectors. Among the most common supplementary pensions are company pension plans. In these plans, the employer commits to providing a supplementary pension for all employees or a specific group of workers. To achieve this, the employer may take out group insurance or, in the case of a large company, establish a pension fund typically reserved for the organizer's personnel. Since the 2000s, supplementary pension systems have also been implemented at the sectoral level (parity commission). A supplementary pension plan generally includes an early death benefit (death coverage). Unlike legal pensions, supplementary pensions are almost always paid out as a lump sum immediately upon retirement, though they can be requested as anniversaries. Sometimes, employees partially contribute to their supplementary pension by deducting their net monthly salary (CSC, 2024).

The third pillar includes pensions people arrange if their financial situation allows it. Examples include pension savings plans and life insurance within the framework of the "long-term savings" tax regime. This type of pension is not mandatory and is independent of the employment status (CSC, 2024).

Now that the system has been explained, explaining how pensions are calculated is essential. Pensions for employees are calculated based on the length of insurance, earnings on which contributions were made (within a ceiling), and family circumstances (S=reference salary). The formulas are:

- For single or married without a dependent spouse: : $S \times 60\% \times lenght\ of\ period\ of\ insurance/45$
- For married with a dependent spouse: $S \times 75\% \times lenght\ of\ period\ of\ insurance/45$

Furthermore, once retired, it is still possible to earn a supplementary income, but the exact amount depends on various factors such as age, career, and the type of pension received. Some conditions have to be followed to work without any restrictions. First, the retiree must be 65 years old and receive a retirement pension or both a retirement and survivor's pension; in this case, there are no limits on the supplementary income. Second, if the retiree is under 65 and can prove that he has worked for 45 years by the time the first retirement pension starts, he can also earn an unlimited supplementary income. Lastly, if the retiree receives a transitional allowance, he is not restricted in his earnings either. There are specific rules regarding a spouse's income for those entitled to a household rate retirement pension. The spouse can earn a supplementary income, but it is limited regardless of whether the spouse is 65 years old or not. In other scenarios, earning a limited supplementary income is necessary. This applies if the retiree is 65 and only receives a survivor's pension. It also applies if the retiree is under 65 and cannot prove that he has worked for 45 years by the time the first retirement pension starts. In these cases, the retiree can work but under some limits on earnings, and the activity must be declared (INASTI, 2024).
In January 2023, retirees received an average legal pension income of €1,956 gross and €1,640 net. Between 2019 and 2023, the average pension increased from €1,551 to €1,933, representing a 24.6% increase (Pensionstat, 2024).

2.3.3 Comparison between the pension systems

Belgium and Germany have distinct pension systems. In Belgium, the system is comprehensive, encompassing employees, self-employed individuals, and public sector workers. The legal retirement age is set to rise gradually from 65 to 67 between 2025 and 2030. Early retirement is an option from age 60 with 44 years of service. In Germany, pension eligibility is linked to participation in compulsory pension insurance. The legal retirement age is also rising, with a target of 67 by 2029. Early retirement is possible from 60 years.

In Belgium, pensions are computed based on various factors, including career duration, equivalent periods, and earnings adjusted for price fluctuations and welfare enhancements. The system also provides survivor pensions to spouses based on the deceased partner's career. The pension schemes encompass Employee Pensions, Self-employed Pensions, and Civil Servant Pension schemes, with funding derived from employer and employee contributions, government subsidies, and other allocated revenues. Pensions are automatically adjusted for price changes and welfare improvements. On the other hand, Germany's pension calculation is based on fee points, access factors, pension values, and pension type factors, all of which are adjusted to average earnings and contributions. The system also offers survivor pensions to dependents of deceased employees. Germany's pension system includes Compulsory Pension Insurance (GRV), Occupational Pensions (bAV), and Private Pensions, with funding sources comprising employer and employee contributions supplemented by federal subsidies. Pensions in Germany are adjusted based on wage developments rather than automatic indexation. In 2022, the average gross pension for individuals with at least 35 years of insurance was €1,550. In 2023, the average gross pension in Belgium was €1,956 (€1,640 net). We can see (Figure A5) that since 2014 Germany has had an at-risk poverty rate for pensioners of between 17% and 20%. This is higher than the European average and higher than Belgium, which has an at-risk poverty rate for pensioners between 13% and 14% (lower than the European average). The difference

in pensioners' salaries in Germany and Belgium explains why the at-risk poverty rate is higher in Germany than in Belgium (Table A1).

Self-employed individuals in Belgium must contribute to the pension system, with government subsidies provided for certain professions. In contrast, most self-employed individuals in Germany are exempt from pension contributions, except for specific professions like artisans, midwives, and artists.

Both countries have complex pension systems, a testament to their commitment to providing income security in retirement. However, they differ in several aspects, including eligibility criteria, funding sources, and calculation methods. Notably, the extent of governmental involvement in pension provision varies, with Belgium's system being more inclusive and Germany's system being more reliant on individual contributions.

2.4 Impact of health shocks on early retirement

Health shocks, characterized by sudden declines in physical health, impact people's work market participation, retirement choices, and income paths. Understanding the intricate interactions between psychological beliefs, regulatory frameworks, marital dynamics, and economic variables is crucial for assessing the impact of health disruptions on job market outcomes.

2.4.1 The effect of health shocks on labor market outcomes

Schurer's (2017) seminal work illuminates the role of control beliefs in shaping individuals' responses to health setbacks. Men with pessimistic control views tend to work fewer hours and are more likely to leave the workforce after a health hiccup than their optimistic counterparts. It highlights the psychological dimension of labor market behavior and the importance of addressing control perceptions in interventions to mitigate the impact of health shocks.

According to Schurer (2017), the association between health shocks and control beliefs notably differs across different education levels. After a health shock, men with strong negative control beliefs are nearly seven percentage points more likely to leave the workforce than their counterparts with strong positive control beliefs. For individuals with intermediate levels of schooling, the difference in dropout probability is four percentage points, both statistically significant at the 10% level. This suggests that differences in education level or insurance status do not affect labor-supply responses to health shocks.

Ilmakunnas & Ilmakunnas (2018) explore the discrepancy between retirement expectations and reality among individuals with varying health statuses. Their findings reveal that those in poor health tend to retire earlier than anticipated, while those in better health tend to prolong their working lives. This highlights the necessity of individualized retirement planning strategies that consider health conditions and emphasizes the significance of financial preparedness when confronting unexpected health challenges.

Furthermore, Ilmakunnas & Ilmakunnas (2018) emphasize the impact of health shocks on retirement probabilities among individuals with differing health levels. 46% of people with poor health retire later than expected, while 23% retire earlier. On the other hand, those with the best health ratings tend to work longer and retire earlier than expected. This discrepancy highlights the significant differences in retirement outcomes based on health status, necessitating nuanced retirement planning and policy formulation approaches.

2.4.2 Cross-country differences and policy implications.

Hagan et al. (2008) explore cross-country variations in retirement probabilities and the role of social security frameworks. There are significant differences in retirement incentives across countries, with some exhibiting more substantial incentives for retirement than others. This underscores the

importance of policy frameworks in shaping retirement decisions post-health shock. Hagan et al. (2008) identified differences in the early retirement eligibility age and the benefit accrual structure. Factors influencing retirement decisions include: the age at which individuals become eligible for public pension benefits, the generosity of pension benefits indicated by the replacement rate and pension wealth levels, and the implicit tax on continued employment. Therefore, the findings highlight substantial differences in retirement probabilities across countries compared to the UK.

2.4.3 Gender dynamics and long-term effects on gender dynamics and long-term effects.

McGeary's (2009) study examines how individuals cope with their health challenges and how marital status affects retirement choices. Differences in the types of health shocks influence retirement decisions for each gender, which affect both males' and females' chances of retiring. Furthermore, marital status plays a crucial role in shaping retirement responses to health shocks, highlighting the importance of social dynamics in shaping labor market outcomes post-health setback.

Jones et al.(2010) identify influential factors in early retirement probabilities, focusing on the role of health limitations and pension arrangements. According to their research, financial preparedness and access to pension benefits are essential in mitigating the impact of health shocks on retirement decisions. This emphasizes the need for comprehensive retirement planning strategies that account for health circumstances and socioeconomic factors.

Duguet and Le Clainche (2014) examine the lasting effects of initial health events on work outcomes. They significantly impact both genders' labor market participation, income levels, and career satisfaction. Accidents and chronic illnesses also significantly impact labor market trajectories, underscoring the long-term consequences of health shocks on economic well-being. Furthermore, their findings highlight the disparities between sexes in the likelihood of relying on minimum assistance revenue following a health ailment, highlighting the necessity for specialized assistance mechanisms to address economic disparities.

Finally, Lenhart (2019) examines the effects of abrupt declines in health status on labor market outcomes using propensity score matching. The negative impacts on individual labor earnings and household incomes are shown in their research. Reduced labor market activity among affected individuals underscores the challenges of adapting to health setbacks in the workforce and highlights the need for comprehensive support mechanisms to facilitate economic recovery. Reduced labor market activity among affected individuals underscores the challenges of adapting to health setbacks in the workforce and highlights the need for

In conclusion, the consequences of ill health on employment outcomes are complex and influenced by psychological assumptions, regulatory frameworks, marital dynamics, and economic determinants. Understanding these dynamics is essential for developing targeted interventions to support individuals and households in navigating the economic consequences of health setbacks. By tackling these issues in depth, authorities, corporations, and communities can foster toughness and uphold fiscal stability when health challenges strike.

2.5 Conclusion

Health shocks, defined as sudden and significant declines in physical well-being, influence individual health trajectories and broader socioeconomic outcomes. A range of severe chronic diseases, including cancer, heart disease, and diabetes, as well as unforeseen mishaps, can all profoundly impact an individual's health and overall well-being.

Health shocks are measured and conceptualized differently across studies, from subjective self-assessments to specific medical diagnoses. The subtleties of such jolts often defy simplistic classifications as they interact with individual perceptions, societal forces, and societal structures. Self-

reported health indicators may not capture the severity of health conditions or their implications for labor market outcomes. Scale effects, measurement bias, and proxy variables complicate the intricate relationship between health and employment.

Early retirement, a concept fraught with ambiguity and subjectivity, is a pivotal outcome influenced by many socioeconomic factors. Personal health status, pension entitlements, employment sector dynamics, household income, and marital status influence retirement decisions and timing. Nuanced methodologies that account for diverse individual perceptions, evolving social norms, and complex pension arrangements are needed to understand retirement dynamics. Furthermore, public guidelines and security protocols are pivotal in shaping retirement paths and pre-retirement alternatives. The importance of policy frameworks in facilitating smooth transitions from work to retirement is underscored by cross-country variations in retirement incentives.

Gender dynamics add additional layers of complexity as differences in retirement responses and long-term economic effects are observed across genders. Financial preparedness, access to pension benefits, and spousal dynamics significantly influence retirement decisions, highlighting the need for tailored interventions and support mechanisms that address gender-specific disparities.

Psychological beliefs, policy frameworks, marital dynamics, and socioeconomic factors are some of the factors that affect labor market outcomes. Understanding these dynamics is essential for effectively developing targeted interventions to mitigate the economic consequences of health setbacks. A comprehensive understanding of these dynamics is imperative for developing targeted interventions. Policymakers, employers, and communities can empower individuals and households to navigate the complexities of health-related disruptions in the labor market by fostering resilience.

Throughout the rest of this work, we will analyze the impact of a health shock on early retirement (permanent illness or early retirement). To carry out the analysis, we use the SHARE database. As mentioned in the literature review, most studies use a self-assessed health variable as the health variable. We will construct an objective health variable comprising physical and mental health shocks using the SHARE database. Furthermore, the number of people taking early retirement and the systems in Germany and Belgium are different, so the study will try to see whether these differences are still observed in the database and whether these differences impact the link between health shocks and early retirement.

3. DATA AND DESCRIPTIVE STATISTICS

3.1 Data

The Survey of Health, Ageing, and Retirement in Europe (SHARE) is a comprehensive longitudinal study that collects data on individuals aged 50 and older across 27 European countries and Israel. Initiated to provide insights into the effects of aging, SHARE gathers information on a wide range of topics, including health, socioeconomic status, and social and family networks.

The same individuals are re-interviewed every two years using harmonized questionnaires, allowing researchers to conduct cross-country comparisons and track changes over time. The data collected includes personal information about the respondents, their parents, childhood conditions, and children. SHARE's extensive and detailed dataset is invaluable for studying various aspects of aging and retirement and their implications for public policy and personal well-being.

In this specific thesis, data from the SHARE database and the easySHARE dataset are used. The easySHARE dataset offers simplified access to key variables such as age, country, gender, marital status, number of siblings, educational level, and number of children. This rich dataset supports examining subjective well-being among older adults, focusing on the parental perspective, and incorporates health and intergenerational support measures as explanatory variables.

This study uses waves 4, 5, 6, 7, 8, and 9 of the SHARE dataset for job status. We selected these waves because they contain detailed employment, pensions, and health care sections. The period covered by waves 4 to 9 provides sufficient time to observe changes and impacts. This longitudinal aspect is crucial for studying health shocks, as it allows researchers to track individuals before and after a health event, thereby offering insights into how such shocks influence the timing and nature of retirement decisions. Starting from wave 4, the SHARE study includes generated health variables that are more detailed and processed than earlier waves. These variables enhance the accuracy of health-related data, providing a more reliable foundation for analyzing the impact of health shocks on early retirement (SHARE Release Guide 9).

Our analysis focuses on the impact of a health shock at time t and early retirement at time $t + 1$. Therefore, we look at the transitions from wave 4 to wave 5, from wave 5 to wave 6, from wave 6 to wave 7, from wave 7 to wave 8, and from wave 8 to wave 9 for the early retirement variable. To examine early retirement, we consider individuals between 45 and 64 years old, as the pension age is 65 in Belgium and Germany, as mentioned in the literature review. We thus have an unbalanced panel.

To construct the “health_shock” variable, we began by creating a physical health shock variable. Specifically, for each wave from wave 4 to wave 8, we defined a physical health shock as the occurrence of one of several serious illnesses (heart attack, stroke, cancer, Parkinson's, Alzheimer's) that was not present in the previous wave. For instance, we generated the variable “ph_transition_w5” and set it to 1 if any of the conditions above appeared for the first time between waves 4 and 5. The process was repeated for the subsequent waves, creating “ph_transition_w6”, “ph_transition_w7”, and “ph_transition_w8”.

We followed a similar process to identify transitions in mental health, specifically focusing on the onset of depression. We generated variables such as “mh_transition_w5” for each wave transition and set them to 1 if depression appeared for the first time between waves 4 and 5. This process was repeated for waves 6, 7, and 8. To create the final “health_shock” variable, we generated the variable “health_shock,” setting it to 1 if either a physical or mental health shock was observed.

We defined another health shock variable to test the heterogeneity of our model. This variable takes into account both people who suffer from an illness and who were not ill before and those who were already ill and are still ill, this other health shock variable is called “health_shock_bis”.

We used the employment data present in the SHARE dataset for the early retirement variable. We created transition variables to identify individuals transitioning from non-retirement (being employed/self-employed, unemployed, homemaker, or other) to retirement or permanent disability status between consecutive waves. We generated a variable indicating whether an individual retired between the two waves for each pair of consecutive waves. For example, for the transition between waves 4 and 5, we generated the variable “retirement_transition_w4”. “retirement_transition_w4” equals 1 if an individual moved from a working status to a retirement situation between waves 4 and 5. Otherwise, it is equal to 0. We repeated this process for each transition between waves 5 and 6, 6 and 7, 7 and 8, and 8 and 9. Similarly, we have created variables to capture transitions to permanent disability. For example, for the transition between waves 4 and 5, we generated the variable “sick_transition_w4”. “sick_transition_w4” is equal to 1 if an individual moved from a working status to a situation of permanent disability between waves 4 and 5; otherwise, it is equal to 0. We repeated this process for each transition between waves 5 and 6, 6 and 7, 7 and 8, and 8 and 9. Finally, we combined the retirement and disability transition variables to create the variable “early_retirement”, which captures any transition to early retirement or permanent disability.

These steps demonstrate how the variables “health_shock” and “early_retirement” were systematically constructed by identifying key transitions in health status and employment status across multiple waves of the SHARE survey. As explained in the literature review, we kept the people from the countries of Belgium and Germany and people aged between 45 and 64. Although early retirement is possible from age 60 in Germany and Belgium, we have chosen a broader age bracket to consider disability. This gives us a larger sample size and allows us to consider several forms of exit from the labor market for people at the end of their careers.

In addition, we used covariates in the model. Covariates include age, gender, education level, household and family composition, income, employment status, job satisfaction, physical difficulty, and the country. Covariates related to age, gender, and level of education are variables regularly used in literature reviews for this kind of analysis, Jones et al. (2010); Duguet and Le Clainche (2014); Lenhart (2019); Jung & Suh (2024); Schurer (2017); McGeary (2009) and García-Gómez (2011) used these variables in their analysis. The literature review also uses variables related to family and household composition. For example, Schurer (2017) and McGeary (2009) included a variable called "married". All the authors cited above refer to income, whether household or individual. Jones et al. (2010), Lenhart (2019), and García-Gómez (2011) include work status and job satisfaction.

3.2 Descriptive statistics

In this study, we analyze the effect of health shocks on early retirement in Germany and Belgium. The total sample is 15,115 observations. 7,183 (47.52%) observations are from Germany, and 7,932 (52.48%) are from Belgium.

First, let us take a closer look at our dependent variable. As previously explained, our dependent variable encompasses individuals who take early retirement and those who go on disability. In each data collection wave, some individuals retire or become disabled. Tables 1 and 2 provide the number of people retiring and becoming disabled in each wave.

Table 1 - Distribution of individuals becoming permanently sick across waves by gender, job status, and country

					Permanently sick		
		Wave 4	Wave 5	Wave 6	Wave 7	Wave 8	Total
N		58	76	27	0	1	162
Gender							
	Female	40	41	17	0	1	99
	Male	18	35	10	0	0	63
Job-status							
	Private sector workers	32	47	17	0	1	97
	Public sector workers	18	15	3	0	0	36
	Self-employed	1	1	1	0	0	3
Country							
	Belgium	54	23	27	0	1	105
	Germany	4	53	0	0	0	57

Source: Own computations based on data from SHARE wave 4 to 8

Across the waves, more females than males became permanently sick, with the largest numbers occurring in the earlier waves. Regarding job status, most of those who became permanently sick were private sector workers, followed by public sector workers, with very few cases among the self-employed. This trend suggests that private sector workers are more represented among those who became permanently sick. When comparing the two countries, Belgium had a significantly higher number of individuals becoming permanently sick, particularly in the earlier waves. In contrast, Germany had a noticeable spike in one of the middle waves but no cases in the latter. The data suggests a substantial difference between the countries regarding when and how individuals became permanently sick.

Table 2 - Distribution of individuals becoming retired across waves by gender, job status, and country

						Retired	
		Wave 4	Wave 5	Wave 6	Wave 7	Wave 8	Total
N		375	404	39	5	1	824
Gender							
	Female	199	207	17	0	1	424
	Male	176	197	22	5	0	400
Job-status							
	Private sector workers	192	150	13	0	0	355
	Public sector workers	119	116	15	2	0	253
	Self-employed	28	28	3	0	0	59
Country							
	Belgium	274	76	34	2	0	386
	Germany	101	328	5	3	1	438

Source : Own computations based on data from SHARE wave 4 to 8

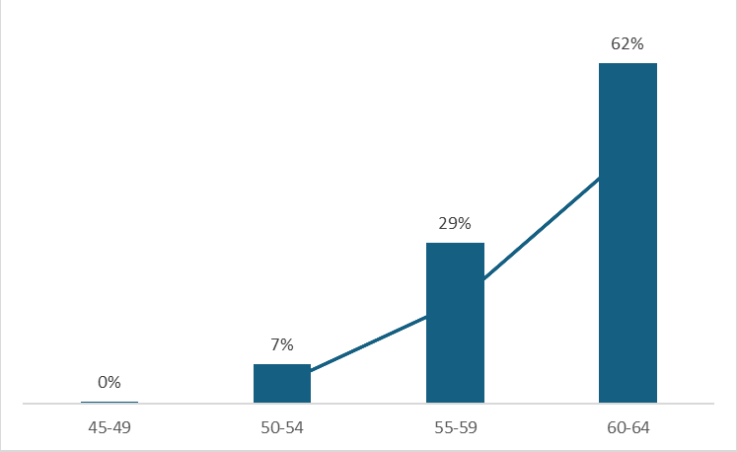
Over the waves, the number of retirees is fairly balanced between females and males, with a slightly higher representation of females. Most retirements occurred in the earlier waves, with very few in the later waves. When examining job status, private sector workers comprise the largest group of retirees, followed by public sector workers and self-employed individuals. This indicates that retirement was most common among those employed in the private sector. Regarding country comparison, the data

reveals a contrast between Belgium and Germany. Belgium saw a higher number of retirements in the early waves. At the same time, Germany experienced many retirements in a particular middle wave, with fewer retirements in the other waves. This suggests a difference in retirement patterns between the two countries over time.

Tables 1 and 2 highlight that while both permanent sickness and retirement are influenced by factors such as gender, job status, and country, the timing and distribution patterns differ significantly between these two outcomes. Permanent sickness tends to occur earlier and is more prevalent in Belgium, especially among private sector workers and females, while retirement is more evenly distributed across waves, with Germany seeing a concentrated peak in retirements. These results give us an initial overview of our dependent variable and the differences between Germany and Belgium.

Next, we will conduct a more in-depth examination of our dependent variable. Figure 3 shows a clear trend where the percentage of early retirees increases significantly as age groups get older. Starting from the youngest age group, there is almost no early retirement. Moving to the next age group, there is a slight increase in the percentage of early retirees. The highest proportion of early retirees is in the 60-64 age group.

Figure 3 - Proportion of early retirees by age group



Source : Own computations based on data from SHARE wave 4 to 8

Table 3 provides an overview of various demographic and socioeconomic factors related to early retirement. It highlights the distribution of individuals who retire early versus those who do not across different categories such as gender, education level, living arrangements, wealth, income, job status, job satisfaction, and physical job difficulty.

Regarding gender, there is a slightly higher percentage of early retirees among men than women. Regarding education levels, individuals with lower education are less likely to retire early, whereas those with medium or high education levels show a slightly higher tendency toward early retirement. The living situation also plays a role, as those living with a partner are less likely to retire early compared to single individuals. Wealth and income are significant factors in early retirement. People with higher wealth levels are more likely to retire early than those with lower wealth, and this pattern is mirrored in income levels, where medium to high-income earners tend to retire earlier than those with lower incomes.

Public sector employees and those facing physical job difficulties are more inclined to retire early than private sector employees and the self-employed. Additionally, job satisfaction impacts early retirement decisions, with individuals who are less satisfied with their jobs or who face physical job difficulties being more likely to opt for early retirement.

Finally, the table compares two countries, Belgium and Germany, where slightly different patterns of early retirement emerge. Overall, the data suggests that higher wealth, income, job satisfaction, and physical job difficulty are associated with a greater likelihood of early retirement.

Table 3 - Demographic and socioeconomic characteristics of early retirement

	Early retirement		
	No	Yes	Total
N	14,129 (93.48%)	986 (6.52%)	15,115
Gender			
Female	8,080 (93.92%)	523 (6.08%)	8,603
Male	6,049 (92.89%)	463 (7.11%)	6,512
Education level			
Low	2,871 (94.63%)	163 (5.37%)	3,034
Medium	5,813 (93.20%)	424 (6.80%)	6,237
High	5,445 (93.17%)	399 (6.83%)	5,844
Living with Partner	11,087 (93.52%)	768 (6.48%)	11,855
Wealth			
Low	6,301 (94.62%)	358 (5.38%)	6,659
Medium	3,559 (92.61%)	284 (7.39%)	3,843
High	4,269 (92.54%)	344 (7.46%)	4,613
Income			
Low	5,708 (94.46%)	335 (5.54%)	6,043
Medium	3,348 (92.28%)	280 (7.72%)	3,628
High	5,073 (93.19%)	371 (6.81%)	5,444
Single	3,022 (93.82%)	199 (6.18%)	3,221
Received Help	2,043 (94.10%)	128 (5.90%)	2,171
Job-status			
Self-employed	895 (93.52%)	62 (6.48%)	957
Private sector employee	4,290 (90.47%)	452 (9.53%)	4,742
Public sector employee	1,847 (86.47%)	289 (13.53%)	2,136
Satisfied with Job	2,764 (87.28%)	403 (12.72%)	3,167
Physical Job Difficulty	1,288 (86.79%)	196 (13.21%)	1,484
Country			
Belgium	7,441 (93.81%)	491 (6.19%)	7,932
Germany	6,688 (93.11%)	495 (6.89%)	7,183

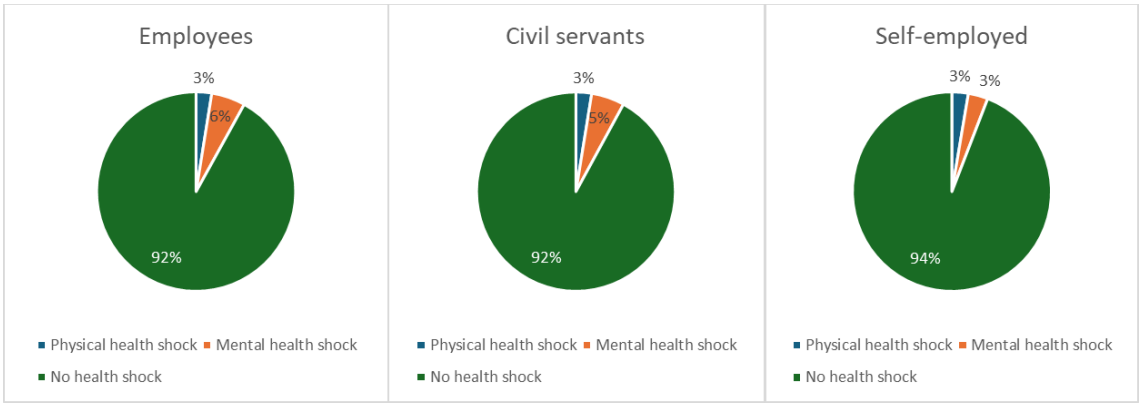
Source : Own computations based on data from SHARE wave 4 to 8

Now that we understand the dependent variable better, it's essential to analyze the socio-economic statistics in connection with the independent variable.

Figure 4 compares the prevalence of health shocks among employees, civil servants, and self-employed individuals. Across all three groups, most individuals have not experienced any health shocks. This suggests that many employees, civil servants, and self-employed remained unaffected by significant health issues. The incidence of health shocks—both mental and physical—is relatively low and consistent, regardless of the employment type.

However, the self-employed group appears to have a slightly larger proportion of individuals who did not experience any health shocks. Despite this, the differences between the groups are minimal, with the distribution of health shocks being quite uniform across employees, civil servants, and the self-employed.

Figure 4 - Proportion of mental and physical health shocks by employment status



Source: Own computations based on data from SHARE wave 4 to 8

Table 4 analyzes the relationship between experiencing a health shock and various demographic and socio-economic variables. It compares the proportion of individuals who have experienced a health shock with those who have not across categories such as gender, education level, living arrangements, wealth, income, job status, job satisfaction, and physical job difficulty.

For gender, women show a slightly higher incidence of health shocks compared to men. When examining education levels, individuals with lower education are more likely to experience a health shock, while those with higher education levels show a lower likelihood of such an event. The living situation also influences health shocks; those living with a partner experience slightly fewer health shocks than those who are single.

Wealth and income levels are also correlated with health shocks. Individuals with lower wealth or income levels experience more health shocks than those with higher wealth or income. This trend suggests that economic stability may play a role in health outcomes.

The relationship between job status and health shocks reveals that self-employed individuals are less likely to experience health shocks than those employed in the private or public sectors. Job satisfaction and physical job difficulty further affect the likelihood of health shocks. Individuals who are less satisfied with their jobs or find their jobs physically demanding are more prone to experiencing health shocks.

Finally, when comparing the two countries in the table, Belgium has a slightly higher incidence of health shocks compared to Germany. The table indicates that lower education, wealth, income, job satisfaction, and higher physical job difficulty are associated with a greater likelihood of experiencing a health shock.

Table 4 - Demographic and socioeconomic characteristics of early retirement

	Health shock		
	No	Yes	Total
N	13,981 (92.50%)	1,134 (7.50%)	15,115
Gender			
Female	7,937 (92.26%)	666 (7.74%)	8,603
Male	6,044 (92.81%)	468 (7.19%)	6,512
Education level			
Low	2,750 (90.64%)	284 (9.36%)	3, 034
Medium	5,791 (92.85%)	446 (7.15%)	6,237
High	5,440 (93.09%)	404 (6.91%)	5,844
Living with Partner	10,996 (92.75%)	859 (7.25%)	11,855
Wealth			
Low	6,172 (92.69%)	487 (7.31%)	6,659
Medium	3,519 (91.57%)	324 (8.43%)	3,843
High	4,290 (93.00%)	323 (7.00%)	4,613
Income			
Low	5,615 (92.92%)	428 (7.08%)	6,043
Medium	3,331 (91.81%)	297 (8.19%)	3,628
High	5,035 (92.49%)	409 (7.51%)	5,444
Single	2,974 (92.33%)	247 (7.67%)	3,221
Received Help	1,926 (88.71%)	245 (11.29%)	2,171
Job-status			
Self-employed	906 (94.67%)	51 (5.33%)	957
Private sector employee	4,406 (92.91%)	336 (7.09%)	4,742
Public sector employee	1,986 (92.98%)	150 (7.02%)	2,136
Satisfied with Job	2,850 (89.99%)	317 (10.01%)	3,167
Physical Job Difficulty	1,325 (89.29%)	159 (10.71%)	1,484
Country			
Belgium	7,255 (91.46%)	677 (8.54%)	7,932
Germany	6,726 (93.64%)	457 (6.36%)	7,183

Source : Own computations based on data from SHARE wave 4 to 8

These analyses provide an overview of certain economic factors that are more or less affected by early retirement or health shock.

Then, having explained and given probabilities with the covariates, let's examine the interactions between early retirement and the health shock.

Table 5 - Early retirement by health shock status

Tabulation of health shock early retirement

	early_retirement		
health_shock	0	1	Total
0	13078	903	13981
1	1051	83	1134
Total	14129	986	15115

Source : Own computations based on data from SHARE wave 4 to 8

Table 6 – Early retirement by health shock status (including people who are already ill)

Tabulation of health_shock_bis early_retirement

	early_retirement		
health_shock_bis	0	1	Total
0	11874	826	12700
1	2255	160	2415
Total	14129	986	15115

Source : Own computations based on data from SHARE wave 4 to 8

In Table 6, the number of individuals experiencing a health shock is significantly higher than in Table 5, which is logical, given that we consider people who are already ill in addition to the health shock in Table 5. In Table 5, the ratio of individuals experiencing a health shock to those who retire early is lower compared to Table 6.

Table 7 – Matrix of correlation (health_shock)

Variables	(1)	(2)	(3)	(4)
(1) health_shock	1.000			
(2) early_retirement	0.009	1.000		
(3) sick_transitio~w	0.017	0.394	1.000	
(4) retirement_tra~w	0.002	0.909	-0.025	1.000

Source : Own computations based on data from SHARE wave 4 to 8

Table 8 – Matrix of correlation (health_shock_bis, including people who are already ill)

Variables	(1)	(2)	(3)	(4)
(1) health_shock_bis	1.000			
(2) early_retirement	0.002	1.000		
(3) sick_transitio~w	0.027	0.394	1.000	
(4) retirement_tra~w	-0.010	0.909	-0.025	1.000

Source : Own computations based on data from SHARE wave 4 to 8

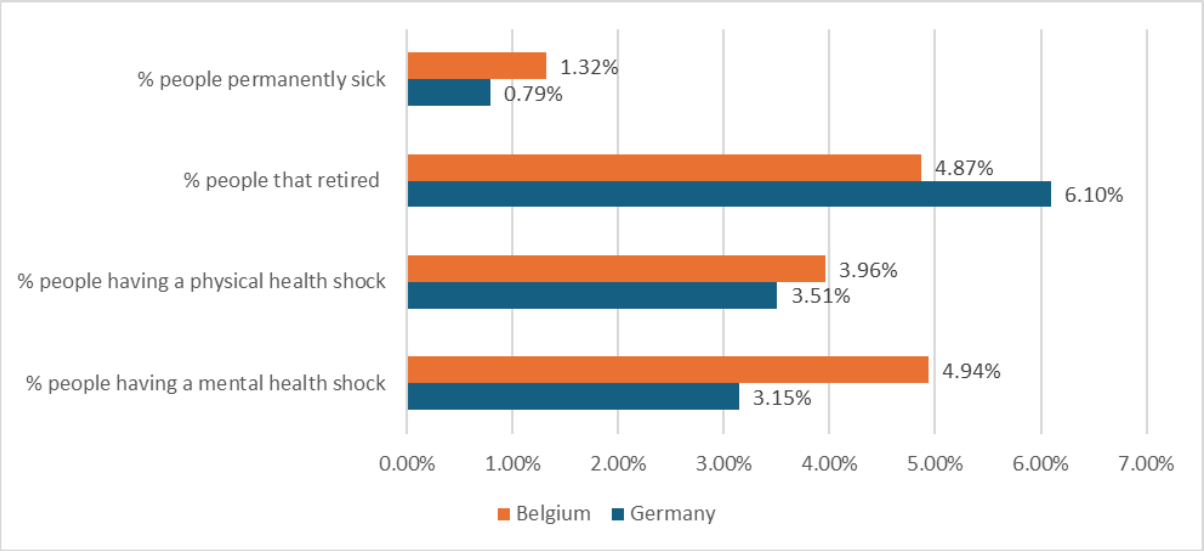
Regarding the correlation between health shocks and early retirement, we can say that the correlation between "health_shock" and early retirement is very low and positive. This indicates a negligible relationship between the original health shock variable and the likelihood of early retirement. The correlation between "health_shock_bis" and early retirement is even lower than in the first table, almost negligible. This suggests that the relationship between health shocks and early retirement is almost non-existent under the broader definition. However, the correlation between "health_shock_bis" and permanently sick is higher than between the other health shock and retirement variables. The broader definition of health shock shows a marginally stronger association with sick transitions. The correlation between health shock and retirement is almost zero for both health shocks, indicating no relationship between the original health shock variable and transitioning into retirement.

This study examines explicitly Germany and Belgium. Analyzing key statistical comparisons between them is essential to better understand their differences regarding retirement and health shocks.

Figure 4 compares Belgium and Germany across four distinct categories: the percentage of people experiencing a mental health shock, a physical health shock, retirement, and permanent sickness. In terms of mental and physical health shocks, a larger proportion of the population in Belgium experiences these compared to Germany.

In regards to retirement, Germany has a significantly higher percentage of people retiring than Belgium. On the other hand, Belgium has a more significant proportion of people who are permanently sick.

Figure 4 - Comparison of Health Shocks, Retirement, and Permanent Sickness Between Belgium and Germany

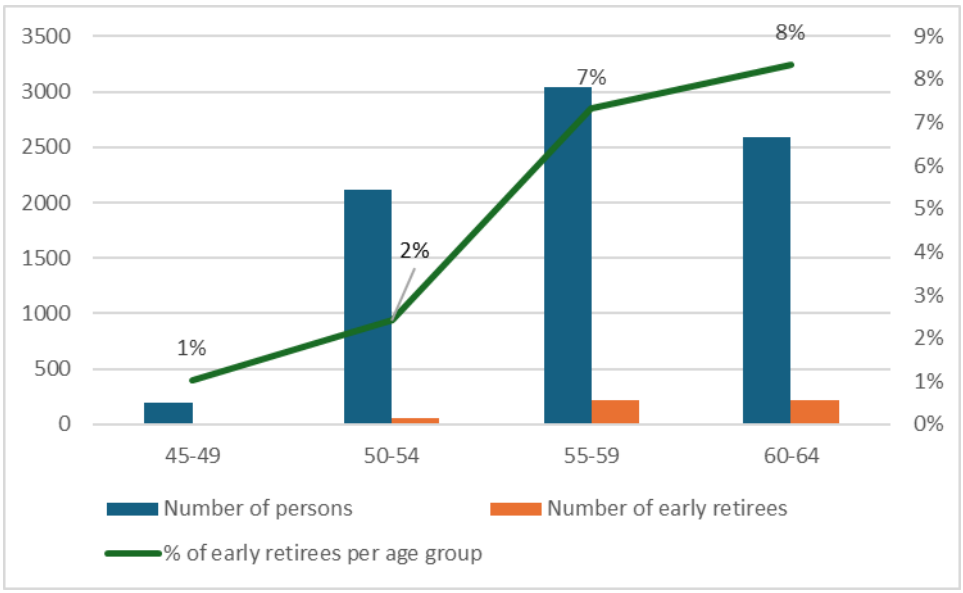


Source : Own computations based on data from SHARE wave 4 to 8

Figures 5 and 6 present the age distribution and the percentage of early retirees by age group in Belgium and Germany. Germany shows a much steeper increase in the percentage of early retirees in the 60-64 age group (17%) compared to Belgium (8%). This suggests that early retirement is more prevalent in Germany, particularly as individuals approach the statutory retirement age. While both countries exhibit a similar trend where the number of individuals peaks in the 55-59 age group, Germany shows a more pronounced rise in early retirement among the older age groups, particularly those between 55 and 64. In Belgium, the rise is more gradual and less pronounced.

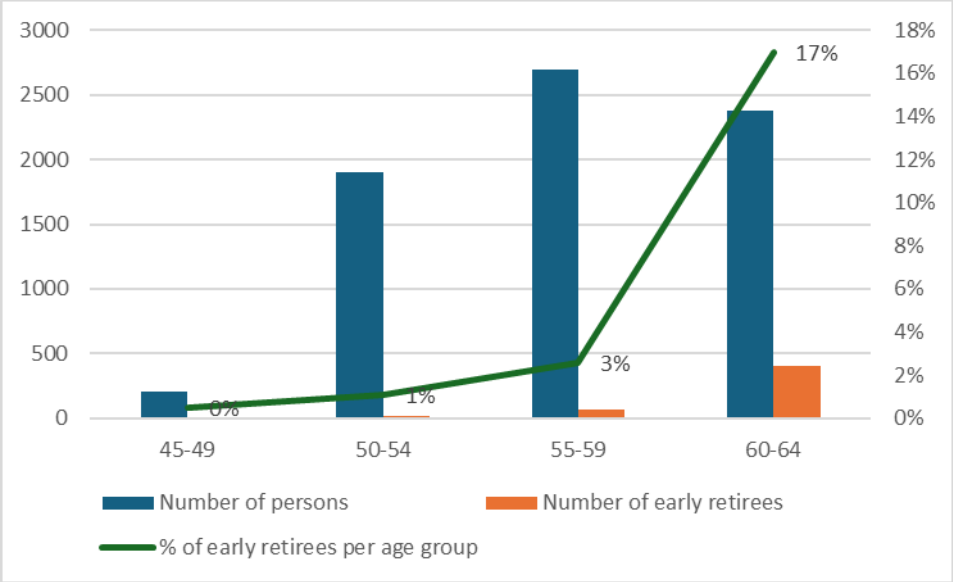
These differences indicate that early retirement patterns vary significantly between Belgium and Germany, with Germany experiencing a higher tendency for early retirement, particularly among those closer to the official retirement age.

Figure 5 - Age distribution and percentage of early retirees by age group in Belgium



Source : Own computations based on data from SHARE wave 4 to 8

Figure 6 - Age distribution and percentage of early retirees by age group in Germany



Source : Own computations based on data from SHARE wave 4 to 8

When considering early retirement, a consistent trend emerges: as individuals age, the likelihood of early retirement increases significantly, peaking in the 60-64 age group. This trend is more pronounced in Germany, where early retirement is notably higher among older individuals, especially those nearing the statutory retirement age. In contrast, Belgium shows a more gradual increase in early retirement rates.

Correlational analysis indicates a weak and almost negligible relationship between health shocks and early retirement. Even when using another definition of health shocks including people who are already ill, the correlation remains low. However, it is higher than with the previous health shock.

The differences between Germany and Belgium are also evident in the patterns of health shocks and retirement. Belgium has a higher prevalence of both mental and physical health shocks, whereas Germany has a higher rate of early retirement. These variations highlight the contrasting socio-economic and health landscapes in the two countries.

4. METHODS

This study aims to quantify the influence of a health shock experienced in period t, whether mental or physical, on the likelihood of early retirement in period $t+1$. Thus, evaluating the divergence in an individual's performance when encountering poor health conditions compared to their expected performance under good health conditions, commonly referred to as the counterfactual scenario, is essential. This study likely faces endogeneity issues for several reasons. First, individuals close to retirement age might be more likely to report health issues as they consider retirement options or take early retirement due to anticipating future health problems. This simultaneous causality creates endogeneity as the causality works both ways. After, if individuals who are more likely to experience health shocks are also more likely to retire early for reasons unrelated to health (e.g., personal preferences, financial readiness), failing to account for this selection process can bias the estimated effect of health shocks on early retirement. While OLS is a powerful tool for estimating relationships between variables, it does not inherently control for endogeneity, which can lead to biased and inconsistent estimates.

In this study, we use the Propensity Score Matching (PSM) method as proposed by Rosenbaum & Rubin (1983, 1985), which effectively addresses endogeneity in observational studies by creating comparable groups based on observed covariates, thus reducing selection bias and improving causal inference. This technique mitigates selection bias by pairing each individual who experiences a health shock with counterparts who do not, based on similar observable characteristics.

In our analysis, individuals experiencing a health shock are designated as the treated group. To conduct our analysis, it is essential to identify individuals with comparable pre-treatment attributes who have not had a health shock. The essence of this methodology lies in comparing individuals who share similar characteristics except for their health status (i.e., experiencing a health shock versus not experiencing one). By pairing individuals with akin propensity scores, which estimate the likelihood of belonging to a specific health condition, the method replicates a hypothetical scenario wherein individuals facing poor health are matched with their counterparts in good health. This approach facilitates a more precise evaluation of the influence of health on performance by effectively isolating the impact of health from other potential confounding variables.

The main control variable in our model is the “health_shock” variable.

$$
\begin{aligned}
Early\ retirement_{i,t+1} &= \beta_0 + \beta_1 PS_{i,t} + \beta_2 health\_shock_{i,t} + \beta_3 gender_{i,t} \\
&+ \beta_4 age_{i,t} + \beta_5 education\_level_{i,t} \\
&+ \beta_6 atleastone\_grandchild_{i,t} \\
&+ \beta_7 remaining\_loanyears_{i,t} + \beta_8 job\_status_{i,t} \\
&+ \beta_9 partner_{i,t} \\
&+ \beta_{10} helpreceived_{i,t} + \beta_{11} wealth_{i,t} + \beta_{12} income_{i,t} \\
&+ \beta_{13} jobphysical_{i,t} + \beta_{14} country_{i,t} + \beta_{15} wave_{i,t}
\end{aligned}
\tag{1}
$$

4.1 Propensity score matching

Various factors, including financial considerations, job satisfaction, and health status, can influence early retirement. One significant factor is the occurrence of health shocks, which can drastically alter an individual's capacity to continue working. To rigorously analyze the impact of health shocks on early retirement, we need a method that accounts for potential confounding variables. Propensity score matching (PSM) is a statistical technique that helps us create a balanced comparison between

individuals who experienced a health shock and those who did not. This ensures that the estimated impact of health shocks on early retirement is not biased by other differences between these groups.

The analysis relies on deux conditions. First is the conditional independence assumption (CIA). The CIA states that there is a set of observed covariates X such that, after controlling for these covariates, the potential outcomes are independent of the treatment status (having a health shock). This can be mathematically expressed as:

$$(Y_0; Y_1) \perp D \mid X \tag{2}$$

where:

- Y_0 and Y_1 are the potential outcomes without and with the treatment, respectively.
- D is the binary indicator of treatment status (e.g., experiencing a health shock or not).
- X is the set of covariates.(Maffioli et al., 2010)

The second condition can be written as follow: $0 < P(D = 1|X) < 1$. The second condition asserts that each subject must have a nonzero probability of receiving either treatment. If the treatment assignment respects the two conditions, conditioning on the propensity score yields unbiased estimates of average treatment effects. The first condition, often called the "no unmeasured confounders" assumption, implies that all variables influencing treatment assignment and outcome have been measured. This is a crucial assumption in propensity score analyses. To address the potential presence of unmeasured confounders, Rosenbaum & Rubin (1983) suggested sensitivity analyses to evaluate the robustness of study conclusions. Additionally, Rosenbaum (1987) recommended using a second control group to test if adjusting for measured covariates successfully removes bias in estimating treatment effects. Notably, the assumption of strongly ignorable treatment assignment, or the absence of unmeasured confounders, is fundamental to propensity score analyses and regression-based methods for estimating treatment effects in observational studies (Austin, 2011).

Propensity scores are calculated based on pretreatment variables using probit models. The dependent variable is the health status, and the covariate simultaneously impacts the health status and the probability of going to early retirement in $t + 1$. The observable characteristics used to obtain these scores include age, gender, household level of education, the physical difficulty of the job if the person receives help outside of the household, the level of wealth, and the level of income. As seen in the literature review, these factors influence both the health status and the fact of going to early retirement. According to Rosenbaum & Rubin (1983, 1985), using the propensity score $P(X)$, a fonction of X, rather than a potentially high-dimensional vector of covariates, implies that:

$$E(Y_0|D = 1, P(X)) = E(Y_0|D = 0, P(X)) \tag{3}$$

As per Rosenbaum and Rubin's methodology, using the propensity score $P(X)$, which is a function of the covariates X, simplifies the estimation process. This approach indicates that the potential outcome for the untreat state (Y_0) is independent of the treatment $(D = 1)$ or non-treatment $(D = 0)$ when conditioned on X (Lenhart, 2019). Therefore, the propensity score can serve as a univariate summary of all observable variables. Consequently, $P(X)$ is known, the Average Treatment effect on the Treated (ATT) can be consistently estimated as follows (Rosenbaum & Rubin, 1983)):

$$\tau_{ATT} = E(Y_1 - Y_0|D = 1) = E(Y_1|P(X), D = 1) - E(Y_0|P(X), D = 0) \tag{4}$$

The probit regression results, represented in Table A6, show that having low education and receiving help from outside the household negatively correlate with a health shock. Similarly, being a woman, age, being single, and having a low level of wealth and income are positively correlated with having a health shock. The household size and the physical difficulty of the job are not significant.

When using matching analysis, there is always a trade-off between bias and efficiency when choosing a matching algorithm. This study used the Kernel propensity score matching method with replacement. The variance is reduced because we use more information to match the individuals than in other matching methods. This technique pairs individuals from a comparison group with program participants based on their propensity scores' similarity. Unlike randomization, kernel matching tackles selection bias by assuming that selection into the program is unrelated to the outcome indicator in the untreated state, given certain observed variables. This means individuals with similar characteristics should have similar expected outcomes regardless of their treatment status (Caliendo & Kopeinig, 2008).

Initially, a non-linear (probit) multiple regression model is applied to estimate the probability of program participation. This model uses pooled data from treated and untreated subjects to estimate the participation probability for each subject. Matching estimation then compares outcome indicators for program participants with those from the comparison group, assigning greater weight to the latter based on the similarity of their estimated probabilities to the participants (Caliendo & Kopeinig, 2008).

Some proponents argue that matching resembles random assignment because it balances observed and unobserved characteristics between treated and untreated units. Matching aims to select a subset of the untreated group that resembles the treated group based on observed characteristics. This helps replicate conditions under which selection into the program would have been random, thus minimizing systematic differences between treated and matched untreated units. Kernel matching estimation adjusts for potential differences between treatment and control groups by considering other factors influencing outcome indicators and using them as covariates in a regression model. It then generates a weight for each matched pair of observations, estimating the program effect as the difference in the outcome indicator variable between individual pairs. The overall estimate is a weighted average of these individual differences, with weights reflecting the closeness of the match based on estimated propensity scores. However, kernel matching's performance may be sensitive to the choice of the kernel bandwidth parameter, which determines the width of the band of values around participants' propensity scores receiving high weights. To address this, a formal cross-validation procedure is often employed to determine the optimal value of this parameter for each model (Handouyahia, 2013).

However, Kernel propensity score matching cannot perfectly match some observations. To reinforce our analysis, we will compute some robustness checks based on another matching method, the Mahalanobis distance (King & Nielsen, 2019), but also cross-validation concerning the means of the dependent variable (X) and th outcome one (Y). Cross-validation offers a convenient method for determining the appropriate bandwidth value, and it tends to perform adequately for certain estimators like the kernel method (Frölich, 2004).

4.2 Robustness checks

To validate our results, we combine matching methods, ensuring that findings are consistent across different matching techniques, thus enhancing the credibility of causal inferences. We use the Mahalanobis distance matching and propensity score matching with general cross-validation for bandwidth selection and propensity score with cross-validation bandwidth and outcome-inclusive selection.

The Mahalanobis distance is a widely used method for matching, particularly in contexts where propensity scores are not applied or where a different matching criterion provides a check against model dependence that can arise from using propensity scores alone. While propensity score matching reduces dimensionality and ensures comparability based on observed covariates, the Mahalanobis distance directly balances covariates considering their distributions. It measures the distance between two points in an N-dimensional space, considering each dimension's statistical variability. Specifically, for points X_i and X_j that share a covariance matrix C, the Mahalanobis distance is calculated as:

$$D(X_i, X_j) = \sqrt{(X_i - X_j)^T C^{-1} (X_i - X_j)} \quad (5)$$

When the covariance matrix C is the identity matrix, this distance reduces to the Euclidean distance. This method has been employed in observational studies to match observations based on the Mahalanobis distance, thereby reducing bias (Pushparaj et al., 2013).

The propensity score matching with cross-validation to select the bandwidth generally, ensures that the propensity score matching is not overly tailored to a specific outcome, providing a general robustness check for overall model balance and performance. It provides a comprehensive robustness check for the matching process (Imbens et al., 2009).

The propensity score matching with cross-validation bandwidth and outcome-inclusive selection (early retirement). This method ensures that the matching is exact for the outcome of interest, in this case, early retirement. This helps validate that the estimated treatment effect is not sensitive to the specifics of the bandwidth selection processes (Imbens et al., 2009).

5. RESULTS

5.1 Preliminary tests

Before running the matching regression, we analyzed the effect of a health shock on early retirement decisions using multiple regression models, such as OLS, fixed effects, and probit models.

The OLS table (Table 9) presents four models that estimate the effect of various factors on early retirement. Each column adds additional variables to the model, which allows us to observe how the estimates change and how the explanatory power of the model (R-squared) evolves.

The coefficient for "Health Shock" starts positive but small in Model 1 and remains consistent across the models, with slight variations. However, its effect size decreases slightly when additional variables are included, suggesting that other factors may influence early retirement more strongly as the model becomes more comprehensive. The lack of statistical significance (indicated by standard errors larger than the coefficient) implies that health shocks alone may not be a strong predictor of early retirement in these models.

The effect of being a woman is positive and statistically significant in the first model but loses significance as more controls are added. By the final model, the effect is negligible, indicating that the initial gender difference in early retirement rates can largely be explained by other variables included in later models, such as education, wealth, and job characteristics.

The age variable consistently shows a highly significant and strong positive relationship with early retirement across all models. This suggests that older workers are more likely to retire early, and this effect remains robust even when controlling for other factors.

The inclusion of educational variables in Model 2 reveals that education has varying impacts on early retirement, though none of the coefficients for education levels are statistically significant. Higher levels of education tend to have a negative relationship with early retirement, particularly for higher stages of tertiary education. However, the effects are not strong enough to draw definitive conclusions.

Wealth has a positive and significant effect on early retirement, particularly for those with medium and high levels of wealth. This suggests that individuals with greater wealth are more likely to retire early. Conversely, income's effect is more complex; medium-income levels initially show a positive relationship. However, this becomes insignificant and even negative for high-income levels as the model controls for additional factors.

Job sector becomes a significant predictor in Model 3, where public sector employees are more likely to retire early, while self-employed individuals are less likely to do so. This indicates that job security and benefits in the public sector might encourage earlier retirement, whereas self-employed individuals might continue working longer.

In the final model, variables such as living with a partner, receiving help, job satisfaction, and the physical difficulty of the job are added. Job satisfaction emerges as a significant predictor, with those satisfied with their job being less likely to retire early. This suggests that contentment with work can delay retirement, even when other factors suggest otherwise.

The R-squared value, which represents the proportion of variance in early retirement explained by the model, increases gradually from Model 1 to Model 4. By Model 4, the R-squared has increased substantially, suggesting that the model with the most controls provides the best fit. However, it still leaves a significant portion of the variation unexplained.

Table 9 – OLS regression

	(1) early_retirement	(2) early_retirement	(3) early_retirement	(4) early_retirement
Health Shock	0.017	0.015	0.005	0.011
	(0.015)	(0.015)	(0.016)	(0.016)
Woman	0.011*	0.010	-0.001	0.001
	(0.006)	(0.006)	(0.007)	(0.007)
Age	0.028***	0.028***	0.028***	0.029***
	(0.001)	(0.001)	(0.001)	(0.001)
Primary education or first stage of basic education		0.027	0.021	0.022
		(0.046)	(0.056)	(0.056)
Lower secondary		0.027	0.017	0.018
		(0.042)	(0.052)	(0.051)
(Upper) secondary education		0.013	0.008	0.010
		(0.041)	(0.051)	(0.050)
Post-secondary non-tertiary education		-0.010	-0.009	-0.005
		(0.043)	(0.052)	(0.052)
First stage of tertiary education		-0.014	-0.022	-0.019
		(0.041)	(0.051)	(0.050)
Second stage of tertiary education		-0.052	-0.067	-0.063
		(0.046)	(0.055)	(0.055)
Low Level of wealth		0.000	0.000	0.000
		(.)	(.)	(.)
Medium Level of wealth		0.036***	0.027***	0.027***
		(0.009)	(0.009)	(0.009)
High Level of wealth		0.022**	0.019**	0.020**
		(0.009)	(0.009)	(0.009)
Low Level of income		0.000	0.000	0.000
		(.)	(.)	(.)
Medium Level of income		0.018**	-0.003	-0.005
		(0.009)	(0.011)	(0.011)
High Level of income		-0.001	-0.026**	-0.025**
		(0.009)	(0.011)	(0.011)
Private sector employee			0.000	0.000
			(.)	(.)
Public sector employee			0.040***	0.040***
			(0.009)	(0.009)
Self-employed			-0.053***	-0.054***
			(0.010)	(0.010)
Single			-0.010	-0.007
			(0.009)	(0.011)
Living with a partner				0.004
				(0.013)
Received help from outside the household				-0.000
				(0.002)
Satisfied with his/her job				-0.040***
				(0.009)
Physical difficulty of the job				0.014
				(0.011)
N	9175	9175	7250	7246
R^2	0.1235	0.1295	0.1439	0.1465

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Source: Own computation from the SHARE database wave 4 to 9

Table 10 investigates the determinants of early retirement among individuals aged 60 and above, focusing on the impact of health shocks and various demographic, educational, and employment-related factors. Compared to the broader analysis presented in the first table, this regression specifically examines how these variables affect older individuals' decisions to exit the labor market early.

In this focused group, a health shock has a positive and statistically significant impact on the likelihood of early retirement. This finding aligns with the preceding analysis, where health shocks also play a significant role, though the effect appears more pronounced in this older cohort and is significant in Table 10.

Interestingly, the variable representing gender shows a slight negative impact on early retirement, which is marginally significant. In contrast, in Table 9, the effect of gender was not as consistent across different specifications. This suggests that among older workers, women might be slightly less inclined to retire early, potentially due to different retirement needs or financial constraints compared to men.

Age remains a strong and consistent predictor of early retirement in both analyses, with older individuals being more likely to retire. However, the effect of age is naturally more critical in this analysis since all individuals are already close to the typical retirement age.

Marital and cohabitation status, represented by the variables for living with a partner and being single, do not significantly influence early retirement among those aged 60 and above. This finding is consistent with the first table, where these variables did not exhibit strong effects either, suggesting that relationship status may not be a decisive factor in retirement decisions for older individuals.

Educational attainment does not appear to significantly influence early retirement in this older group. While those with primary or secondary education levels have positive coefficients, these are not statistically significant. Table 9 showed limited influence from education, though the coefficients were somewhat different across educational levels. This indicates that education might play a lesser role in retirement decisions as individuals approach the traditional retirement age.

Wealth and income levels present a more nuanced picture. A medium level of wealth is marginally associated with a higher likelihood of early retirement, consistent with the broader analysis where medium wealth also showed a positive effect. Interestingly, a high income level negatively impacts early retirement, mirroring the broader analysis. This suggests that higher-income individuals, regardless of their age, may choose to stay in the workforce longer, possibly due to continued financial incentives or greater satisfaction with their work.

Employment sector continues to play a significant role in determining early retirement. Public sector employees are more likely to retire early, consistent with the findings in the first table, likely due to favorable retirement benefits. Conversely, self-employed individuals are less likely to retire early, which also aligns with the broader analysis, indicating the flexibility and later retirement tendencies of the self-employed.

Job satisfaction is another critical factor influencing early retirement. In both analyses, lower job satisfaction significantly increases the likelihood of early retirement, underscoring the importance of job satisfaction in the decision-making process. The physical difficulty of the job, however, does not significantly affect early retirement in this older group, which contrasts with the broader analysis where job physicality had a more noticeable impact.

The pseudo R-squared value of 0.065 in this model indicates that while the model captures some important factors influencing early retirement, a substantial portion of the variation remains

unexplained. This is consistent with the preceding analysis, where the R-squared values also indicated that other unobserved factors likely play a role in these decisions.

In summary, this heterogeneity test reveals that health shocks are a crucial driver of early retirement among individuals aged 60 and above. Gender, income, and job satisfaction also significantly influence retirement decisions in this age group. When comparing these findings to the broader analysis, the results suggest that while some factors like health shocks and job satisfaction are universally important, other factors such as income levels and employment sector have nuanced effects that may vary depending on the age of the individuals in question.

Table 10 – OLS regression: Heterogeneity test people aged 60-64 years

	(1) early_retirement	
Health Shock	0.032**	(0.016)
Woman	-0.011*	(0.006)
Age	0.012***	(0.001)
Living with a partner	0.016	(0.011)
Single	0.004	(0.010)
Primary education or first stage of basic education	0.038	(0.046)
Lower secondary	0.046	(0.040)
(Upper) secondary education	0.020	(0.039)
Post-secondary non-tertiary education	0.013	(0.040)
First stage of tertiary education	-0.001	(0.039)
Second stage of tertiary education	-0.035	(0.040)
Received help from outside the household	-0.001	(0.002)
Low Level of wealth	0.000	(.)
Medium Level of wealth	0.015*	(0.008)
High Level of wealth	0.010	(0.008)
Low Level of income	0.000	(.)
Medium Level of income	0.001	(0.010)
High Level of income	-0.017*	(0.010)
Private sector employee	0.000	(.)
Public sector employee	0.030***	(0.008)
Self-employed	-0.033***	(0.007)
Satisfied with his/her job	-0.031***	(0.007)
Physical difficulty of the job	0.007	(0.009)
N	5745	
pseudo R^2	0.0665	

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Source: Own computation from the SHARE database wave 4 to 9

In Table 11, we do a heterogeneity test using the health shock variable with people who were already sick and not just those receiving a health shock. The new analysis, with the adjusted health shock variable and different dependent variables, offers additional insights into the effect of health shock on early retirement. The updated health shock variable demonstrates its strong influence on transitioning to a disability, whereas its impact on early retirement is not significant. This emphasizes that health shocks can more pronouncedly affect health outcomes rather than retirement decisions.

The effects of wealth and income on early retirement are consistent with previous findings, highlighting the complex relationship between financial resources and retirement timing. However, the updated model shows a clearer picture of how income affects the sick transition.

The insignificant effects of education in this analysis contrast with previous findings, suggesting that educational attainment might not be as crucial in influencing retirement and health transitions as initially thought.

The impact of the employment sector on early retirement remains significant, with public sector employees more likely to retire early. The role of self-employment in both early retirement and health transitions continues to be a notable finding.

The updated OLS regressions reveal that the impact of health shocks, wealth, income, and job satisfaction on retirement and health transitions varies. Some factors remain consistent with previous analyses, while others, such as the effect of the new health shock variable, provide deeper insights into how these dynamics play out in specific contexts. Most importantly, for people aged 45 to 64, health shock has a bigger impact on permanent sickness.

Table 11 - OLS regression: Heterogeneity test with the health shock including people who are already ill

	(1) early_retirement	(2) sick_transition_w
Health Shock with people who are already sick	0.010	0.020***
	(0.012)	(0.007)
Woman	0.001	0.001
	(0.007)	(0.003)
Age	0.029***	0.000
	(0.001)	(0.000)
Living with a partner	0.004	0.003
	(0.013)	(0.005)
Single	-0.007	-0.000
	(0.011)	(0.005)
Primary education or first stage of basic education	0.022	0.006
	(0.056)	(0.034)
Lower secondary	0.018	0.009
	(0.051)	(0.031)
(Upper) secondary education	0.011	0.002
	(0.050)	(0.031)
Post-secondary non-tertiary education	-0.005	-0.006
	(0.052)	(0.031)
First stage of tertiary education	-0.018	-0.004
	(0.050)	(0.031)
Second stage of tertiary education	-0.063	-0.009
	(0.055)	(0.031)
Received help from outside the household	-0.000	-0.002
	(0.002)	(0.001)
Low Level of wealth	0.000	0.000
	(.)	(.)
Medium Level of wealth	0.027***	0.002
	(0.009)	(0.005)
High Level of wealth	0.020**	-0.004
	(0.009)	(0.005)
Low Level of income	0.000	0.000
	(.)	(.)
Medium Level of income	-0.005	-0.013**
	(0.011)	(0.006)
High Level of income	-0.025**	-0.013**
	(0.011)	(0.006)
Private sector employee	0.000	0.000
	(.)	(.)
Public sector employee	0.040***	-0.001
	(0.009)	(0.004)
Self-employed	-0.054***	-0.017***
	(0.010)	(0.003)
Satisfied with his/her job	-0.040***	-0.012***
	(0.009)	(0.004)
Physical difficulty of the job	0.014	0.018***
	(0.011)	(0.005)

N	7246	7246
R^2	0.1465	0.0159

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Source: Own computation from the SHARE database wave 4 to 9

After, we ran the fixed-effect regression (Table A5 and Tabel A6). Fixed-effects regressions control for time-invariant characteristics of individuals that could confound the relationship between health shocks and early retirement. This is crucial for more accurate estimates when dealing with panel data, where individual-specific traits (e.g., inherent ability, and work ethic) might influence health and retirement decisions.

Finally, we ran probit regressions on Table 12. Probit regression is used for modeling binary dependent variables. In this case, the dependent variable is early retirement, which takes one if the individual retirers and 0 otherwise. They account for non-linear probability distributions, offering insights into how a health shock affects the probability of early retirement. With this new regression we shall see if the effect of health shock on early retirement is higher and more significant than the OLS regression. The probit regression with the health shock variable including the people that are already ill is in the appendix (Table A7).

Age, physical difficulty of the job, and wealth levels emerge as significant predictors. In contrast, health shocks, gender, education levels, job satisfaction, marital status, and external support do not show significant effects. The pseudo r-squared is higher than the r-squared in the OLS regression.

Table 12 – Probit regression with health shock

	(1) early_retirement	
early_retirement		
Health shock	0.032	(0.078)
Woman	-0.029	(0.044)
Age	0.177***	(0.007)
Primary education or first stage of basic education	0.236	(0.354)
Lower secondary	0.181	(0.334)
(Upper) secondary education	0.125	(0.331)
Post-secondary non-tertiary education	-0.040	(0.355)
First stage of tertiary education	-0.038	(0.332)
Second stage of tertiary education	-0.450	(0.423)
Living with a partner	0.002	(0.076)
single_w	-0.055	(0.073)
Satisfied with his/her job	-0.014	(0.050)
Received help from outside the household	0.001	(0.015)
Physical difficulty of the job	0.146**	(0.060)
Private sector employee	0.000	(.)
Public sector employee	0.263***	(0.049)
Self-employed	-0.461***	(0.080)
Low Level of wealth	0.000	(.)
Medium Level of wealth	0.164***	(0.060)
High Level of wealth	0.114*	(0.062)
Low Level of income	0.000	(.)
Medium Level of income	-0.029	(0.066)
High Level of income	-0.152**	(0.069)
N	7831	
pseudo R^2	0.201	

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

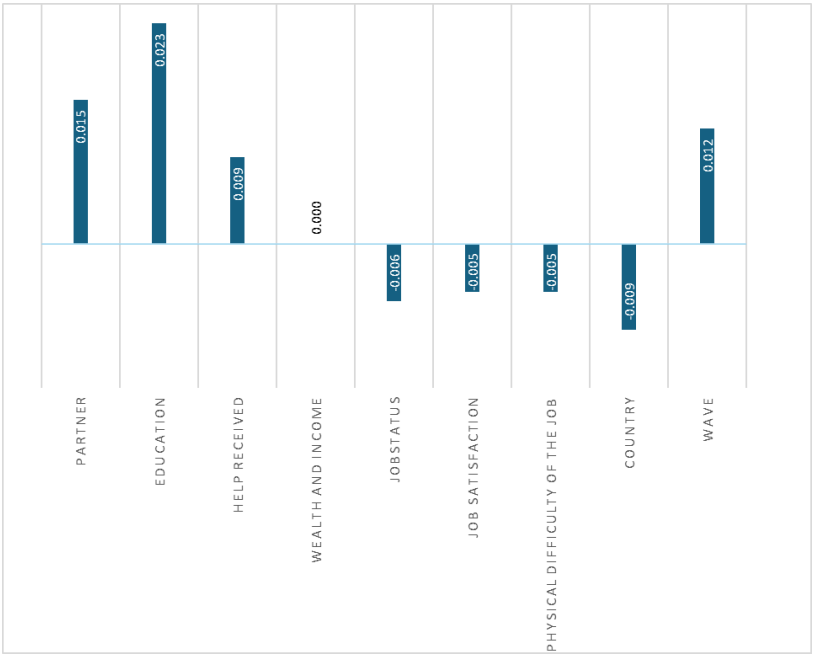
Source: Own computation from the SHARE database wave 4 to 9

Running multiple models ensures robust results across different specifications and methods. If the effect of a health shock is consistent across OLS, fixed effects, and probit models, the validity of the findings will be strengthened. For the moment, in the regressions that have been carried out, health shock has a positive and significant impact on retirement only in two cases: when the age is restricted to people between 60 and 64 and when people who are already ill are included in the health shock in addition to those receiving a health shock, and when we look at its impact on disability. In the next section, we will test the impact of health shock on early retirement using propensity score matching.

5.2 Interpretation of the results

After performing OLS, fixed effect and probit regression, we perform propensity score matching.In the matching process, we gradually added variables to see how they influence the results. Figure 7 shows how the ATT evolves when different variables are added to the matching.

Figure 7 - Importance of variables in the model



Source : Own computations based on data from SHARE wave 4 to 8

Table 13, presents the results of the Average Treatment Effect on the Treated (ATT) for various groups, highlighting how experiencing a health shock influences early retirement outcomes across different demographic and socioeconomic factors. Overall, the ATT is positive, but it is not statistically significant, indicating that the treatment had a small and uncertain effect.

When broken down by gender, men and women show a positive ATT, with men having a slightly higher effect. However, neither effect is statistically significant. Country-wise, Belgium exhibits a higher positive ATT than Germany, but again, neither is statistically significant, the result seems logical regarding the information gathered in the introduction and the literature review. Regarding age, the treatment effects are minimal and insignificant for both the 45-54 and 55-64 age groups. The older group even shows a slight negative effect. Public sector employees experience the highest positive ATT when considering job status, though this effect is still not statistically significant. Private sector employees and the self-employed show minimal positive effects, neither of which are significant.

Table 13 - Average treatment effect on the treated (ATT) estimating the impact of health shock on early retirement (exact matching[3] with replacement)

GROUPS		# TREATED	# CONTROL	ATT	S.E.
All		472	6,774	0.012	0.019
Gender					
	Male	185	3,117	0.024	0.033
	Female	287	3,657	0.022	0.025
Countries					
	Belgium	257	3,078	0.021	0.028
	Germany	215	3,696	0.006	0.027
Age					
	45-54	132	2,750	0.010	0.026
	55-64	340	4,024	- 0.006	0.026
Job-status					
	Private sector employee	270	4,077	0.006	0.026
	Public sector employee	138	1,878	0.027	0.039
	Self-employed	45	819	0.003	0.049

*Note : ***, ** and * stands for the statistically significant at the 1%, 5% and 10% levels respectively*

Source : Own computations based on data from SHARE wave 4 to 8

Since the impact of a health shock has no impact on retirement, we will perform a heterogeneity test to deepen the analysis and attempt to examine differences between sub-groups. Table 14 shows the impact of the health shock on disability and retirement separately. For those who become permanently sick, the Average Treatment Effect on the Treated (ATT) is positive, suggesting that health shocks slightly increase the probability of this type of exit. This effect is more precisely estimated, as indicated by the standard error, but it is not statistically significant, meaning the evidence for a substantial impact is weak. In contrast, the ATT is negative for retirement, implying that health shocks might reduce the likelihood of retiring. However, this result is not statistically significant either, indicating high uncertainty and a lack of strong evidence for a real effect. However, the impact of the health shock on permanent illness is greater than on the early retirement variable.

Table 14 – Impact of health shock on different types of labor market exits: Heterogeneity test

GROUPS		# TREATED	# CONTROL	ATT	S.E.
TYPES OF EXIT FROM THE LABOR MARKET					
	Permanently sick	472	6,774	0.016	0.010
	Retired	472	6,774	-0.004	0.827

*Note : ***, ** and * stands for the statistically significant at the 1%, 5% and 10% levels respectively*

Source : Own computations based on data from SHARE wave 4 to 8

Since a health shock involving only those who have suffered a shock does not appear to have any impact on early retirement, let us look at the ATT of a health shock involving those who are already ill and those who have suffered a shock on early retirement. This second health shock increases the number of people treated as more people have a health shock. The health shock has a small, positive

[3] Exact matching on the variables: female, partner, country and wave.

effect on early retirement. However, this effect is not statistically significant, indicating uncertainty about whether the health shock truly influences early retirement for the general population.

The effect of the health shock differs by gender. For men, the impact is positive and statistically significant at a marginal level, suggesting that health shocks slightly increase the likelihood of early retirement among men. For women, however, the effect is negative and insignificant, implying that health shocks might decrease their likelihood of early retirement, but this result is uncertain.

In both Belgium and Germany, the health shock has a small positive effect on early retirement. However, these effects are not statistically significant, indicating no strong evidence of a country-specific impact.

The impact of health shocks varies with age. For the younger group (45-54), there is a positive and statistically significant effect, suggesting that health shocks increase the likelihood of early retirement for this age group. For the older group (55-64), the effect is close to zero and not significant, indicating that health shocks have little to no impact on early retirement for them.

The effect of health shocks on early retirement also varies by job status. For private sector employees, there is a small positive and marginally significant effect, suggesting that health shocks slightly increase the likelihood of early retirement. For public sector employees and the self-employed, the effects are negative and not significant, indicating no strong evidence that health shocks lead to early retirement in these groups.

Overall, the table shows that health shocks may have a modest impact on early retirement but the impact is higher than in Table 13.

Table 15 - Average treatment effect on the treated (ATT) estimating the impact of health shock (including people who are already ill) on early retirement (exact matching[4] with replacement)

GROUPS		# TREATED	# CONTROL	ATT	S.E.
All		951	6,295	0.016	0.015
Gender					
	Male	328	2,974	0.046*	0.026
	Female	623	3,321	-0.021	0.020
Countries					
	Belgium	525	2,810	0.032	0.020
	Germany	426	3,485	0.014	0.021
Age					
	45-54	283	2,599	0.034**	0.014
	55-64	668	3,696	0.005	0.020
Job-status					
	Private sector employee	583	3,783	0.031*	0.018
	Public sector employee	273	1,743	-0.010	0.031
	Self-employed	95	769	-0.016	0.048

*Note : ***, ** and * stands for the statistically significant at the 1%, 5% and 10% levels respectively*

Source : Own computations based on data from SHARE wave 4 to

Since a health shock does not impact retirement, we will perform a heterogeneity test to deepen the analysis and see if the impact could be stronger when we separate sickness and retirement. Table 16 examines the impact of a health shock, including people who are already ill, on different types of labor

[4] Exact matching on the variables: female, partner, country and wave.

market exits. The impact of the health shock on retirement is slightly negative but not statistically significant again. However, the health shock has a positive and statistically significant impact on the likelihood of becoming permanently sick.

Table 16 – Impact of health shock (including people who are already ill) on different types of labor market exits: heterogeneity test

GROUPS		# TREATED	# CONTROL	ATT	S.E.
TYPES OF EXIT FROM THE LABOR MARKET					
	Permanently sick	951	6,295	0.020***	0.007
	Retired	951	6,295	-0.003	0.013

*Note : ***, ** and * stands for the statistically significant at the 1%, 5% and 10% levels respectively*

Source : Own computations based on data from SHARE wave 4 to 8

the test of Table 16 shows that the impact is significant when we look at the impact of the health shock including people who are already ill on the disability departure. So we will repeat the matching with these two variables and see if the impact on the sub-groups becomes significative.

Table 17 – Average treatment effect on the treated (ATT) estimating the impact of health shock (including people who are already ill) on permanent sickness (exact matching[5] with replacement)

GROUPS		# TREATED	# CONTROL	ATT	S.E.
All		951	6,295	0.020***	0.007
Gender					
	Male	328	2,974	0.025*	0.014
	Female	623	3,321	0.017	0.010
Countries					
	Belgium	525	2,810	0.029***	0.010
	Germany	426	3,485	0.022**	0.009
Age					
	45-54	283	2,599	0.032**	0.013
	55-64	668	3,696	0.010	0.009
Job-status					
	Private sector employee	583	3,783	0.027***	0.009
	Public sector employee	273	1,743	0.025**	0.012
	Self-employed	95	769	0.023	.

*Note : ***, ** and * stands for the statistically significant at the 1%, 5% and 10% levels respectively*

Source : Own computations based on data from SHARE wave 4 to

In Table 17, the health shock significantly increases the likelihood of transitioning to being sick across the entire sample. This indicates that experiencing a health shock has a strong and statistically significant effect on becoming sick.

The impact of the health shock is positive for both men and women. However, the effect is marginally significant for men, suggesting a slightly stronger but less certain effect compared to women, for whom the effect is positive but not statistically significant. The health shock significantly increases the likelihood of transitioning to sickness in both Belgium and Germany. The effect is slightly stronger in

[5] Exact matching on the variables: female, partner, country and wave.

Belgium, with both countries showing statistically significant results, indicating a consistent impact across these regions.

The impact of the health shock is stronger and statistically significant for the younger age group (45-54), indicating that health shocks have a more pronounced effect on transitioning to sickness for this group. For the older age group (55-64), the effect is positive but smaller and not statistically significant, suggesting a weaker impact.

The health shock significantly increases the likelihood of becoming sick for private sector employees and public sector employees, with both groups showing statistically significant effects. The impact is slightly stronger for private sector employees. For the self-employed, the effect is positive but not statistically significant, suggesting that the health shock's impact is less certain in this group

Table 17 shows that health shocks have a generally strong and significant impact on the likelihood of transitioning to sickness, with some variation in the strength and significance of the effect across different demographic groups. The results highlight that the impact is more pronounced for younger individuals, private and public sector employees, and residents of Belgium and Germany.

5.3 Robustness checks

Conducting robustness checks is essential in empirical research to ensure the results are reliable and not sensitive to the specific method or model used. By performing multiple robustness checks, researchers can confirm that the previous findings are consistent across different specifications, thus increasing confidence in the results.

This table presents the results of an Average Treatment Effect on the Treated (ATT) estimation for the outcome "sick_transition," which measures the likelihood of transitioning to sickness after a health shock. The ATT is estimated using four matching methods based on the Mahalanobis distance. The first column represents the ATT estimated using Mahalanobis distance with exact matching. The second column uses Mahalanobis distance with Propensity Score Weighting. The third column applies Mahalanobis distance with Cross-Validation Bandwidth Selection. The fourth column incorporates cross-validation bandwidth selection and outcome information in the Mahalanobis distance matching. Across all four methods, the ATT is consistently positive and statistically significant at the 1% level. This consistency across different matching techniques suggests the result is robust: experiencing a health shock significantly increases the probability of leaving the labor market because of sickness. The slight variations in ATT values and standard errors across methods are minimal, further supporting the reliability of the findings.

Table 18 - Average treatment effect on the treated (ATT) estimation with Mahalanobis distance : (1) with exact matching[6], (2) with Propensity Score Weighting, (3) with Cross-Validation Bandwidth Selection and (4) with Cross-Validation Bandwidth Selection Including Outcome

ATT Results

	MD	MD Mix	MD X	MD Y
	(1)	(2)	(3)	(4)
	sick_transition	sick_transition	sick_transition	sick_transition
ATT	0.017***	0.017***	0.017***	0.018***
	(0.006)	(0.006)	(0.007)	(0.006)
N	7831	7831	7831	7831
pseudo R^2				

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Source : Own computations based on data from SHARE wave 4 to 8

[6] Exact matching on the variables: female, partner, country and wave.

The analysis also utilized Propensity-Score Kernel Matching (PS), as in Table 19. The table presents the results of estimating the Average Treatment Effect on the Treated (ATT) using Propensity Score Matching (PSM) methods under two different scenarios: cross-validation bandwidth selection and cross-validation bandwidth and outcome-inclusive selection. In both methods, the ATT values are positive.

Table 19 - Average treatment effect on the treated (ATT) estimation with Propensity score matching methods: (1) with Cross-Validation Bandwidth Selection and (2) Cross-Validation Bandwidth and Outcome-Inclusive Selection

	ATT Results	
	PS X	PS Y
	(1)	(2)
	sick_transition	sick_transition
ATT	0.017***	0.019***
	(0.006)	(0.006)
N	7831	7831
pseudo R^2		

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Source: Own computations based on data from SHARE wave 4 to 8

The results across different tables demonstrate a robust and consistent positive impact of experiencing a health shock on the likelihood of transitioning to sickness and exiting the labor market. By employing various matching methods—including Mahalanobis distance with different specifications and Propensity Score Matching (PSM) with cross-validation techniques—the analysis shows that the Average Treatment Effect on the Treated (ATT) remains statistically significant at the 1% level across all models. This robustness, indicated by the consistent positive ATT values and minimal variations in standard errors, reinforces the reliability of the findings.

Multiple robustness checks, such as incorporating exact matching, Propensity Score Weighting, and Cross-Validation Bandwidth Selection, ensure that the results are not sensitive to the specific method applied. This consistency across diverse methodologies suggests that the observed effect is genuine and not an artifact of the particular analytical approach used.

5.4 Limitations

This study investigates the impact of health shocks on early retirement decisions using various regression models and matching methods. While the findings provide valuable insights, several limitations must be acknowledged. These limitations include omitted variable bias, issues with causal inference, generalizability, model specification, and concerns regarding sample size and power. Understanding these limitations is crucial for interpreting the results and future research directions.

One of the primary concerns in this analysis is the potential for omitted variable bias. Despite controlling for several observed factors such as gender, age, education, wealth, and employment status, there may still be unobserved variables that influence both health shocks and early retirement decisions. It would have been interesting to include more family-related variables in the model. Initially, there was a variable indicating whether an individual had a grandchild. However, many missing values were in the dataset, so we lost too many observations when including this variable. There were similar issues with variables related to the number of years remaining credit for individuals; there were too many missing data points. There was also a variable in the dataset that indicated the likelihood of the government increasing the pension age. Unfortunately, it did not include this variable in the model due to too many missing values.

Establishing causality in observational studies is inherently challenging. Although matching methods and regression models such as OLS, fixed effects, and probit regressions attempt to infer causal relationships, they cannot entirely rule out endogeneity. Endogeneity can arise from reverse causality, where the decision to retire early might influence the reporting of a health shock, or from simultaneous determination, where unobserved factors simultaneously affect health shocks and retirement decisions. While robustness checks and different model specifications help strengthen the findings, they only eliminate these issues partially.

Another limitation is the generalizability of the results. The study is based on a specific dataset, which may not represent other populations or regions. Cultural, economic, and policy differences can significantly influence the relationship between health shocks and early retirement. For instance, countries with different healthcare systems, pension schemes, or labor market conditions might exhibit different patterns. Therefore, caution must be exercised when extrapolating these findings to other contexts.

The choice of model specification and bandwidth selection in kernel matching can influence the results. Different matching methods, such as Mahalanobis distance (MD) and Propensity-Score Kernel Matching (PS), ensure robustness. However, these methods come with their assumptions and limitations. For example, the choice of bandwidth in kernel matching can affect the balance between bias and variance in the estimates. Ensuring that the chosen model specification is appropriate for the data is crucial yet challenging, and different specifications might yield slightly different results.

While the overall sample size in the study is reasonably large, subgroup analyses (e.g., by gender and education level) might involve smaller sample sizes. Smaller sample sizes in these subgroups can affect the statistical power and precision of the estimates, leading to wider confidence intervals and less reliable results. Ensuring sufficient sample sizes for subgroup analyses is essential for drawing robust conclusions.

This study provides valuable insights into the impact of health shocks on early retirement decisions. However, several limitations must be acknowledged. Omitted variable bias, challenges in establishing causality, issues with generalizability, model specification concerns, and sample size limitations all affect the interpretation of the results. Future research should address these limitations by incorporating additional variables, using more accurate data collection methods, employing advanced causal inference techniques, and ensuring sufficient sample sizes for subgroup analyses. Addressing these limitations will enhance the robustness and reliability of findings in this critical area of research.

6. CONCLUSION AND DISCUSSION

This study provides an in-depth analysis of the impact of health shocks on early retirement decisions in Germany and Belgium. The findings reveal significant insights into how health-related factors influence retirement timing in both countries, adding to the existing literature on the subject.

The results demonstrate that health shocks play a role in the decision to quit the labor market and go to permanent sickness, with notable differences observed between Germany and Belgium. Specifically, the study found that health shocks are a more pronounced determinant of permanent sickness in Belgium than in Germany.

The findings align with previous research highlighting health's importance in retirement decisions. However, this study contributes novel insights by contrasting the impact of health shocks between Germany and Belgium and considering permanent sickness. While earlier studies have explored health as a retirement determinant, this research emphasizes the differential impact across these two countries and the exit type, filling a gap in the literature. The results may highlight that in Belgium, people tend to go into permanent sickness rather than early retirement when they have a health shock. This may be due to differences in legislation and the social security system, as well as the benefits received in case of illness between Belgium and Germany.

While this study offers valuable insights, it is not without limitations. The data may not capture the full range of health conditions or consider other unobserved variables that could influence retirement decisions. Future research could explore these aspects in more detail, potentially expanding the analysis to include additional countries or more granular health data. Additionally, longitudinal studies could provide a more dynamic understanding of how health shocks influence retirement over time.

Recognizing the significant impact of health shocks on early retirement, especially as they often result in permanent disability, governments should prioritize investment in preventive healthcare. Improving access to preventive measures can decrease the frequency and severity of such health crises, allowing more individuals to continue working into later stages of life. In addition, there is a critical need for effective workplace health programs. Employers should be incentivized to implement comprehensive health and wellness initiatives. These programs support early detection and management of potential health issues, acting as a buffer against the long-term effects of health shocks. Consequently, they can substantially extend the productive years of employees, benefiting both the workforce and the economy.

In conclusion, this study contributes to the ongoing discourse on early retirement by providing evidence of the significant role of health shocks, with a comparative focus on Germany and Belgium. The results underscore the importance of considering national contexts in retirement research and offer practical insights for policymakers aiming to address the challenges associated with an aging workforce.

APPENDIX

A.1 Pension systems

Table A1 - Comparison between the German and the Belgian pension system

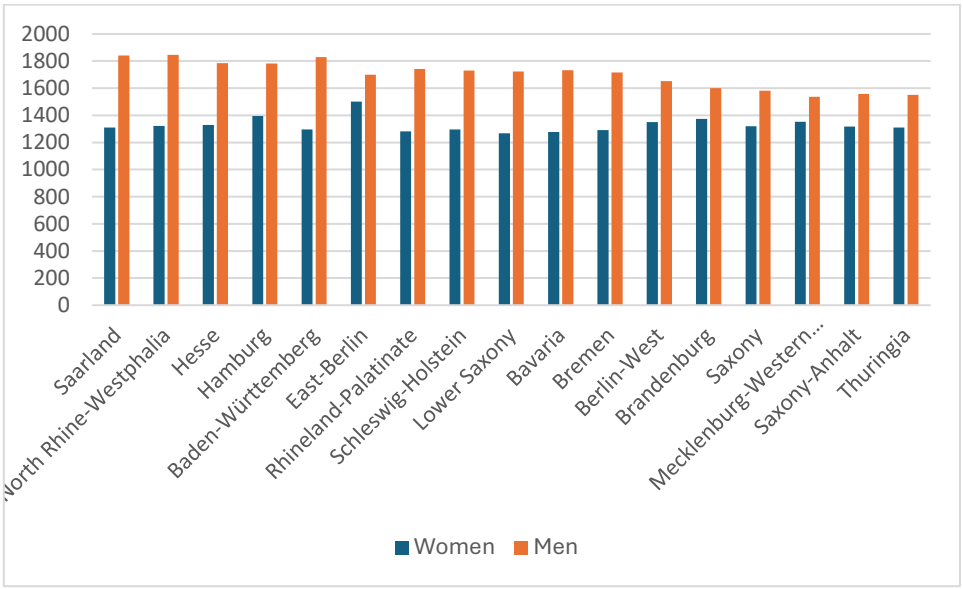
Aspect	Belgium	Germany
Eligibility	Employees, self-employed, and public-sector workers	Participants in compulsory pension insurance
Legal retirement age	65 (until January 31, 2025), 66 (February 1, 2025 - January 31, 2030), 67 (from February 1, 2030).	65 but it is slowly increasing to 67
Legal early retirement age	From age 63 with 42 years of service; exceptions for long careers (60 with 44 years, 61 with 43 years).	From age 63, after 35 years of pension insurance periods
Pension calculation	Based on career duration, equivalent periods, and earnings. Adjusted for price changes and welfare improvements.	Based on fee points, access factor, pension values, and pension type factor
Survivor pensions	Provided to surviving spouse based on deceased partner's career.	Provided to dependents of deceased employees under pension schemes.
Pension schemes	Employee Pension Scheme, Self-employed Pension Scheme, and Civil Servant Pension Scheme	Compulsory Pension Insurance (GRV), Occupational Pensions (bAV) and Private Pensions
Funding sources	Employer and employee contributions, Government subsidies, Income from alternative financing, and Other allocated revenues	Employer and employee contributions and federal subsidies
Indexation	Automatic indexation for price changes and welfare improvements.	Pension adjusted based on wage developments.
Working while retired	The amount of earnings is not limited if the retiree is above 65 or has worked at least 45 years and can prove it. If the retiree does not satisfy these conditions he can work but with limited earnings	There is no earnings limit if the retiree is 65, but if the retiree is under 65, the limit is 6,300€ annually
Average Pension Amount	**2023** €1,956 gross (€1,640 net)	**2022** €1,550 gross (average for at least 35 years of insurance)
Pension pillars	Legal Pensions, Occupational Pensions (company pension plans, sectoral supplementary pension plans) and Private Pensions	Compulsory Pension Insurance (GRV), Occupational Pensions (bAV), and Private Pensions (e.g., retirement insurance, savings plans, securities, real estate)

Self-employed Contributions	Contributions are required, with government subsidies and additional resources supporting management.	Generally exempt, except for certain professions (e.g., artisans, midwives, coastal sailors, skippers, artists, publicists, and teachers).

Source: Summary from the literature review: Deutsche Institut für Altersvorsorge (2023), Deutsche Rentenversicherung (2023) and European Commission 2023.

A.1.1 German pension system

Figure A1 - Average pension for men and women by region in Germany in 2022

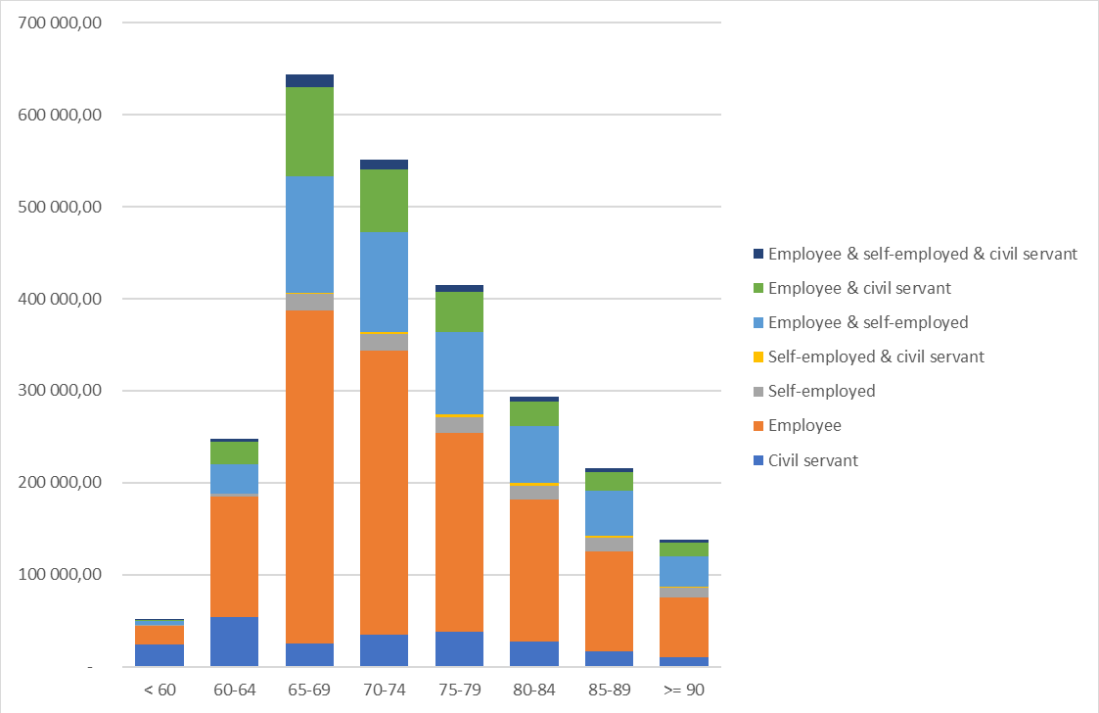


Source: Own computations from the statistics of the "Deutsche Rentenversicherung."[7]

[7] Deutsche Rentenversicherung. (2023). Vorauszug Rentenatlas. Retrieved from https://www.deutsche rentenversicherung.de/DRV/DE/Ueber-uns-und-Presse/Presse/Meldungen/2023/230710-vorauszug-rentenatlas.html

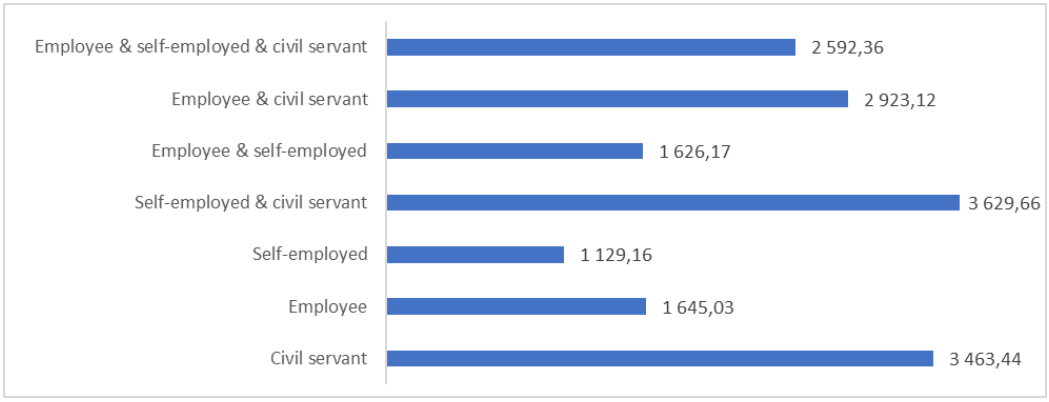
A.1.2 Belgian pension system

Figure A2 - Breakdown of the number of pensioners by age group and type of regime in Belgium



Source: Own computations from the statistics of the "Pensionstat.be"[8]

Figure A - Average income per pension regime without survivor's pension in Belgium



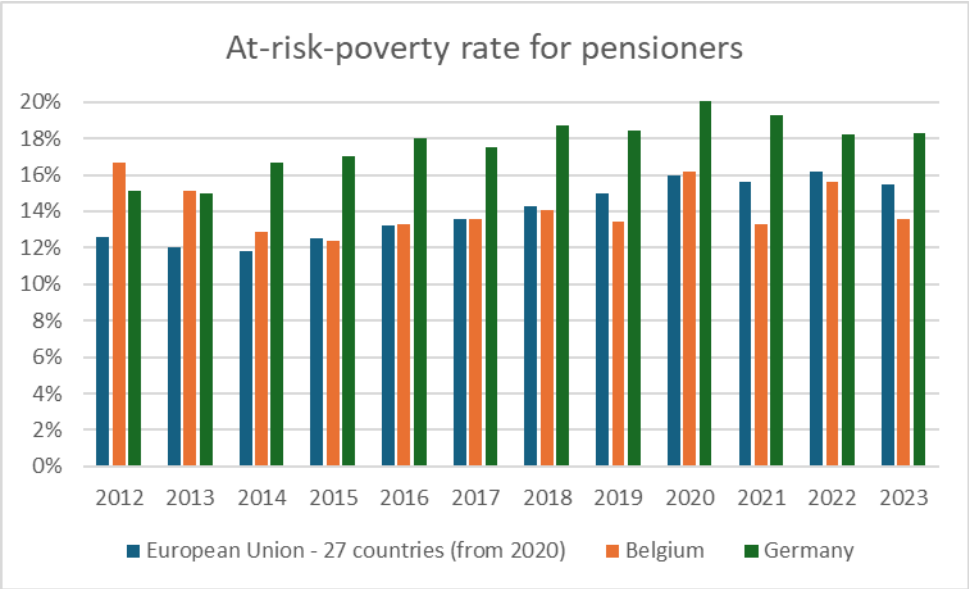
Source: Own computations from the statistics of the "Pensionstat.be"[9]

[8] PensionStat.be. (2023). Pensionnés. Retrieved from https://www.pensionstat.be/fr/chiffres-cles/pension-legale/pensionnes

[9] PensionStat.be. (2023). Pensionnés. Retrieved from https://www.pensionstat.be/fr/chiffres-cles/pension-legale/pensionnes

A.1.3 Comparison between the pension systems

Figure A5 - At risk of poverty rate for pensioners in Germany and Belgium (cut-off point: 60% of median equivalised income after social transfers)



Source: Own computations from Eurostat[10]

[10] Eurostat. (2024, June 20). At-risk-of-poverty rate for pensioners - EU-SILC survey (Online data code: tespn100). https://doi.org/10.2908/tespn100

A.2 Descriptive statistics

Table A2 - Descriptive Statistics of the main variable

Descriptive Statistics

Variables	Obs	Mean	Std. Dev.	Min	Max	p1	p99	Skew.	Kurt.
health shock	15115	.075	.263	0	1	0	1	3.226	11.41
female	15115	.569	.495	0	1	0	1	-.279	1.078
age	15115	57.498	4.1	45	64	47.8	63.9	-.315	2.267
Education	15115	1.186	.744	0	2	0	2	-.313	1.857
Partner	15115	.784	.411	0	1	0	1	-1.383	2.911
Single	15115	.213	.41	0	1	0	1	1.401	2.963
Help received	12045	4.279	1.538	1	5	1	5	-1.664	3.768
Job-status	7835	1.517	.703	1	3	1	3	.995	2.659
Wealth	15115	1.865	.853	1	3	1	3	.262	1.424
Income	15115	1.96	.871	1	3	1	3	.077	1.323
wave	15115	4.771	.649	4	8	4	6	.487	3.375
country	15115	.525	.499	0	1	0	1	-.099	1.01
early retirement	15115	.065	.247	0	1	0	1	3.521	13.399

Source: Own computation from the SHARE database wave 4 to 9

Table A3 – Matrix of correlation of the main variable

Matrix of correlations

Variables	(1)	(2)	(3)	(4)
(1) female	1.000			
(2) education	-0.028	1.000		
(3) age	-0.077	-0.031	1.000	
(4) early retirement	-0.021	0.019	0.180	1.000

Source: Own computation from the SHARE database wave 4 to 9

Matrix of correlations

Variables	(1)	(2)	(3)	(4)
(1) partner	1.000			
(2) wealth	0.221	1.000		
(3) Income	0.322	0.562	1.000	
(4) early retirement	-0.003	0.038	0.023	1.000

Source: Own computation from the SHARE database wave 4 to 9

Matrix of correlations

Variables	(1)	(2)	(3)	(4)	(5)	(6)
(1) single	1.000					
(2) Help received	-0.066	1.000				
(3) Job-status	0.010	-0.010	1.000			
(4) wave	-0.041	-0.028	-0.004	1.000		
(5) ctr	0.094	0.106	0.043	-0.216	1.000	
(6) early retirement	-0.002	0.008	-0.001	-0.112	0.045	1.000

Source: Own computation from the SHARE database wave 4 to 9

A.3 Regression results

Table A4 - Fixed effect regression with health_shock variable

	(1) early_retirement	(2) early_retirement if female = 1	(3) early_retirement if female = 0
Health Shock	-0.045**	-0.023	-0.079**
	(0.019)	(0.023)	(0.034)
Woman	0.000	0.000	0.000
	(.)	(.)	(.)
Age	0.017***	0.016***	0.020***
	(0.003)	(0.004)	(0.004)
Living with a partner	-0.011	-0.033	0.007
	(0.033)	(0.048)	(0.044)
Single	-0.004	-0.033	0.027
	(0.041)	(0.065)	(0.050)
Primary education or first stage of basic education	0.000	0.000	0.000
	(.)	(.)	(.)
Lower secondary	0.000	0.000	0.000
	(.)	(.)	(.)
(Upper) secondary education	0.000	0.000	0.000
	(.)	(.)	(.)
Post-secondary non-tertiary education	0.000	0.000	0.000
	(.)	(.)	(.)
First stage of tertiary education	0.000	0.000	0.000
	(.)	(.)	(.)
Second stage of tertiary education	0.000	0.000	0.000
	(.)	(.)	(.)
Received help from outside the household	0.005	0.004	0.008*
	(0.003)	(0.005)	(0.005)
Low Level of wealth	0.000	0.000	0.000
	(.)	(.)	(.)
Medium Level of wealth	0.021	0.032	0.002
	(0.018)	(0.023)	(0.029)
High Level of wealth	0.032	0.051*	-0.001
	(0.022)	(0.028)	(0.035)
Low Level of income	0.000	0.000	0.000
	(.)	(.)	(.)
Medium Level of income	-0.001	0.011	-0.020
	(0.017)	(0.023)	(0.024)
High Level of income	0.010	0.031	-0.023
	(0.018)	(0.023)	(0.026)
Private sector employee	0.000	0.000	0.000
	(.)	(.)	(.)
Public sector employee	0.035	0.015	0.086*
	(0.025)	(0.029)	(0.050)
Self-employed	-0.050	0.000	-0.091
	(0.039)	(0.050)	(0.058)
Satisfied with his/her job	0.071***	0.062***	0.081***
	(0.012)	(0.015)	(0.018)
Physical difficulty of the job	0.026*	0.042**	0.006
	(0.013)	(0.017)	(0.020)
N	7831	4251	3580
pseudo R^2			

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Source: Own computation from the SHARE database wave 4 to 9

Table A5 - Fixed effect regression with health_shock_bis variable

	(1) early_retirement	(2) early_retirement if female = 1	(3) early_retirement if female = 0
Health Shock with people who are already sick	-0.048***	-0.034*	-0.073**
	(0.015)	(0.018)	(0.029)
Woman	0.000	0.000	0.000
	(.)	(.)	(.)
Age	0.017***	0.015***	0.020***
	(0.003)	(0.004)	(0.004)
Living with a partner	-0.012	-0.034	0.006
	(0.033)	(0.048)	(0.044)
single_w	-0.005	-0.033	0.025
	(0.042)	(0.066)	(0.050)
Primary education or first stage of basic education	0.000	0.000	0.000
	(.)	(.)	(.)
Lower secondary	0.000	0.000	0.000
	(.)	(.)	(.)
(Upper) secondary education	0.000	0.000	0.000
	(.)	(.)	(.)
Post-secondary non-tertiary education	0.000	0.000	0.000
	(.)	(.)	(.)
First stage of tertiary education	0.000	0.000	0.000
	(.)	(.)	(.)
Second stage of tertiary education	0.000	0.000	0.000
	(.)	(.)	(.)
Received help from outside the household	0.005	0.003	0.008*
	(0.003)	(0.005)	(0.005)
Low Level of wealth	0.000	0.000	0.000
	(.)	(.)	(.)
Medium Level of wealth	0.020	0.031	0.002
	(0.018)	(0.023)	(0.029)
High Level of wealth	0.032	0.051*	-0.000
	(0.022)	(0.028)	(0.035)
Low Level of income	0.000	0.000	0.000
	(.)	(.)	(.)
Medium Level of income	0.000	0.012	-0.019
	(0.017)	(0.023)	(0.024)
High Level of income	0.010	0.032	-0.024
	(0.018)	(0.023)	(0.027)
Private sector employee	0.000	0.000	0.000
	(.)	(.)	(.)
Public sector employee	0.034	0.014	0.087*
	(0.025)	(0.029)	(0.050)
Self-employed	-0.053	-0.004	-0.093
	(0.039)	(0.049)	(0.058)
Satisfied with his/her job	0.074***	0.066***	0.084***
	(0.012)	(0.015)	(0.018)
Physical difficulty of the job	0.028**	0.044**	0.007
	(0.013)	(0.018)	(0.021)
N	7831	4251	3580
pseudo R^2			

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Source: Own computation from the SHARE database wave 4 to 9

Table A7 - Probit regression results with health shock (with people who are already sick)

	(1) early_retirement	
early_retirement		
Health shock with people who are already sick	0.045	(0.060)
Woman	-0.030	(0.044)
Age	0.177***	(0.007)
Primary education or first stage of basic education	0.234	(0.354)
Lower secondary	0.178	(0.334)
(Upper) secondary education	0.121	(0.330)
Post-secondary non-tertiary education	-0.045	(0.355)
First stage of tertiary education	-0.041	(0.331)
Second stage of tertiary education	-0.455	(0.423)
Living with a partner	0.001	(0.076)
single_w	-0.056	(0.073)
Satisfied with his/her job	-0.015	(0.050)
Received help from outside the household	0.002	(0.015)
Physical difficulty of the job	0.144**	(0.060)
Private sector employee	0.000	(.)
Public sector employee	0.263***	(0.049)
Self-employed	-0.462***	(0.080)
Low Level of wealth	0.000	(.)
Medium Level of wealth	0.165***	(0.060)
High Level of wealth	0.116*	(0.062)
Low Level of income	0.000	(.)
Medium Level of income	-0.028	(0.066)
High Level of income	-0.151**	(0.069)
N	7831	
pseudo R^2	0.201	

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Source: Own computation from the SHARE database wave 4 to 9

A.4 SHARE acknowledgement

A.4.1 SHARE Database

This paper uses data from SHARE Waves 1, 2, 3, 4, 5, 6, 7, 8 and 9 (DOIs: 10.6103/SHARE.w1.900, 10.6103/SHARE.w2.900, 10.6103/SHARE.w3.900, 10.6103/SHARE.w4.900, 10.6103/SHARE.w5.900, 10.6103/SHARE.w6.900, 10.6103/SHARE.w7.900, 10.6103/SHARE.w8.900, 10.6103/SHARE.w8ca.900, 10.6103/SHARE.w9.900, 10.6103/SHARE.w9ca900) see Börsch-Supan et al. (2013) for methodological details.(1) The SHARE data collection has been funded by the European Commission, DG RTD through FP5 (QLK6-CT-2001-00360), FP6 (SHARE-I3: RII-CT-2006-062193, COMPARE: CIT5-CT-2005-028857, SHARELIFE: CIT4-CT-2006-028812), FP7 (SHARE-PREP: GA N°211909, SHARE-LEAP: GA N°227822, SHARE M4: GA N°261982, DASISH: GA N°283646) and Horizon 2020 (SHARE-DEV3: GA N°676536, SHARE-COHESION: GA N°870628, SERISS: GA N°654221, SSHOC: GA N°823782, SHARE-COVID19: GA N°101015924) and by DG Employment, Social Affairs & Inclusion through VS 2015/0195, VS 2016/0135, VS 2018/0285, VS 2019/0332, VS 2020/0313 and SHARE-EUCOV: GA N°101052589 and EUCOVII: GA N°101102412. Additional funding from the German Ministry of Education and Research, the Max Planck Society for the Advancement of Science, the U.S. National Institute on Aging (U01_AG09740-13S2, P01_AG005842, P01_AG08291, P30_AG12815, R21_AG025169, Y1-AG-4553-01, IAG_BSR06-11, OGHA_04-064, BSR12-04, R01_AG052527-02, HHSN271201300071C, RAG052527A) and from various national funding sources is gratefully acknowledged (see www.share-eric.eu).

A.4.2 EasySHARE

This paper uses data from the generated easySHARE data set (DOI: 10.6103/SHARE.easy.900), see *Gruber et al. (2014) for methodological details. The easySHARE release 9.0.0 is based on SHARE Waves 1, 2, 3, 4, 5, 6, 7, 8 and 9 (DOIs: 10.6103/SHARE.w1.900, 10.6103/SHARE.w2.900, 10.6103/SHARE.w3.900, 10.6103/SHARE.w4.900, 10.6103/SHARE.w5.900, 10.6103/SHARE.w6.900, 10.6103/SHARE.w7.900, 10.6103/SHARE.w8.900)*.

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EXECUTIVE SUMMARY

This thesis examines how significant adverse health events influence early retirement decisions in Belgium and Germany. With an aging population putting pressure on social security systems, understanding the role of health shocks is very important to discover why people are retiring and trying to find political solutions. The study finds that health shocks do not increase early retirement but increase the exit from the labor market to permanent sickness, with variations between Belgium and Germany due to different pension systems and labor market conditions. Utilizing data from the Survey of Health, Aging, and Retirement in Europe (SHARE) and robust matching methods, the research highlights the need for policy measures such as healthcare improvements and pension reforms to mitigate these impacts.[11]

[11] Words count : 17,817