Erasmus School of Economics MSc Policy Economics

Impact of retirement on mortality:
Evidence from Spain

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Abstract

This paper aims to estimate the long-run health effects of retirement in Spain looking at mortality within five years. I use a Regression Discontinuity Design to exploit Spanish age-specific early and statutory retirement ages controlling for month of birth. Using the *Muestra Continua de Vidas Laborales* (MCVL) Spanish administrative data I find heterogeneity on retirement effect. Exiting the labour market at early retirement age decreases the long-run probability of death by 6.1 percentage points whereas retiring at statutory retirement age increases mortality within five years by 2.1 percentage points. The results are robust to several sensitivity tests. Moreover, I document heterogeneity at each age threshold depending on personal and professional characteristics. For instance, retiring from high physical strain occupations leads to a health-preserving effect at both eligibility ages.

Contents

1 Introduction

Over most OECD countries there have been substantial gains in life expectancy at retirement. The average remaining years at retirement age for women is 21.3 and 18.2 for men. By 2060, both are projected to increase by 4.5 years. For instance, Spain, together with Japan and Switzerland, leads a large group of countries in which life expectancy exceeds 80 years (OECD, 2017).

Together with the lengthening of life, developed countries face a decreasing number of births. The coincidence of both demographic trends leads to an ageing population. Which generates a threat to the financial sustainability of government budgets. To exemplify, pay-as-you-go pension systems may suffer from economic instability through two pathways. First, the period elderly spent on the government's payroll is longer than expected. And second, the share of working age population shrinks. Thus, fewer workers will be paying taxes to support each retiree.

It is well documented that OECD countries tried to mitigate the outflows from employment at late working years by adjusting several factors of pension systems. For instance, by increasing both early and statutory ages or strengthening financial penalties at early retirement (OECD, 2017). Nevertheless, the effect of retirement on health must not be neglected in the political debate. Research on ageing is of important relevance today and in the future for developed countries. Policy changes need to be based on empirical research to ensure countries to elude unplanned economic instability. To exemplify, reforms affecting the pension system may have an impact on other public policies such as on public health expenditure.

The aim of my paper is to estimate the long-run effect of retirement on health measured by mortality within five years for the Spanish population. However, the endogeneity between retirement and health is well documented. First, retirement is a choice and might be motivated by unobservable health characteristics (Sánchez-Martin et al., 2014). To exemplify, if poor health endowment triggers retirement, then the probability of death increases. Second, retirement and health may show a reverse causality as retirement may affect health. Either retirement can have a positive impact on health. If, for instance, retirement offers a relief from stressful activities or additional time to be spent on leisure, which ultimately affect health outcomes (Eibich, 2015). Or on the opposite direction, individuals when working perform mental activities. Thus, retirement can accelerate the age-related neurodegeneration and lead to a significant decline of cognitive abilities (Mazzonna et al., 2017).

I use the MCVL administrative panel data from 2006 to 2017 which offers detailed information on my variables of interest being retirement and expiration dates. The results are estimated using a Regression Discontinuity Design at both eligibility retirement ages in the Spanish Social Security system controlling for month of birth. The birth cohorts included in my paper are from 1937 until 1955. In addition, individuals who exit the labour market did it between 1954 and 2009.

The literature inferring causality on this topic is large, though, shows mixed results. In order to overcome the endogeneity, the authors exploit quasi-experimental variation, the majority of them use reform based exogeneous variation. Moreover, most of the previous research is focused on subjective health outcomes, mental and physical health. As a consequence, the estimates show limited external validity and are not easily comparable across countries. There are some authors who overall find a protective effect of retirement on health (Charles, 2004; Bound and Waidmann, 2007; Neuman, 2008; Coe and Lindeboom, 2008; Johnson and Lee, 2009; Brockmann et al., 2009; Coe and Zamarro, 2011; Coe et al., 2012; Insler, 2014; Eibich, 2015; Hallberg et al., 2015; Bloemen et al., 2017; Bloemen et al., 2017; and Zulkarnain and Rutledge, 2018). Whereas other authors conclude that retirement has a detrimental effect on health (Dave et al., 2006; Grip et al., 2012; Bonsang et al., 2012; Behncke, 2012; Mazzonna and Peracchi, 2017; Celidoni et al., 2017; Kuhn et al., 2018; Garrouste, 2019; and Bozio et al., 2019). Finally, Hernaes et al. (2013) and Hagen (2018) document non-significant effects of retirement on health.

From the empirics I found some limitations. Firstly, most of the authors estimate country-specific results when exploiting institutional changes. Secondly, the impact of retirement *per se* might be different from delaying or advancing retirement age. And finally, most of the authors use health outcomes which are difficult to be extrapolated to other countries. As a result, the contribution of my paper to the existing literature is of important value for several reasons. To begin with, I use age-specific pension features which are similar to other OECD countries. Moreover, I estimate the effect on mortality, an outcome which offers an easier comparability. And finally, I analyse heterogeneous effects based on individuals' personal and professional characteristics.

Overall, I find heterogeneous effects of retirement depending on the age threshold. Retiring at early retirement age decreases the probability of death within five years by 6.1 percentage points. Whereas retirement at statutory retirement age increases mortality within five years by 2.1 percentage points. In addition, I also analyse heterogenous treatment effects. Accounting for differences in occupational strain level, I document heterogeneity on retirement consequences. However, estimates across gender and educational levels are in line with the baseline results.

The rest of the paper is organised as follows. Section 2 covers previous research on the topic. Section 3 describes the Spanish Public Pension system. The description of the dataset and the sample selection are detailed in Section 4. Section 5 covers how the variables of interest are defined and descriptive statistics. The empirical strategy used is presented in Section 6. Section 7 offers the results. I test the the validity of the results to several robustness checks in Section 8. Finally, Section 9 concludes.

2 Previous research

A large literature investigates the impact of retirement on health; however, the evidence is inconclusive. Discrepancies on empirical results might be explained by different factors. For instance, literature shows that pension provisions generate distortions of labour-retirement decisions. And it is known that the institutional setup of pension systems differs from country to country. Moreover, although within the same institutional framework, the finding of different results might be due to the usage of different econometric methods, identification strategies and or health outcomes (Motegi et al., 2016).

When looking at previous research, I focus on literature that estimates the causal effect of interest by exploiting quasi-experimental variation. For example, using age-specific retirement features, being eligibility ages, or institutional changes. The usage of exogeneous variation allow the authors to overcome the endogeneity. Overall, thirteen studies find that retirement has a non-negative effect on health whereas nine studies document a negative impact. Finally, two studies show non-significant consequences of retirement on health.

To begin with, the following authors overall conclude that retirement has a health-preserving effect for several OECD countries (Charles, 2004; Bound and Waidmann, 2007; Neuman, 2008; Coe and Lindeboom, 2008; Johnson and Lee, 2009; Brockmann et al., 2009; Coe and Zamarro, 2011; Coe et al., 2012; Insler, 2014; Eibich, 2015; Hallberg et al., 2015; Bloemen et al., 2017; and Zulkarnain and Rutledge, 2018).

Charles (2004), Coe and Lindeboom (2008), Neuman (2008), and Coe et al. (2012) use Health and Retirement Study (HRS) data for the US and exploit reform-based variation in the Social Security system to instrument retirement. Charles (2004) show that retirement has a positive effect on subjective well-being for men. Coe and Lindeboom (2008) find no negative effects of early retirement on men's health, but a temporary increase in self-reported health and improvements in health of highly educated workers. Neuman (2008) documents that retirement preserves and improves the perceived-health of retirees. Coe et al. (2012) find no clear relationship between retirement duration and later-life cognition for white-collar workers and, if anything, a positive relationship for blue-collar workers. Moreover, Bound and Waidmann (2007) using the English Longitudinal Sutdy of Ageing (ELSA) and Johnson and Lee (2009) using the Health Survey for England, exploit age-specific rules at statutory retirement age for the UK using a *fuzzy* Regression Discontinuity Design. The authors show that retirement has a positive effect on men's self-reported health measures. Brockmann et al. (2009) analyse adjusted hazard ratios for death of members of a compulsory German health insurance fund and document selective and protective processes of retirement, in the long-term early retirement lowers mortality risks for both male and female. Coe and Zamarro (2011) using the Survey of Health, Ageing and Retirement in Europe (SHARE) and Eibich (2015) using German data, exploit country-specific eligibility ages using a *fuzzy* Regression Discontinuity Design. Overall, the authors find a positive effect on self-reported health. Insler (2014) uses workers' self-reported probability of working past ages 62 and 65 as an instrument for the US and shows that retirement effects on health are significantly beneficial through additional leisure time and healthier habits. Hallberg et al. (2015) exploit a reduction in the early retirement age in the Swedish retirement system for male military officers and show that it leads to a reduction in mortality and inpatient care for them. Bloemen et al. (2017) exploit a change in the Dutch retirement system that progressively decreases the eligibility age for a group of civil servants as an instrument. The authors find that retirement decreases the probability of dying within five years for males. Finally, Zulkarnain and Rutledge (2018) use the "Doorwerkbonus" (DWB) tax-reduction program, which encourages Dutch old workers to delay retirement, and documents a reduction of mortality rates within 5 years for men aged 62-65.

On the opposite, the following authors find that retirement has a negative effect on health (Dave et al., 2006; Grip et al., 2012; Bonsang et al., 2012; Behncke, 2012; Mazzonna and Peracchi, 2017; Celidoni et al., 2017; Kuhn et al., 2018; Garrouste, 2019; and Bozio et al., 2019).

Dave et al. (2006) estimate a quasi-reduced form of labour supply function and health demand for the US, being instrumented by full eligibility age using data from the HRS, and show that retirement leads to an increase in difficulties associated with morbidity, daily activities, and illness conditions, and a decline in mental health. Bonsang et al. (2012) using HRS data and eligibility age for Social Security benefits as an instrument, find a detrimental effect of retirement on cognitive skills. Grip et al. (2012) show a strong negative impact on mental health for Dutch civil servants already before retiring generated by an unexpected delayed on early retirement age. Behncke (2012) uses non-parametric matching and Instrumental Variables methods on ELSA data for the UK and documents that retirement significantly raises the risk of severe cardiovascular disease and cancer. Mazzonna and Peracchi (2017) use SHARE data and show that retirement has a detrimental effect on cognitive skills. Celidoni et al. (2017) exploit age-specific rules using the SHARE database and find that retirement has a long-term detrimental effect on cognition for individuals who retire at statutory retirement age, whereas the authors document a protective effect for individuals retiring at early retirement age. Kuhn et al. (2018) exploit a change in the Austrian unemployment insurance system, which allowed older workers in eligible regions to advance early eligibility age, and document that the advancement leads to an increase in the probability of dying for blue-collar males and no effect on females. Finally, Bozio et al. (2019) using *Caisee Nationale d'Assurance Vieillesse* data and Blake and Garrouste (2019) using data from the Health Barometer survey, exploit a reform in the French retirement system lengthening compulsory contribution period at early retirement age. The former authors find an increase in mortality rate for older cohorts. The latter document a negative effect of delaying retirement on perceived health, physical health and mental health.

Lastly, empirics also document non-significant effects of retirement on health. Hernaes et al. (2013) exploit a reduction in the early retirement age in the Nordish retirement system, and do not find statistically significant effects on mortality for those individuals who were offered the advancement of retirement. And Hagen (2018) uses a delay on the statutory retirement age in Sweden for local civil servants and documents no evidence of a significant impact on mortality for women aged 65-69.

The following three limitations detected in the previous research motivate the reason of my paper. Firstly, the outcomes of health that attracted most of the previous literature –i.e. self-reported health, physical and mental health–, are not easily comparable across countries. Secondly, most of the empirics use reform-based exogeneous variation to estimate the results which leads to a low external validity as estimates might be policy- and country-specific. Finally, the effect of retirement might differ from the effect of delaying or advancing the eligibility age. These limitations make it difficult to directly apply the estimated results for other Social Security systems to the Spanish Social Security system.

Thus, the aim of my paper is to analyse the long-term effect of retirement on health exploiting age-specific retirement features in Spain. Using cumulative mortality within five years as health outcome. On account of the prior arguments, the contribution of my paper to the existing literature is fivefold. First, it provides evidence on the effect of retirement on mortality for Spain on this core field for policymakers in the context of ageing. Second, it uses administrative panel-data, complete and free of measurement error, rather than cross-sectional self-reported data. For a long period and for a representative sample of the Spanish Social Security affiliates. Third, using mortality as an outcome provides comparable estimates across countries. It has been shown that perceived health status depends on individual socioeconomic status and country culture. As stand by Bhattacharya et al. (2014), in self-reported health surveys high-income individuals routinely self-report better health on a scale range than low-income individuals. Moreover, Steptoe et al. (2015) find that self-reported life-satisfaction or psychological wellbeing follows a U-shape with age reaching the minimum at age range 50-53. Also, self-reported depression follows an inverse U-shape with the peak value around 42-44 years (Blanchflower and Oswald, 2008). Fourth, I present results for a varied range of occupations and for both genders. Finally, I document heterogeneity in retirement effects between early and statutory retirement ages in Spain.

3 The Spanish Public Pension system

The Spanish Public Pension or Social Security (SS) system covers a set of contingencies related to ageing (retirement), death (survivors' benefits and family allowances), jobless (unemployment insurance) and illness (disability insurance). There are two basic types of pensions: contributory and compulsory pensions –i.e. retirement pensions, survival pensions, unemployment and disability programs, and those to other family members–, and non-contributory pensions (de Cos et al., 2017). Contributory pensions are divided into the two following schemes: general SS scheme, *Régimen General de la Seguridad Social* (RGSS) and special SS schemes, *Regímenes Especiales de la Seguridad Social* (RESS). The latter includes five special schemes: self-employed workers and professionals, sailors and coal miners, domestic helpers, agricultural workers and farmers, and civil servants and central government employees.

I restrict my analysis around contributory and compulsory retirement pensions under the general SS scheme (RGSS) from 1954 until 2009. The RGSS offers the same retirement features for the 76 percent of the total affiliates[1] compared to special SS schemes which only includes the remaining 24 percent. Contributory retirement pensions are funded by SS contributions of employers and employees under a mandatory pay-as-you-go scheme (Boldrin et al., 2004). Once eligibility conditions for SS benefits are met, the total withdrawal amount is calculated on the basis of a defined-benefit criteria which weight contribution years and earning bases (de Cos et al., 2017).

In Spain, as in other developed countries, the retirement behaviour of old workers is affected by retirement pension incentives, but also by unemployment and permanent disability programs. Previous empirical evidence shows that both programs offer an alternative pathway to early retirement (Sánchez-Martin et al., 2014; García-Pérez et al., 2013; García-Gómez et al., 2012; Boldrin et al., 2010; Boldrin et al., 2004). Consequently, all three pension programs will be taken into account for the analysis.

Accounting for the three compulsory SS programs, the Spanish SS system experienced several reforms on its key variables from 1984 to 2013. These policy reforms are briefly covered in Table A1 in the Appendix constructed from García-Gómez et al. (2018). It is worth mentioning that the retirement features used in this paper are the ones in force during the period of interest (until 2009) and the analysis of the several reforms is beyond the scope of this paper.

Until 2009 the standard retirement program offers three eligibility ages for SS benefits under the general SS scheme (RGSS): early retirement age (ERA) at 60 years old only for workers whose first SS contribution was before 1967 and at age 61 for whom started contributing after 1967; and statutory retirement age (SRA) at 65 years old. Partial retirement is also possible for workers older than the SRA. It enables them the possibility to combine retirement status and part-time employment.

Furthermore, retirement between ERA and SRA is penalized with a higher reduction of the replacement rate and social security wealth the closer the age to ERA. On the opposite, late retirement is incentivised with a premium for retiring after SRA.

4 Data set and sample selection

In this section I briefly present the main characteristics of the MVCL and the process used to select the reduced sample.

4.1 Data set

I use administrative data from the *Muestra Continua de Vida Laborales* (MCVL) published by the Spanish Ministry of Labour, Migrations and Social Security. The MCVL is a Spanish anonymized

[1] Statistics published by the Spanish Ministry of Labour, Migrations and Social Security in 2019.

micro-data for the period 2004-2017. It is comparable to the "Austrian Social Security Database (ASSD)", the German "Sample of insured persons and their insurance accounts (VKST)" or the Swedish "Labour Market and Social Security (PASS)" and "Sample of Integrated Labour Market Biographies (SIAB)" (Pérez-Salamero, et al., 2016).

The MCVL is a non-stratified random sample of 4% of the stock of SS affiliates (workers, pensioners and unemployment benefit recipients) which constitute the reference sample. The database includes individuals from different contributory schemes (RGSS and RESS) except civil servants and other central government employees which are not covered by the SS administration. The MCVL provides information on SS records covering individuals' complete labour market history at the end of each year *t*. It is updated yearly, and a panel-data can be generated by combining following editions as the same individuals are followed until they expire. Individuals are identified using unique personal numbers and once someone expires it is randomly replaced by another SS affiliate.

For the interest of my paper, the MCVL contains the following information, among other individual and professional characteristics. Personal information (e.g. birth and death date, gender and educational level), labour market history (e.g. individuals' employment spells, economic activity, regime scheme, and, if it is the case, the cause of exiting the labour market) and pension payments' information (e.g. starting date of payment eligibility or the pension type). On top of that, the MCVL contains precise information on the date of retirement (date of exiting the labour market) and the date of death until 2017.

Unfortunately, the dataset has some limitations which affected my sample selection and the subsequent analysis. First, it does not include central government employees nor civil servants. And second, it lacks personal or family characteristics, such as marital status, number of children or grandchildren, used in other papers to analyse heterogeneous effects.

4.2 Sample selection

There are some sample restrictions necessary to analyse the effect I am interest on. The data used in my paper covers MCVL waves between 2006 and 2017. I use information on labour market status from waves published from 2006 to 2009. And then I use information on mortality about the same individuals until 2017. Firstly, because data prior to 2006 do not follow the same structure as the succeeding waves. Secondly, the reform introduced in 2002 delaying ERA had a progressive stronger effect on younger birth cohorts. For instance, the share of birth cohorts who were able to retire at age 61 in 2010 was higher than in previous years. And finally, to avoid the subsequent reforms introduced in 2011 which progressively delayed both eligibility ages.

I restrict the sample to individuals aged between 55 and 70 years old and who are receiving pension on behalf of their own contributions to the SS. Therefore, excluding orphanhood, widowhood and survival pensions. This first step reduces the number of observations from around one million to 700,780 which represent 223,872 individuals. Additionally, I exclude individuals under other schemes than the general SS scheme (RGSS) as the SS features of special SS schemes (RESS) are occupation-specific. Consequently, the individuals left are 150,009 which correspond to 455,621 observations which I consider as the "reduced sample".

5 Variables of interest and Descriptive statistics

This section contains the definition of the variables of interest, being retirement status and mortality within five years. Then, descriptive statistics on retirement and mortality are covered in detail and the treatment discontinuity is graphically documented.

Overall, the reduced sample contains birth cohorts between 1937 and 1955, the data are panel data and covers a time period between 2006 and 2017. It contains 150,009 individuals which correspond to 455,621 observations. Table 1 Panel A shows demographic characteristics of the individuals in the reduced sample aged as of 31st December of a given year *t*. The average age of the sample is around 61 years old, being lower for non-retirees than for retirees, 59 and around 64 years old, respectively. Also, that almost a 65 percent of the sample is over 60 years old (ERA) and more than a 67 percent over 65 years old (SRA). Finally, the presence of females in the sample is of 33 percent, most of them still active in the labour market.

Table 1. Descriptive statistics

				Non-retirees			Retirees		
	%	Individuals	N	%	Individuals	N	%	Individuals	N
Panel A. Demographics									
*Age on December 31st**	61.54	150,009	455,621	59.09	87,529	219,199	63.82	92,813	236,422
Over ERA (60)	64.48	93,614	266,482	39.27	36,758	74,734	77.83	72,864	191,748
Over SRA (65)	67.36	47,622	111,574	5.83	2,778	4,666	96.18	45,801	106,908
Females (%)	32.92	49,390	139,440	65.49	32,344	79,723	55.66	27,489	63,376
Panel B. Retirement status									
Total share of retirees (%)	61.87	92,813	236,422	-	-	-	-	-	-
Yearly inflow of retirees (%)	33.66	50,494	78,586	-	-	-	-	-	-
SS contributed years	23.80	71,404	198,770	-	-	-	-	-	-
Panel C. Mortality (%)									
Within 1 year	2.60	3,897	3,897	18.07	704	704	81.93	3,193	3,193
Within 2 years	3.53	5,297	7,941	23.77	1,259	1,669	82.48	4,369	6,272
Within 3 years	4.47	6,710	12,252	26.45	1,775	2,777	82.40	5,529	9,475
Within 4 years	5.51	8,259	16,824	27.93	2,307	4,011	82.06	6,777	12,813
Within 5 years	6.58	9,876	21,752	28.55	2,820	5,332	81.82	8,081	16,420
Within 6 years	7.75	11,631	26,949	29.61	3,444	6,780	81.48	9,477	20,169
Within 7 years	8.99	13,497	32,471	30.43	4,107	8,357	81.15	10,953	24,114
Within 8 years	10.32	15,474	38,417	31.52	4,878	10,163	80.61	12,474	28,254

Note: The percentage share (%) in column (1) is calculated based on the total number of individuals. The percentage shares (%) in columns (4) and (7) are calculated based on the total number of individuals on each row. (*) numbers on the first row in columns (1), (4) and (7) express means. The sample includes all the observations between 55 and 70 years old.

Source: MCVL, own calculations.

5.1 Endogenous variable: retirement status

The first variable of interest is retirement status. As defined by Charles (2004), Coe, Zamarro (2011) and Eibich (2015) retirement refers to the state in which individuals who were previously active in the labour force have permanently ceased being active.

Following the previous authors, retirement status in my paper accounts for individuals who left the labour market either through standard retirement, permanent disability or unemployment programs[2]. The date used as exiting the labour force corresponds to the official date of withdrawing from SS affiliation recorded in MCVL. Consequently, the proposed date leads to a free of measurement error advantage. Compared with other empirical studies where authors use self-reported retirement status.

The treatment group is composed by retirees. As inferred from Table 1 Panel B, they represent nearly the 62 percent of the reduced sample which correspond to 92,813 individuals –26,901 are women and 65,954 men– aged between 55 and 70 years old. Who withdrew from the labour force between August 1954 and December 2009. The yearly inflow of retirees represents almost the 34 percent of the total share of them.

Finally, the control group contains individuals who are still active in the labour market at the end of year *t*. Hence, are considered as non-retirees, active or working individuals in this paper. It is composed by 87,529 individuals from which 31,849 are women and 55,705 men.

It is worth mentioning that the use of panel data leads to have a non-constant retirement status along time within the same individual (see Table 1 Panel A columns (2), (5) and (8)). The numbers regarding individuals by retirement status –columns (5) and (8) – sum up more than the total number of individuals –column (2) –. Nevertheless, the number of observations in columns (6) and (9) sum up the total number of observations in column (3). It can be explained with the following example. A woman who is 64 years old and still works in 2006, the next year is eligible for retirement. If in 2007 she becomes a retiree, in 2006 is considered as active while from 2007 onwards as retired. When considering all years and grouping individuals between retirees and non-retirees this woman appears in both groups.

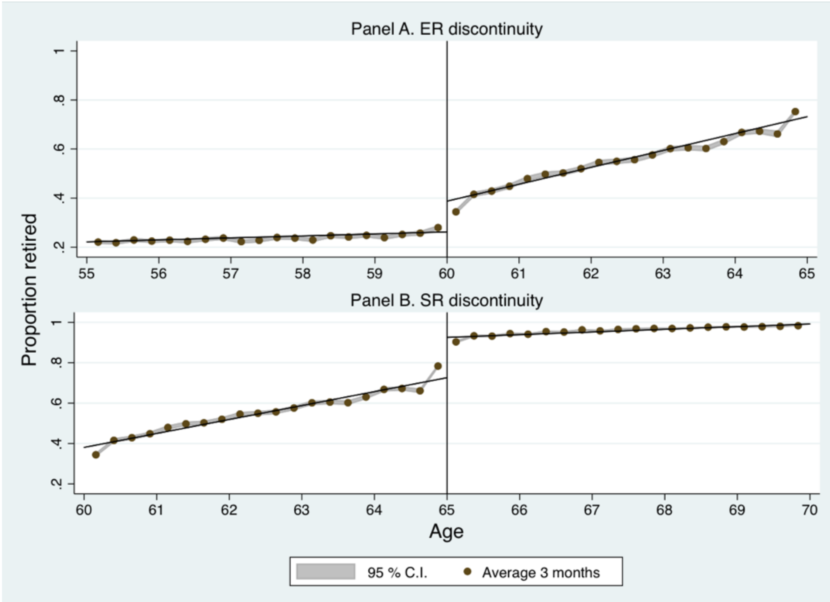
5.1.1 Discontinuity in retirement status

In RD design is important to verify that a discontinuity exists between the treatment variable and the cut-off rule (Lee and Lemieux, 2010). Figure 1 plots the treatment discontinuity of the total share of

[2] Standard retirement represents the 32 percent of the retirees, individuals under unemployment programs the 18 percent and under permanent disability the16 percent. Being unemployed does not strictly mean that individuals permanently cease their labour market activity. Thus, I test the robustness of my results in Section 8.

retirees at every age between 55 and 70 in the MCVL, where dots represent average probability of retirement for every three months[3]. Overall, it documents that both early and statutory retirement ages are significant predictors for retirement behaviour.

Figure 1. Treatment discontinuity for the total share of retirees



Note: Shaded areas show 95% confidence interval, dots represent averages over bins of 3 months and the polynomial fit is of order 1. The sample includes all the observations between 55 and 70 years old. Month of birth is included as a covariate.
Source: MCVL, own calculation.

Figure 1 Panel A focuses on early retirement treatment discontinuity. It documents the evolution of the stock of retirees until 2009 by age, for individuals aged between 55 and 65 years old. It plots a total of 344,047 observations (147,284 individuals) out of which 189,139 (81,725) are on the left of the threshold and 154,908 (65,559) on the right.

Between age 55 and 60 there is a non-increasing 20 percent share of individuals who already exit the labour market. Together with Table A2 in the Appendix, it can be seen that retirement before age 60 is totally explained by unemployment and disability programs. After that, at age 60 a small jump can be seen between age 59.9 and 60.3 of around 7 percentage points, which is followed by another at age 60.6 of similar magnitude. The absence of a unique discontinuity at age 60 can be explained by the effect of the reform introduced in 2002 delaying ERA. Which has a major impact on younger birth cohorts. Finally, the trend between age 60 and 65 is positive and the probability of being retired increases nearly 50 percentage points until age 64.9, without remarkable discontinuities. This trend is in line with the

[3] To justify the aggregation of retirement data along the beforementioned years, I plot the data for each year separately regarding treatment discontinuity for the stock of retirees (see Figure A1 in the Appendix). The plots show a similar trend along the period of interest.

institutional setting. Financial penalties imposed to disincentivise early retirement are progressively reduced as the worker approaches the SRA of 65 (García-Pérez et al., 2013). Table A2 shows furthermore that from age 60 onwards standard retirement becomes more important in explaining the retirement behaviour among old age workers observed in Figure 1.

Now turning to Figure 1 panel B, it focuses on statutory retirement treatment discontinuity and plots individuals aged between 60 and 70 years old. There is a total of 266,482 observations (113,181 individuals), from which 154,908 (65,559) are on the left of the threshold and 111,574 (47,622) on the right.

The positive trend between ages 60 and 65 has been already explained. However, it is worth mentioning the illustrated jump between 64.5 and 65 years old. It is justified by the fact that most of the individuals who retired half a year before the 65 years old, have been contributing into the SS on average 40 years. According to the retirement rules in force, they face the lowest financial penalty of retiring early. Hence, for those individuals the losses of working one additional year are higher than the gains, and decided to withdraw the labour market early. After that, it can be seen that at age 65 the proportion of retirees changes discontinuously and increases by 10 percentage points between age 64.9 and 65.3. After that, nearly 90 percent of the individuals are retired, and it keeps progressively increasing until 100 percent by age 70.

5.2 Outcome variable: mortality within five years

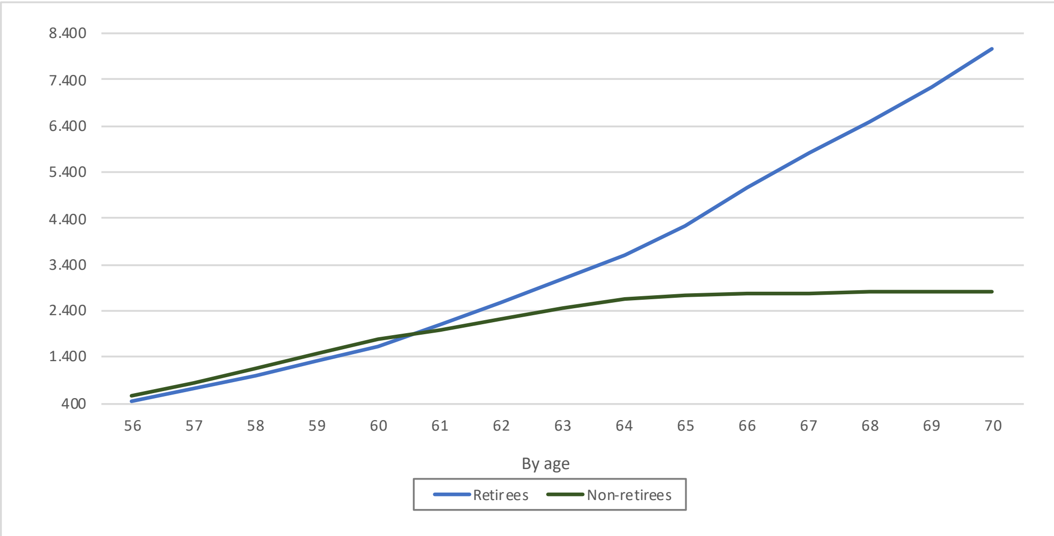
The outcome variable is the cumulative mortality from all causes within five years after a given year *t*. The effect of retirement on health might not be instantaneous (Bonsang et al., 2012). For instance, diseases affecting mortality may evolve progressively, therefore it is optimal to account for a long-run period. Finally, the concrete period of five years is chosen following previous research such as Bloemen et al. (2017) and Zulkarnain and Rutledge (2018).

Mortality as a health outcome offers advantages compared to other measures used in the previous literature. Mortality is an objective measure and a summary of health issues individuals may have experienced during their lives. Moreover, mortality allows for international comparison given that its measurement does not vary across countries. Using mortality as an outcome I offer free measurement-error estimates compared to other studies which use self-reported health as seen in Section 2.

Table 1 Panel C shows statistics of cumulative mortality rates. The more recent MCVL wave I have is 2017, therefore the maximum years after a given year *t* starting at wave published on 2006 and ending at 2009 are eight. It can be seen that the number of deaths keeps increasing from slightly less than 3 percent to 10 percent of the sample. Moreover, deaths are more common among retirees than active individuals.

Panel C shows that 6.6 percent of individuals expired within five years. Figure 4 plots furthermore the trend of the total number of individuals who died within five years distinguishing between retirees and active individuals. From the graph a positive trend can be seen for both groups. However, the number of deaths among non-retirees is slightly higher than among retirees for individuals aged between 56 and 61 years old. After that, mortality among active individuals aged older than 61years old shows a flatter trend than among retirees. Mortality among the latter suddenly increases from age 61 until age 70 (see Table A3 in the Appendix for more details).

Figure 2. Mortality within five years by age



Note: The y-axis plots the cumulative number of deaths and the x-axis age. The sample includes all the observations between 55 and 70 years old.
Source: MCVL, own calculations.

5.2.1. Discontinuity in probability of death

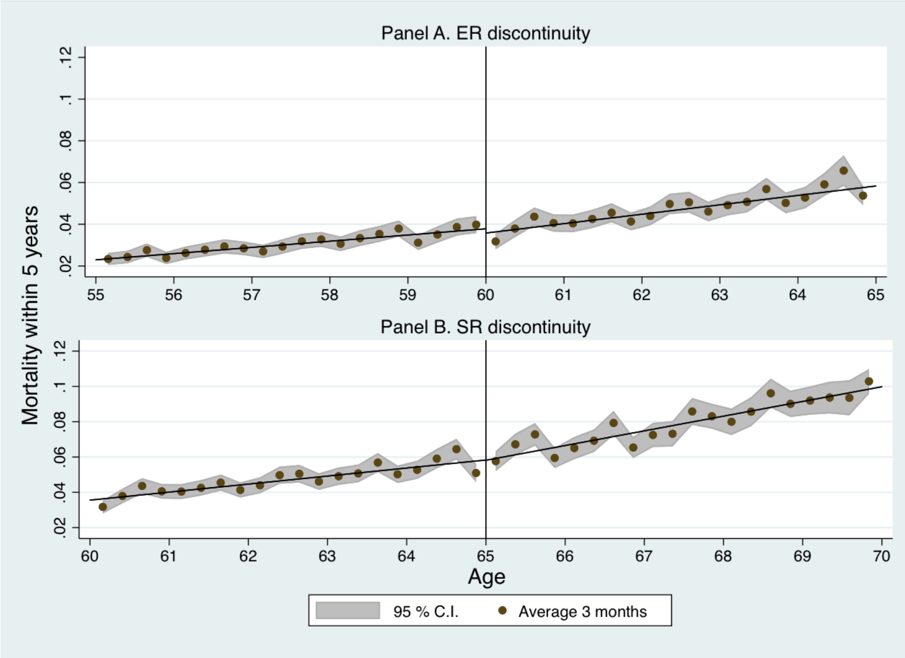
Figure 3 plots the average mortality rates within five years after a given year *t* by age, where dots represent bins of three months[4]. Age is determined as of 31st December of a given year *t*. Thus, individuals born at the beginning of the year are represented by the dots situated at the end of each age range. As they are older than individuals born at the end of the year, who are represented by the dots at the beginning of each age range.

As already documented, the death probability within five years follows a positive trend as individuals ageing. Mortality increases from 2 percent at age 55 until slightly less than 6 percent at age 59.9 (see Figure 3 Panel A). Now looking at Panel B, the probability of death increases by 7 percentage points during the same length period, yet now starting at 60 years old. Overall, from Figure 3 a clear

[4]To justify the aggregation of retirement data along the beforementioned years, I plot the data for each year separately regarding the yearly discontinuity in probability of mortality within five years (see Figure A2 in the Appendix). The plots show a similar trend along the period of interest.

discontinuity at the cut-offs cannot be seen neither at ERA nor at SRA. If anything, the plotted data show that the probability of death within five years at ERA decreases and at SRA it slightly increases.

Figure 3. Average probability of death within five years after a given year *t* by age



Note: Shaded areas show 95% confidence interval, dots represent averages over bins of 3 months and the polynomial fit is of order 1. The sample includes all the observations between 55 and 70 years old. Month of birth is included as a covariate.

Source: MCVL, own calculation.

Figure 3 shows furthermore a seasonal distribution of the probability of death which depends on month of birth. The probability of death within five years increases for individuals born from December until April. It reaches its peak for individuals born between April and June. And after that, it decreases for individuals born between March and January. Finally, the probability of death of individuals born in December of the following year is higher than the one for the individuals born in January of the previous year. The fact that the death probability reaches its peak at spring months (April – June) is in line with Doblhammer and Vaupel, (2001) findings.

6 Empirical strategy

The aim of my research is to test the hypothesis that retirement affects the probability of death in the long-run for Spanish population. In an undistorted setting, the best time to retire for any individual is when the marginal disutility of work equals her marginal productivity at work. Consequently, we would expect people with health issues to retire earlier than people with better health status (Sánchez-Martin et al., 2014). Hence, a simple OLS regression of retirement on mortality will lead to biased estimates.

6.1 Endogeneity and age-specific exogenous variation

There are two different sources of endogeneity between retirement and health being omitted variable bias and reverse causality. Omitted variable bias will occur if there are unobserved individual characteristics which affect both mortality and retirement. For example, an individual how shows poor health endowment is more likely to retire earlier. As a consequence, the probability of death after retirement increases. Moreover, also reverse causality can be observed between retirement and health. Empirics show that retirement has an effect on health as well (see Section 2).

To eliminate both omitted variable bias and reverse causality I use a Regression Discontinuity Design exploiting Spanish eligibility ages for retirement as an exogenous source of variation. The impact of institutional features on labour market withdrawal it is well documented. The following authors overall find significant impact of pension incentives on the decision to withdraw the labour market for either employed or unemployed old Spanish workers (Jiménez-Martín and Sánchez-Martín, 2004; Boldrin et al., 2004; Argimón et al., 2009; Cairó-Blanco, 2010; García-Pérez et al., 2013; Sánchez-Martín et al, 2014; and García-Gómez et al., 2018).

When focusing on the impact of the eligibility age threshold on retirement in Spain, age has been found to be an important predictor of retirement behaviour for both employed and unemployed individuals as stand by García-Pérez et al. (2013). Also, Sánchez-Martin et al. (2014) find a large increase in labour supply of Spanish individuals older than 50 years after the two-year delays in both the ERA and SRA in 2011. Moreover, García-Gómez et al. (2018) find a positive and significant effect of both ERA and SRA on the decision to exit the labour market for employed individuals. Finally, the labour market effects of the eligibility ages are confirmed when looking at Figure 1 in Section 5. The plot of the treatment discontinuity corroborates a jump at both eligibility ages.

Moreover, I assume that neither permanent disability nor unemployment programs affect the impact of retirement eligibility age on the probability of retirement at ERA and SRA. The eligibility ages for claiming their benefits are lower than for standard retirement programs[5].

Nevertheless, neither early nor statutory retirement ages have something special to influence mortality since they are not linked to any particular individual's health. Therefore, I assume that there are no other discontinuities in health status at these ages except those induced by retirement.

[5] Eligibility ages regarding permanent disability are from 52 years old if the disability degree is higher than 65 percent and from 56 years old if it is higher than 45 percent. For those individuals under long-term involuntary unemployment who had contributed more than 33 years into the SS there are two special provisions for individuals older than 52 and 55 years old.

For identification I use age 60 as ERA and not age 61, which was introduced by law in 2002 for the individuals whose first contribution to the SS was after 1967. I assume that the effect of the reform has a weak impact on the birth cohorts included in my reduced sample (born between 1937 and 1955). For instance, if individuals born between 1937 and 1949 – which represent the 63 percent of the reduced sample – have been contributing to SS since they turned eighteen. Then, all of them were eligible to retire at age 60 because their first contribution to SS was before 1967. Therefore, I assume that the effect of the reform on the rest of the birth cohorts (born between 1950 and 1955) does not significantly threat my estimates. Finally, as already explained, until 2009 the SRA in Spain is at age 65.

6.2 The model: Regression Discontinuity Design

The Regression Discontinuity Design (RDD) uses treatment assignment rules to eliminate endogeneity bias by exploiting discontinuities in the treatment assignment. The design is based on the fact that the probability of receiving the treatment changes discontinuously as a function of the value of an underlying assignment variable, being either in one side or the other of a fixed cut-off (Imbens and Lemieux, 2007). If there is no other reason for treatment recipients to be treated, than the fact that the value of the assignment variable exceeds the cut-off, then the discontinuous jump in the outcome variable at the threshold is interpreted as the treatment effect of interest (Lee and Lemieux, 2010).

I am interested on estimating the effect of a binary treatment, retirement status ($r_{it} \in \{0,1\}$), on a binary outcome, cumulative mortality within five years ($d_{it+5} \in \{0,1\}$); where the assignment variable is age (A_{it}) expressed as of 31st December of a given year *t,* calculated using the day of birth, and the fixed cut-off rule is eligibility age for retirement (EA_{it}) at ERA and SRA.

Using the "potential outcomes framework", $d_{it+5}(0)$ is the outcome when individual *i* is active in year *t* and $d_{it+5}(1)$ when retired. I am interested in the comparison of $d_{it+5}(0)$ and $d_{t+5i}(1)$. However, the fundamental problem of causal inference is that we never observe both potential outcomes for each individual simultaneously. Thus, to uncover the causal effect of the treatment $d_{it+5}(1) - d_{it+5}(0)$, I assume that individuals aged just below the cut-off are a valid counterfactual for those individuals aged just above the cut-off. In other words, in the absence of treatment, individuals close to the cut-off are similar (Hahn et al., 2001).

The Spanish Social Security system allows individuals to exit the labour market before ERA and SRA under certain conditions -e.g. unemployment or disability insurance programs-. Moreover, retirement at the SRA is not compulsory, therefore, the system generates imperfect compliance of the treatment at the cut-off. As a consequence, my paper uses a *fuzzy* Regression Discontinuity Design (*fuzzy* RDD) to estimate the effect of retirement on mortality.

In the *fuzzy* RDD, the probability of receiving the treatment is partly determined by the assignment variable (Imbens and Lemieux, 2008). Nevertheless, the conditional probability is known to be discontinuous at the cut-off (Hahn et al., 2001). Which is equivalent to say that there is a first-stage relationship between crossing the age threshold and retirement status at the threshold:

$$\lim_{A\downarrow EA} \Pr(r_{it} = 1|A_{it} = EA_{it}) \neq \lim_{A\uparrow EA} \Pr(r_{it} = 1|A_{it} = EA_{it})$$

The first identification assumption needed for the *fuzzy* RDD estimand to be valid, is continuity of the conditional expectation of counterfactual outcomes in the assignment variable (McCrary, 2008). The absence of sorting or self-selection into treatment is the idea behind the smooth variation of the assignment variable at the cut-off. On the opposite, if individuals perceive the treatment as desirable and they have a precise control over the assignment variable, this would be discontinuous at the cut-off. Sorting into treatment can be checked by analysing the density function of the assignment variable as proposed by McCrary (2008). Evidence on testing the density function of the assignment variable at the cut-off is detailed in subsection 6.2.2.

The second identification assumption needed for identification in *fuzzy* RDD is that the error term is stochastic in the assignment variable (Lee and Lemieux, 2010). It implies that all observed and unobserved pre-determined characteristics have identical distributions on either side of the cut-off in the limit. The corresponding specification check in RDD consists on analysing the smoothness of pre-determined characteristics around the cut-off using balancing tests. The continuity of the pre-treatment variables at the threshold is tested in subsection 6.2.3.

6.2.1 Choice of the bandwidth

For RD design the choice of the window width around the cut-off is essential. At best, I will be able to uncover the average effect of the treatment over subpopulations, $E[d_{it+5}(1)|A]$ and $E[d_{it+5}(0)|A]$ to the right and the left of the cut-off, respectively (Lee and Lemieux, 2010).

When deciding on the size of the interval around the threshold -i.e. bandwidth choice- the following trade-off between bias and variance of the estimate arises. On one side, shrinking the bandwidth around the age threshold increases the variance of the estimate. Hence, estimates are more likely to vary across samples. But at the same time, it will lead estimates to have lower bias because more observations are near the threshold. On the opposite, a wider interval will reduce the variance, while the estimates of the average treatment effect may be biased as observations are further from the age threshold (Lee and Lemieux, 2010). An optimal bandwidth, therefore, balances this trade-off.

To analyse the effect at both eligibility ages, I estimate two separate identification strategies. Following Calonico et al. (2017), the optimal bandwidth for the ERA specification is 1.8 years and 0.9 years for SRA identification strategy, accounting for clustering at individual-level. However, with a 0.9 years window width at SRA, the identification may suffer from low inference power as the narrower the area around the cut-off, the less data there are. Consequently, I decide to widen the age window up to 1.8

years as at ERA identification strategy. In Section 8 I test the robustness of the results to changes of the age window.

6.2.2 RD Manipulation test: McCrary

In my specification, the non-sorting assumption holds by construction. Individuals cannot have a precise control over age. Moreover, data regarding birth dates come from an administrative dataset, therefore it is not self-reported by individuals.

Nevertheless, I test the null hypothesis of no manipulation using the RD Manipulation test proposed by Cattaneo et al. (2018) which estimates a p-value of 0.389 for ERA and 0.834 for SRA using the optimal bandwidth detailed in the previous subsection. Consequently, there is evidence to not reject the null hypothesis of no manipulation.

6.2.3 Balancing tests

At the optimum, observed and unobserved individual characteristics should be compared between treatment and control group at the cut-off. However, unobservable characteristics are untestable. Thus, if treatment and control groups are similar in their observed baseline covariates at the threshold, this implies that unobserved characteristics are also similar. On the opposite, if other covariates also jump at the cut-off, then the discontinuity of interest will potentially be biased for the treatment effect (Lee and Lemieux, 2010).

To test the baseline characteristics, I replace the outcome variable in specification (2) by the following covariates: birth region, proportion of males, educational level and nationality. I regress a total of 47 placebo tests for ERA and SRA, respectively, under the null hypothesis of no discontinuity. As there are many covariates, some discontinuities will be statistically significant by chance. I find a significant coefficient for three and eight covariates for ERA and SRA, respectively (see Tables A4 and A5 in the Appendix). However, the estimated treatment discontinuity at the threshold is always nearly zero.

6.3 Estimation

In *fuzzy* RD design the estimated causal effect is the Local Average Treatment Effect (LATE) for compliers provided monotonicity holds (Lee and Lemieux, 2010). Being a complier implies that $r_i(EA)$ is equal to 1 if individual i takes or receives the treatment if the assignment variable is equal to or higher than the cut-off and not otherwise (Imbens and Lemieux, 2008). In other words, it measures the impact of retirement on mortality for those whose decision to retire is a function of their age. The effect of interest is estimated as a Two-Stage Least Squares (2SLS) model separately for each discontinuity given the exogeneous variation offered by the Spanish Social Security retirement eligibility ages: age 60 (ERA) and age 65 (SRA).

6.3.1 First-stage specification

The first-stage estimates the relationship between retirement status and the cut-off rule (EA). I estimate two separate models for each retirement eligibility age.

$$r_{it} = \alpha_0 + \alpha_1 EA_{it} + \alpha_2(A_{it} - c) + \alpha_3 EA_{it}(A_{it} - c) + \theta_{im} + \varepsilon_{it} \tag{1}$$

where r_{it} is a dummy variable and equals 1 if individual *i* is retired in year *t*. Then, the cut-off is indicated by the threshold EA_{it} (Eligibility Age of individual *i* at year *t*), which is a dummy variable with value 1 if the individual *i* in year *t* is older than 60 or 65 years old and zero otherwise. And α_1 estimates the treatment discontinuity at the threshold. After that, $(A_{it} - c)$ is a smooth linear function of age at the end of the year *t* which centres the specification at the threshold, where $c \in \{ERA, SRA\}$. Fourthly, $EA_{it}(A_{it} - c)$ is an interaction term that allows for different age trends before and after the cut-off, centred at the threshold, where $c \in \{ERA, SRA\}$. Moreover, I control for the relationship between month of birth and mortality using dummies for each month of birth (θ_{im}) (García-Gómez and Gielen, 2014 and Doblhammer and Vaupel, 2001). Finally, ε_{it} is the error term clustered at individual-level which accounts for any dependence within individuals over time, in other words heteroskedasticity and serial correlation in the error terms.

6.3.2 Second-stage specification

The second-stage estimates the relationship between mortality and retirement status and it gives the treatment effect of retirement. Similar as with the first-stage identification strategy, I estimate two separate models for each eligibility age for retirement.

$$d_{it+5} = \beta_0 + \tau\hat{r}_{it} + \beta_1(A_{it} - c) + \beta_2 EA_{it}(A_{it} - c) + \theta_{im} + \eta_{it+5} \tag{2}$$

where d_{it+5} is a dummy variable with value 1 if the individual *i* dies within five years after a given year *t*. Then, $\hat{r}_{it}$ is the predicted value from equation (1), and τ is the treatment effect of retirement. After that, $(A_{it} - c)$, $EA_{it}(A_{it} - c)$ and θ_{im} are specified as in equation (1). Finally, η_{it+5} is the error term clustered at individual-level which also accounts for heteroskedasticity and serial correlation in the error terms within the same individuals along time.

7 Results

The estimation of the abovementioned equations (1) and (2) using local linear regression and following Calonico et al. (2017) yielded the results presented in this Section. Estimates at early retirement age are estimated separately from estimates regarding statutory retirement age.

In subsection 7.1 I present the homogeneous treatment effect estimates of retirement on the probability of death within five years. After that, in subsection 7.2 I analyse the treatment effect estimates along time in periods of 1 to 8 years after a given year *t*. Finally, in subsection 7.3 I relax the assumption that the treatment effect is homogeneous across different individuals including heterogeneity in the identification.

7.1 Homogeneous treatment effect estimates

Table 2 presents the first-stage and the treatment effect estimates at both eligibility ages. The first-stage coefficients show that eligibility ages are an important predictor of retirement behaviour for Spanish old age workers. The estimates are significant at 1 percent level in both cases. This finding is in line with the beforementioned empirical evidence on the impact of pension incentives on labour market exit decisions (see Section 6) and the treatment discontinuities plotted in Figure 1 (see Section 5). Within a bandwidth of 1.8 years around the cut-off, Table 2 shows that being over the ERA increases significantly the propensity to retire by 7 percentage points and by almost 15 percentage points when individuals are over the SRA.

Table 2 Panel A documents furthermore that individuals who retire at age 60 have a 6.1 percentage point lower probability of death within five years and it is significant at 10 percent level. On the opposite, Table 2 Panel B shows that for individuals who retire at SRA, the probability of death within five years increases by 2.1 percentage points, however, it is insignificant.

Interpreting these estimates as causal effects, hence, assuming that there are no other changes than retirement at both eligibility ages. Retiring at ERA has a health-preserving effect on health slowing down the pace of the cumulative mortality. While retiring at SRA has a detrimental effect on health, thus, accelerating the probability of death. In Section 8 I show that these results are robust to various robustness checks.

Table 2. First-stage and treatment effect estimates of retirement on mortality

Panel A. *fuzzy* RDD at age 60	
Probability of retired	0.068 (0.005)***
Mortality within 5 years	-0.061 (0.032)*
N	126,043
Individuals	85,200
Panel B. *fuzzy* RDD at age 65	
Probability of retired	0.146 (0.005)***
Mortality within 5 years	0.021 (0.020)
N	98,093
Individuals	66,183

* Significant at 10%.
** Significant at 5%.
** Significant at 1%.

Note: standard errors are given in parenthesis and are clustered at individual-level. Each estimate comes from an independent regression and all identification strategies include a dummy for eligibility age threshold, a linear age trend centred at the threshold, an interaction between the dummy for eligibility and age, and dummy variables for month of birth. The sample includes all the observations within a 1.8 years age window.
Source: MCVL, own calculations.

7.2 Homogeneous treatment effect estimates along time

The aim of this subsection is to analyse the effect of retirement on health along time. Together with the estimate of interest, I present the treatment effect for periods of 1 to 8 years after a given year *t*.

Looking at Table 3 column (1), at ERA the effect of retirement on the probability of death is consistently protective along time. The coefficients are always negative which translates into a persistent decrease in the probability of death. Table 3 column (1) shows furthermore that the major effect of retirement on health at ERA is within the fifth and the eight year. Decreasing the probability of death by 6 and 7 percentage points, respectively.

On the other side, Table 3 column (2) shows that at SRA retirement has a protective short-run effect followed by a persisted negative impact on health from the second year forward. The protective estimates found after one year can be explained by the so-called *honeymoon phase* (Atchley, 1976). Individuals who retire once eligible at SRA now can participate in some activities that were postponed due to time constraints when working. However, from the cumulative second year and forward, estimates of treatment effect show that retirement accelerates the process of death for those individuals who decide to retire at SRA after being eligible. The major impact of retirement on health at SRA is within the sixth and the seventh year increasing the probability of death by around 3 percentage points.

Table 3. Treatment effect estimates of the probability of death within 1 and 8 years

	At age 60	At age 65
Mortality		
Within 1 year	-0.0151 (0.0150)	-0.0058 (0.0097)
Within 2 years	-0.0233 (0.2000)	0.0070 (0.0130)
Within 3 years	-0.0263 (0.0248)	0.0005 (0.0162)
Within 4 years	-0.0480 (0.0284)*	0.0149 (0.0182)
Within 5 years	-0.0612 (0.0317)*	0.0215 (0.0204)
Within 6 years	-0.0431 (0.0346)	0.0256 (0.0226)
Within 7 years	-0.0323 (0.0377)	0.0268 (0.0247)
Within 8 years	-0.0696 (0.0416)*	0.0118 (0.0268)
N	126,043	98,093
Individuals	85,200	66,183

* Significant at 10%.
** Significant at 5%.
** Significant at 1%.

Note: standard errors are given in parenthesis and are clustered at individual-level, each estimate comes from an independent regression and all identification strategies include a dummy for eligibility age threshold, a linear age trend centred at the threshold, an interaction between the dummy for eligibility, and age and dummy variables for month of birth. The sample includes all the observations within a 1.8 years age window.
Source: MCVL, own calculations.

7.3 Heterogenous treatment effect estimates

So far, I assume that the effect of retirement on mortality is homogeneous across individuals with different personal characteristics and professional careers. However, retirement may affect health differently. In this subsection I disaggregate the homogeneous effect in several categories based on gender, educational level and occupational strain.

In general, Table 4 shows that the correlation between retirement and both eligibility ages is similar to the baseline estimates presented in subsection 7.1. They are negative at ERA and positive at SRA. Nevertheless, some occupational strain levels document a negative effect at SRA as well. Table A6 in the Appendix present the details for the first-stage estimates for each identification strategy.

Table 4. Heterogenous treatment effect estimates

	At age 60	At age 65
Panel A. Baseline results		
Treatment effect	-0.061 (0.032)*	0.021 (0.020)
N (Individuals)	126,043 (85,200)	98,093 (66,183)
Panel B. Gender		
Males	-0.084 (0.043)*	0.031 (0.027)
N (Individuals)	126,043 (85,200)	98,093 (66,183)
Females	-0.002 (0.038)	0.006 (0.020)
N (Individuals)	40,861 (27,997)	25,192 (17,442)
Panel C. Educational level		
No education	-0.050 (0.050)	0.005 (0.027)
N (Individuals)	75,737 (52,351)	63,773 (43,817)
Primary education	-0.093 (0.044)**	0.045 (0.039)
N (Individuals)	37,195 (26,239)	25,888 (18,211)
Higher education	-0.019 (0.100)	0.063 (0.053)
N (Individuals)	13,111 (9,298)	8,432 (5,926)

	At age 60	At age 65
Panel D. Occupational strain		
Low physical strain	-0.062 (0.077)	0.030 (0.041)
N (Individuals)	24,314 (17,362)	13,715 (9,793)
Medium physical strain	-0.070 (0.057)	-0.001 (0.029)
N (Individuals)	52,784 (38,930)	45,963 (33,508)
High physical strain	-0.046 (0.051)	-0.003 (0.060)
N (Individuals)	30,275 (22,086)	17,662 (12,888)
Low psychological strain	-0.010 (0.070)	-0.012 (0.078)
N (Individuals)	12,344 (9,442)	6,681 (5,157)
Medium psychological strain	-0.210 (0.165)	-0.012 (0.041)
N (Individuals)	27,845 (20,608)	16,243 (11,890)
High psychological strain	-0.048 (0.039)	0.014 (0.028)
N (Individuals)	67,184 (48,043)	54,416 (38,935)
Panel E. Nationality		
Only Spanish	-0.058 (0.032)*	0.022 (0.020)
N (Individuals)	122,823 (82,735)	96,909 (65,288)

* Significant at 10%.
** Significant at 5%.
** Significant at 1%.

Note: standard errors are given in parenthesis and are clustered at individual-level. I estimate independent regressions for ages 60 and 65 and all identification strategies include a dummy for eligibility age threshold, a linear age trend centred at the threshold, an interaction between the dummy for eligibility and age and dummy variables for month of birth. The sample includes all the observations within a 1.8 years age window.
Source: MCVL, own calculations.

Gender. The motivation of including heterogeneous effects by gender is justified by two facts. First, health status differs between females and males –e.g. life expectancy (OECD, 2017) – and second, there are historical differences in labour market participation between gender groups. It is documented that along time females in Spain show lower labour force participation and employment rates than men (see Figure 1 García-Gómez, et al., 2018). In line, the representativeness of affiliated males in the Spanish SS doubles the one of females (see Table 1 Panel A).

Table A6 Panel B in the Appendix shows the first-stage relationship by gender. The influence of eligibility age on retirement status is similar in magnitude and significance to the baseline results for both females and males. Except for females at ERA where the first-stage estimate is still significant, but the magnitude is close to zero.

Moreover, Table 4 Panel B shows that the direction of the effect of retirement on health is the same as the baseline results at both eligibility ages (protective at ERA and detrimental at SRA). Meaning that the effects are relatively homogeneous. More in detail, the effect on males is higher than the baseline estimates whereas the effect on females is lower and close to zero. From these results I conclude that retirement does not play an important role on explaining why females live longer than males.

Educational level. The positive association between education and health is well known. For instance, Mazzonna et al., (2017) find a significant impact of education on the level of cognitive abilities. Hence, I am interested on the disaggregated effect of retirement on health by educational level.

In MCVL the educational level is divided in four levels according to the Spanish National Classification of Education 2014 (CNED-2014): no education, primary, secondary and tertiary education. However, in order to increase the inference power of the estimates, I further reclassify the four groups into three: no education, less than twelve years of schooling (primary education) and more than twelve years of schooling (secondary and tertiary education).

Table 5 Panel A divides the sample into the listed educational levels. It can be seen that almost the 67 percent of the sample has no education or an educational level lower than primary education. These statistics are in line with the period the birth cohorts lived (individuals born between 1937-1955). First, Spain suffered the Spanish Civil War (1936-1939) which was followed by the dictatorship of Franco (1939-1975). Periods during which a high share of the population remained illiterate. Among them, the share of retirees is higher than active individuals.

Table 5 Panel A shows furthermore, that slightly more than the 30 percent has at least primary education (between one and twelve years of education) and within those, non-retirees are slightly more abundant than retired individuals. Finally, the two highest educational levels (secondary and tertiary education) represent together the 11 percent and are mostly represented by non-retirees.

As can be interpreted from Table A6 Panel C in the Appendix, the first-stage estimates by educational level are all significant. At ERA individuals with at least primary school are the most affected by eligibility age, the probability of being retired increases discontinuously by 0.088. While at SRA the more respondent individuals are the ones with at least secondary education or higher, for whom the probability of being retire increases discontinuity by 0.178.

Then looking at Table 4 Panel C, in general all educational levels keep the same direction as the baseline results at both eligibility ages. The educational levels that experience a higher impact of retirement on health are individuals retiring at ERA with at least primary education (-0.093), followed by illiterate individuals (-0.050), and at SRA individuals with higher education experience the highest effect of retirement (0.063). However, the inference power is low, more concretely within individuals with higher education.

Occupational Strain level. Finally, retirement can relief individuals from activities that involve high strenuous activities. Therefore, retiring may have different long-run effects based on the characteristics of the sector of employment you are retiring from. For instance, Eibich (2015) already finds heterogeneity on retirement effect between low and high occupational strain.

The MCVL classifies all economic activities into 15 codes regarding sector of employment or economic activity, according to the Spanish National Classification of Economic Activities 2009 (CNAE-09). Following Eibich (2015), I use the Job Exposure Matrices proposed by Kroll (2011, 2015) where the author ranges occupations according to their job strenuous demand.

More in detail, Kroll (2011) explains the methodology used to rank the occupations. According to the author, environmental and ergonomic loads are important components when calculating the physical occupational strain. And mental stress, social burdens such as conflicts, and time exposure are considered when classifying the occupations into different levels of psychological strain.

Then, Kroll (2015) offers the list where he orders almost all the occupations in the International Standard Classification of Occupations 2008 (ISCO-08). In a scale from 10 to 1 for both physical and psychological occupational strain following the methodology detailed in Kroll (2011).

In order to have a similar list as in Kroll (2015). First, I match the different occupations in ISCO-08 with the sectors of employment detailed in the MCVL –i.e. CNAE-09–. As a result, there are several occupations within the same sector of employment. Then I pair the punctuation in Kroll (2015) to the matched ISCO-08/CNAE-09 code using 2-digit, 3-digit or 4-digit code, at best. After that, in case different occupations within the same industry sector have different punctuation, I calculate the average among all of them. Finally, I reclassify the sectors of employment into three levels: low occupational strain if the average is lower or equal 5, medium if the average is lower or equal 7 and high if it is higher than 7.

On top of that, it is worth mentioning that there are some differences between the Spanish CNAE-09 and the ISCO-08. While the former classification offers a structure of economic activities for Spain, the latter is an international classification of employment occupations. Thus, the matching method I used may lead my heterogeneous estimates to suffer from measurement error. Furthermore, the classification of economic activities in CNAE-09 is broad in a sense that very different careers such as veterinary and law professionals are both classified under "Professional and Scientific services" among other examples.

Table 5 Panel B shows the statistics for the physical and psychological occupational strain and their levels. It can be inferred that most of the individuals in the sample are exposed to a medium physical strain (58 percent) and to a high psychological strain (66 percent). Overall, retirees are more abundant than active individuals within these two majority occupational strain levels.

Sectors of employment with maximum physical strain include construction, and transport and storage workers, whereas accountants and Real Estate agents experience low physical strain. Sectors of employment with high psychological strain include health services professionals whereas construction workers face low psychological strain.

Table A6 Panel D in the Appendix shows that the first-stage is significant for all cases. Both at ERA and SRA individuals retiring from high physical strain (0.090 and 0.185, respectively) and from low psychological strain (0.096 and 0.175, respectively) are the most affected groups by eligibility age.

Looking at the heterogeneous treatment effect by occupational strain in Table 4 Panel D, the effect at ERA is in line with the baseline results. Retiring from any occupational strain level at ERA decreases the probability of death within five years. Individuals who retired from medium psychological strain occupations experience the strongest effect (-0.210), yet insignificant. The effect at SRA differs from the negative baseline results. For some occupational strain levels retirement at SRA also has a protective effect on health. For instance, retiring at SRA from high (-0.003) and medium physical strain (-0.001), and from low (-0.012) and medium psychological strain (-0.012) leads to a health improvement. However, I am well aware that estimates may suffer from low inference power and from measurement error.

Table 5. Descriptive statistics on educational and professional characteristics

					Non-retirees			Retirees	
	%	Individuals	N	%	Individuals	N	%	Individuals	N
Panel A. Educational level (%)									
No education	66.85	100,281	282,299	54.33	54,479	126,804	63.70	63,883	155,495
Primary education	30.45	45,671	128,517	60.31	27,546	64,634	58.87	26,887	63,883
Higher education	11.20	16,807	44,805	86.89	14,603	37,024	71.29	11,982	30,153
Panel B. Occupational strain (%)									
Physical strain									
Low strain	22.44	33,667	82,238	67.44	22,705	51,684	44.24	14,895	30,554
Medium strain	58.39	87,585	197,922	52.18	45,701	87,404	61.74	54,073	110,518
High strain	29.40	44,110	99,183	60.00	26,464	53,793	51.08	22,531	45,390
Psychological strain									
Low strain	14.10	21,145	41,059	64.11	13,556	24,676	43.95	9,293	16,383
Medium strain	28.20	42,305	93,057	62.83	26,582	54,081	48.28	20,423	38,976
High strain	66.45	99,675	245,227	54.11	53,936	114,124	60.75	60,548	131,103

Note: The percentage share (%) in column (1) is calculated based on the total number of individuals. The percentage shares (%) in columns (4) and (7) are calculated based on the total number of individuals on each row. The sample includes all the observations between 55 and 70 years old.
Source: MCVL, own calculations.

8 Robustness checks

In order to test the robustness of my estimates presented on Table 2, I do several sensitivity analyses following Lee and Lemieux (2010) recommended “checklist for implementation”. The results for some of the proposed tests are already presented in Section 6 such as the manipulation RD test and parallel RD analysis on the baseline covariates.

In this section I check the sensitivity of the results to: the inclusion of baseline covariates, the change of the functional form, the change of the bandwidth, and to changes in the sample selection. Additionally, I check for placebo discontinuities as suggested by Imbens and Lemieux (2008).

Table 6 presents the results of the treatment effect estimates regarding all the robustness checks previously mentioned. And Table A7 in the Appendix offers the first-stage estimates for each equation. In general, Table A7 shows that all specifications keep a statistically significant first-stage at 1 percent level and similar magnitude as the baseline results. Except, as expected, the placebo discontinuities whose first-stage estimates are insignificant.

Table 6. Robustness check

	At age 60	At age 65		At age 60	At age 65
Panel A. No controls			**Panel E. Sample selection**		
Treatment effect	-0.061 (0.032)*	0.021 (0.020)	I. Retirement without unemployed	-0.076 (0.039)*	0.027 (0.025)
			N (individuals)	126,043 (85,200)	98,093 (66,183)
Panel B. Covariates					
Gender	-0.065 (0.032)**	0.023 (0.020)	II. RGSS and RESS	-0.035 (0.036)	-0.002 (0.013)
Year	-0.060 (0.031)*	0.022 (0.020)	N (individuals)	190,684 (127,680)	154,537 (103,627)
Nationality	-0.060 (0.032)*	0.022 (0.020)			
Educational level	-0.063 (0.032)**	0.021 (0.020)	**Panel F. Nationality**		
			Only Spanish	-0.058 (0.032)*	0.022 (0.020)
Panel C. Functional form			N (Individuals)	122,823 (82,735)	96,909 (65,288)
Quadratic age trend	-0.310 (0.132)**	0.075 (0.050)			
			Panel G. Other discontinuities		
N	126,043	98,093	Age 57.5	0.459 (0.725)	
Individuals	85,200	66,183	N (individuals)	138,892 (93,902)	
Panel D. Bandwidth choice			Age 62.5	0.084 (0.386)	
BW 0.9	-0.278 (0.117)**	0.068 (0.051)	N (individuals)	114,360 (76,830)	
N (individuals)	62,849 (62,776)	49,012 (48,948)			
			Age 67.5	-8.587 (22.808)	
BW 3.6	-0.034 (0.017)**	0.013 (0.014)	N (individuals)	81,264 (54,614)	
N (individuals)	246,152 (120,033)	190,174 (91,637)			

* Significant at 10%.
** Significant at 5%.
** Significant at 1%.

Note: standard errors are given in parenthesis and are clustered at individual-level. Each estimate comes from an independent regression which are individually specified in the following paragraphs.
Source: MCVL, own calculations.

Covariates. To test the results to the inclusion of covariates, the estimated results come from equation (2) including the specified covariates and the chosen bandwidth detailed in Section 6.

As seen in Table 6 Panel B, the inclusion of covariates does not change significantly the magnitude of the estimates of the treatment effect, and moreover it does not affect their significance either. Thus, estimates in Table 2 are robust to the inclusion of covariates.

Change the degree of the specification. One of the strengths of the RD design is the graphical representation. From Figure 1, I consider that a low-order polynomial such as a linear specification is a very good approximation of the plotted data. Nevertheless, moving away from the cut-off in order to increase the statistical inference by increasing the data used for estimation, generates a dependence between the estimate and the chosen functional form which may lead to generate misspecification (Lee and Lemieux, 2010).

In order to check the goodness-of-fit, I regress specification (2) including a quadratic age trend. Results can be seen in Table 6 Panel C. Increasing the polynomial order of age increases the magnitude of the coefficients, yet it keeps the significance unaffected.

Change of the bandwidth. In this section I test the external validity of my results varying the age window between 50 and 200 percent of the chosen bandwidth in equation (2).

As seen in Table 6 Panel D, the point estimates with the smaller sample (50 percent of the chosen bandwidth) are bigger than my baseline results. At ERA the coefficient keeps being negative and significant at 10 percent level, and at SRA the estimate is positive and still insignificant. These results imply that individuals who are closer to the cut-off, experience a stronger treatment effect.

Additionally, the point estimate with the wider sample (200 percent of the chosen bandwidth) is smaller than my baseline coefficients. At ERA the coefficient is still negative and significant at 5 percent while at SRA the estimate keeps being positive and insignificant. From the results I conclude that the further the individuals are from the cut-off the less affected is their health status by retirement.

Sample selection I: without unemployed. The exit route through unemployment accounts for more than two-thirds of the transitions into retirement among Spanish workers (García-Pérez et al., 2013). I am interested on testing the results to a more conservative definition of retirement status, and I consider unemployed as active individuals.

From Table A7 Panel E I, I can corroborate my assumption that unemployment programs do not affect significantly the impact of retirement eligibility age on the probability of retirement, at neither ERA nor SRA. The estimates for the first-stage with the new definition of the retirement variable are not significantly different than the baseline coefficients.

As can be seen in Table 6 Panel E I, the point estimates of equation (2) using the new definition of retirement status are not significantly different, and it does not change the significance of the estimates either.

Sample selection II: RGSS and RESS. In this case instead of restricting the sample only to individuals under the general SS scheme (RGSS), I also include special SS schemes (RESS) keeping the exclusion restriction criteria. After including them the number of observations increases to 700,780 (223,872 individuals). From whom 136,329 individuals are in the treatment group and 133,697 individuals in the control group.

The reason why I exclude them is because the pension system for affiliates under special SS regimes (RESS) is markedly different from the general SS scheme (RGSS). Not only regarding eligibility ages but also in other pension features. From Table A7 Panel E II, as expected, it can be seen that the effect of eligibility ages on retirement is weaker at ERA than the baseline results, however, statistically significant.

Moreover, Table 6 Panel E II shows that the estimates and the significance of the results are affected by the inclusion of individuals who contribute under special SS schemes. I conclude that this evidence corroborates my decision to exclude them from my reduced sample.

Nationality. The MCVL contains 26 different nationalities. It is shown that there are differences in health and life expectancy between individuals from different ethnic backgrounds (García-Gómez and Gielen, 2014). However, 90 percent of the reduced sample is Spanish, followed by immigrants coming from Morocco and Ecuador which represent only the 0,35 percent each. As Spanish individuals represent the majority of the sample, it drives the homogeneous estimated effects. As inferred from Panel F in Table A7 in the Appendix and Table 6, both first-stage and treatment effect baseline estimates are driven by Spanish individuals.

Placebo discontinuities. The aim of checking other discontinuities is to test for a zero effect on age ranges where it is known that the effect should be zero. Imbens and Lemieux (2008) suggest testing for jumps at the median of the two subsamples on either side of the cut-off. Therefore, I test for discontinuities at 57.5, 62.5 and 67.5 years old. It is worth mentionioning that with the proposed bandwidth in Section 6 of 1.8 years, the ERA and SRA cut-offs are not included.

Table A7 in the Appendix shows that all specifications have a weak first-stage. Moreover, Table 6 Panel G shows that the estimates are positive at 57.5 and 62.5, and negative at 67.5, yet all of them insignificant.

9 Discussion and concluding remarks

I estimate the long-term effects of retirement on health measured by cumulative mortality within five years using age-specific features as exogeneous variation to overcome the endogeneity. Whereas most of the authors use reform-based exogeneous variation or focus on other health outcomes different from mortality. Hence, my estimated results might be not directly comparable to most of the previous literature. To mitigate the lack of straight comparability, in this section I consider empirics that either use age-specific features as exogeneous variation or mortality as an outcome.

The *fuzzy* RD design used in this study is very similar to the *fuzzy* RDD used by Eibich (2015). However, with the difference that I estimate the effect of retirement on mortality for both eligibility ages separately. I am concerned that compliers at each age threshold might differ in unobservable characteristics which can lead to observe heterogeneous effects of retirement on health. For instance, individuals who retire at ERA they exit the labour market as soon as possible facing a reduction of financial benefits. Whereas individuals who wait and retire at SRA are eligible to receive the full withdrawal amount.

In Section 7 Table 2, I find heterogeneity when estimating the homogeneous treatment effect of retirement on health at ERA and SRA. In Spain, individuals who retire from the RGSS at ERA experience a significant decrease in the probability of death within five years of -0.061, significant at 10 percent level. Whereas I find an insignificant detrimental effect of retirement on health at SRA. Where the mortality within five years increases by 0.021, yet insignificantly. The results have been shown to be robust to several sensitivity tests in Section 8.

As covered in previous literature, some authors also estimate the effect of retirement on health using age-specific pension features as exogeneous variation and overall report heterogeneity in retirement effect depending on age (Celidoni et al., 2017; Eibich, 2015; Coe and Zamarro, 2011; Bonsang et al., 2012; and Bound and Waidmann, 2007). In line with my findings, Celidoni et al., (2017) find a protective effect of retirement on cognitive skills at ERA and a negative effect at SRA.

Then focusing on the effect of retirement on mortality at ERA. I find a protective effect in line with Bloemen et al., (2017). Although my estimates are bigger in magnitude and the type of occupations are different. The authors find that early retirement decreases the mortality within five years by -0.026 significant at 10 percent level for Dutch civil servants.

Now looking at the treatment effect at SRA. My estimates are in line with Hernaes et al. (2013) and Hagen (2018) who do not find a significant effect of retirement on health, and if anything, a detrimental effect of it by increasing the probability of death.

Moreover, in Table 6 I allowed for heterogenous treatment effect on health based on gender, educational level and occupational strain. When analysing the effect of eligibility age on retirement, none of them show a weak first-stage relationship. Moreover, I find that most of the treatment effects on health are relatively homogeneous across heterogeneous groups. However, it is of importance to highlight that the results obtained by physical strain level are in line with the one found by Eibich (2015). Similar to Eibich (2015) findings, I document in Table 6 Panel D that individuals retiring from high physical strain occupations experience a health-preserving effect on health at both ERA and SRA. However, low inference power threatens the validity of these estimates.

To conclude, my research uses a Regression Discontinuity Design and eligibility retirement ages to overcome the endogeneity between retirement and health generated by omitted variable bias and reverse causality. Using the MCVL waves published between 2006 and 2017 which provide detailed information of my variables of interest, being retirement status and mortality. I find a significant protective effect of retirement at early retirement age, and a non-significant detrimental effect on health of retiring at statutory retirement age for Spanish workers who contribute under the general Social Security scheme (RGSS). The estimates presented in Table 2 are in line with some of the most comparable previous research estimates and robust to several robustness checks. However, the results have some limitations. This paper analyses generations which are already retired. I assume that younger cohorts may face different life conditions than the ones experienced by birth cohorts born between 1937 and 1955 in Spain. Therefore, the results might not be directly extrapolated to younger cohorts who will withdraw the labour force in the following years.

Nevertheless, my findings contribute to the existing literature in several ways. First, it provides evidence for Spain on the effect of retirement on mortality in line with results found on previous literature. Second, the baseline results are free of measurement error as the variables of interest are generated based on administrative data rather than self-reported information. Third, mortality is an objective health measure and offers straight comparability across countries. Fourth, I document heterogeneity in retirement effects depending on the eligibility age. Finally, the paper also infers heterogeneous effects by occupational strain level.

The policy implications of my findings are ambiguous and mainly affect the government budget through two public policies. The Spanish public pension system and public health expenditures. Results show that retirees withdrawing the labour force at ERA will experience a deceleration on their death probability in the long-run. Thus, it will lead to an increase of their life expectancy, which generates a necessity of extending government's pay-outs, and to claim health services during a longer time. However, retirees exiting the labour market at SRA will face an increase in mortality within five years. It leads to a reduction on the years spent on retirement but might lead to an increase of health expenditures as well. Therefore, the net impact of retirement on the government budget will depend on the prevailing effect.

Nevertheless, more research is needed in the context of ageing in Spain. Empirical evidence should be the keystone of the policy reforms aimed to relief the economic burden of the Spanish pension system. Moreover, research is also crucial to forecast the trend of health expenditure together with demographic evidence.

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Appendix

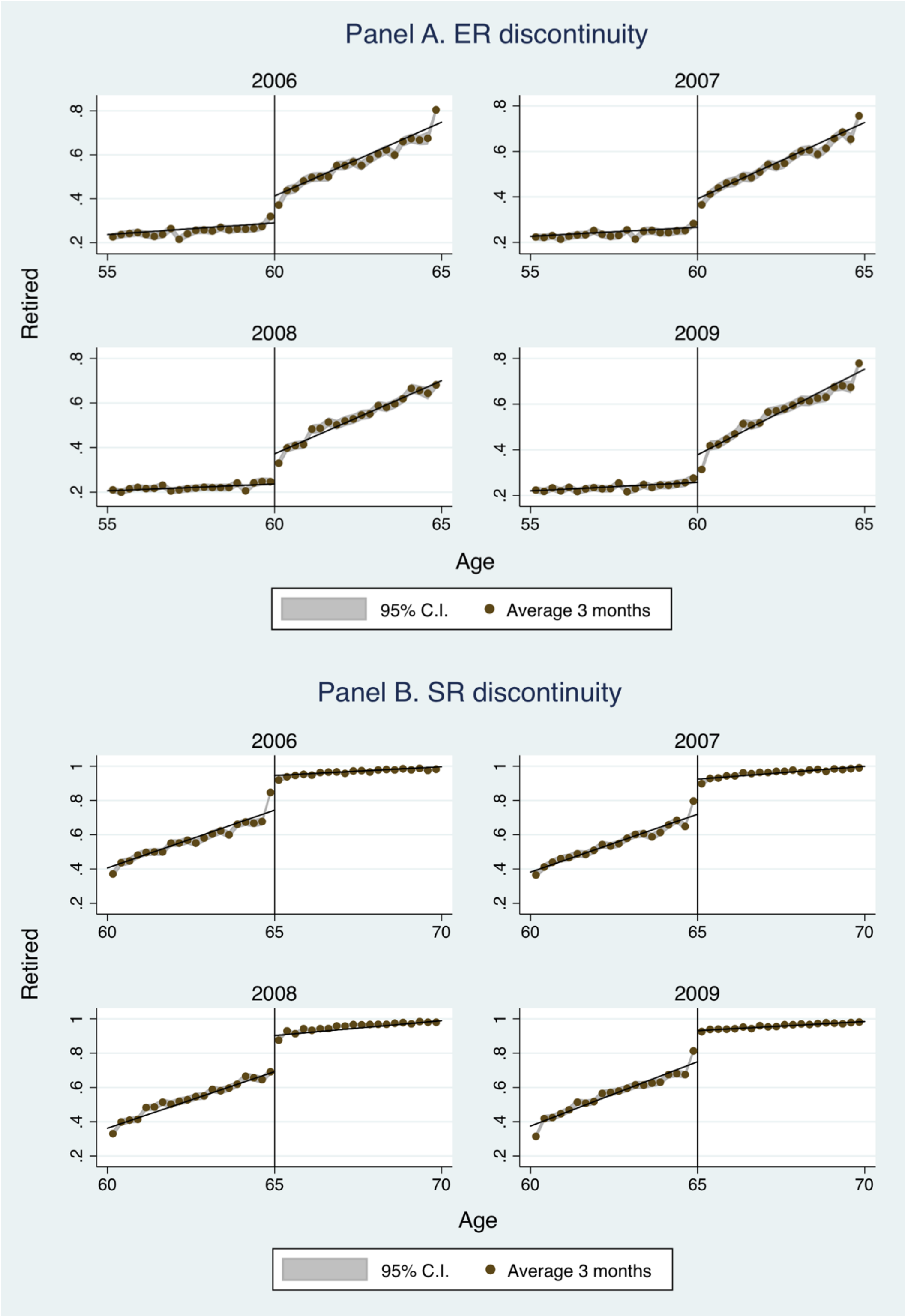
Table A1. Reforms of the Spanish Social Security system 1985 – 2013

Year	Retirement pension	Disability benefits	Unemployment benefits
1984			Special provision for 55+ years under scheme counted as contributive years to SS
1985	Minimum years of contribution from 8 to 15 Introduction of partial and special retirement Increase the number of contributive years to compute the pension from 2 to 8 Early retirement schemes	Tightening eligibility criteria	
1989			Special provision if age 52+
1990		Means-tested non-contributory DI pensions for age 65+ and disabled age 18+ Tightening eligibility and generosity sickness benefits	
1997	Increase the number of contributive years to compute the pension from 8 to 15 Reduction of the replacement rate Decrease penalty of ER if contributed years 40+	Compatibility between work and DI non-contributory benefits Permanent DI pensions age 65+ are converted to retirement pensions	
1998		Stricter disability and health status control	
2002	ER increase to 61 if first contribution to SS after 1967 Combine pension payments and earnings (impulse partial retirement) Incentives to retire after 65		Unemployment benefits are compatible with earnings if age 52+
2004-2005		Stricter monitoring and sickness absentees	
2007	Penalty reduction of ER if contributive years 30+ Increase incentives to retire after 65		Increase contributions made by SS for individuals under UB 52+
2011	Increase the number of contributive years to compute the pension from 15 to 20 SR increase to 67 (progressively by 2027) ER increase to 63 (progressively by 2027) Increase incentives to retire after 65		
2012			Reduction of the replacement rate after 180 days of unemployment spell
2013	Sustainability factor New scheme combine pension payments and earnings		

Note: ER = Early Retirement and SR = Statutory Retirement

Source: Figure 2, Table 1 and Table 2 García-Gómez et al. (2018). Trends in employment and Social Security incentives in the Spanish Pension system 1980 – 2016

Figure A1. Discontinuity of treatment by year (stock of retirees)



Note: Shaded areas show 95% confidence interval, dots represent averages over bins of 3 months and the polynomial fit is of order 1. The sample includes all the observations between 55 and 70 years old. And I control for month of birth.

Source: MCVL, own calculation.

Table A2. Stock of retirees and active individuals across age ranges

	Age range [55-60)			Age range [60-65)			Age range [65-70)		
	%	Individuals	N	%	Individuals	N	%	Individuals	N
Disability benefits	6.82	10,224	22,657	7.93	11,898	27,555	6.06	9,086	20,875
Retirement	0.10	154	296	13.79	20,689	43,879	74.85	35,672	83,508
Unemployment benefits	10.83	16,250	21,721	7.14	10,710	13,406	2.26	2,237	2,525
Active	43.80	65,711	144,465	23.54	35,313	70,068	4.18	2,778	4,666

Note: The percentage share (%) in column (1) is calculated based on total the number of individuals in Table 1. Numbers regarding individuals do not sum up as Table 1 as individuals change their retirement status in different ages and/or years. The sample includes all the observations between 55 and 70 years old.

Source: MCVL, own calculation.

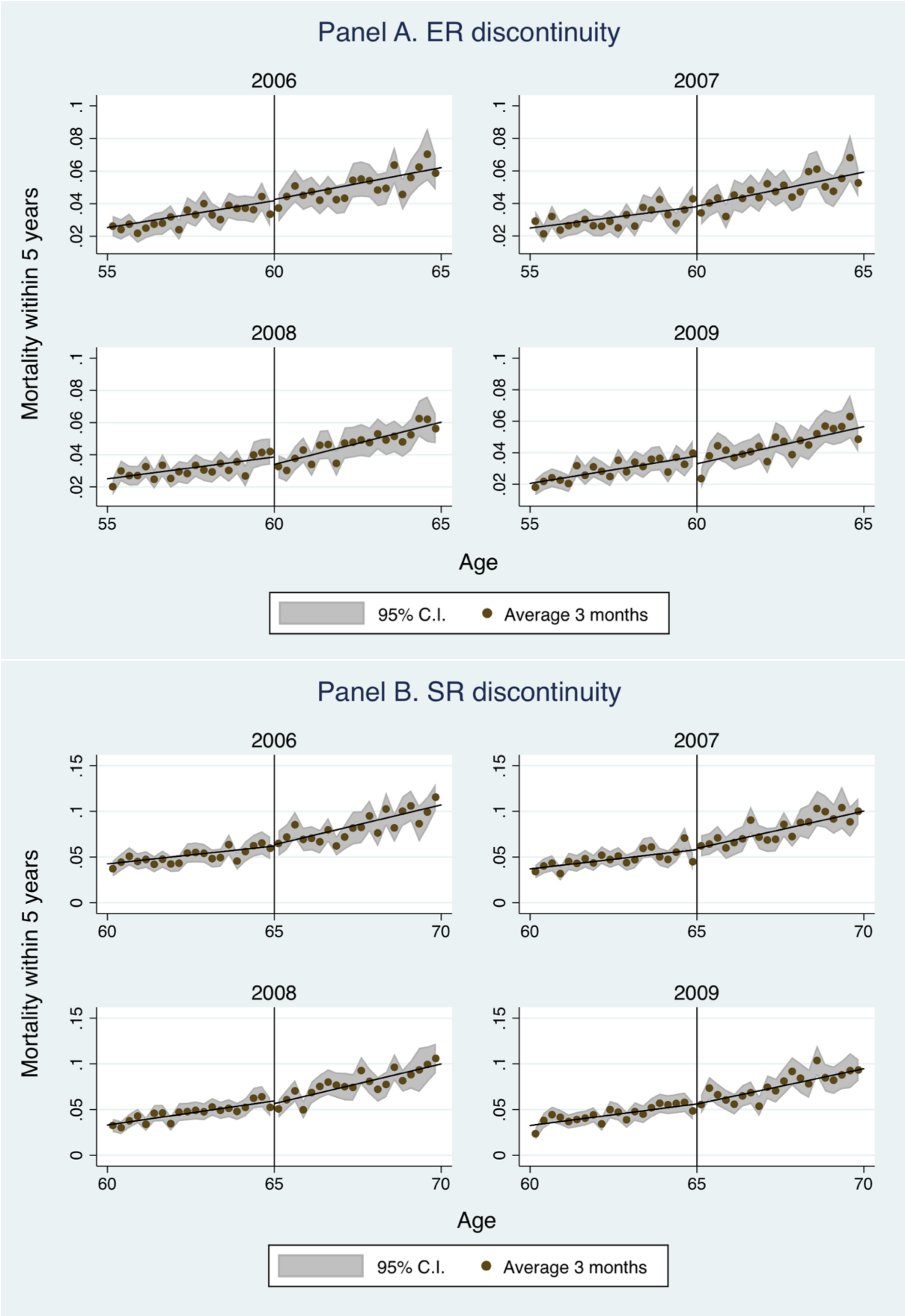
Table A3. Mortality within five years by age

	Total sample			Non-retirees			Retirees		
	%	Individuals	N	%	Individuals	N	%	Individuals	N
By age 56	0.68	1,015	1,018	1.73	554	555	5.03	462	463
By age 57	0.99	1,480	2,113	2.07	854	1,163	5.20	716	950
By age 58	1.32	1,981	3,242	0.00	1,160	1,766	0.01	1,005	1,476
By age 59	1.68	2,527	4,489	0.00	1,490	2,453	0.01	1,299	2,036
By age 60	2.03	3,046	5,757	0.00	1,771	3,112	0.01	1,611	2,645
By age 61	2.40	3,604	7,060	0.00	1,992	3,613	0.01	2,087	3,447
By age 62	2.82	4,225	8,455	0.00	2,236	4,082	0.01	2,572	4,373
By age 63	3.25	4,874	9,919	0.00	2,454	4,514	0.01	3,094	5,405
By age 64	3.66	5,494	11,439	0.00	2,637	4,903	0.01	3,619	6,536
By age 65	4.09	6,142	13,025	0.00	2,747	5,188	0.01	4,241	7,837
By age 66	4.57	6,849	14,680	0.00	2,767	5,233	0.01	5,076	9,447
By age 67	5.06	7,594	16,387	0.00	2,784	5,267	0.01	5,817	11,120
By age 68	5.51	8,261	18,088	0.00	2,794	5,292	0.01	6,478	12,796
By age 69	6.02	9,029	19,855	0.00	2,812	5,317	0.01	7,234	14,538
By age 70	6.58	9,876	21,752	0.00	2,820	5,332	0.01	8,081	16,420

Note: Percentage share (%) in column (1) is calculated based on the total number of individuals in Table 1. Numbers regarding individuals in columns (5) and (8) do not sum up as individuals in column (2) as individuals change their retirement status in different years. Percentage change (%) of columns (5) and (8) are calculated based on the number of total individuals on each group (i.e. non-retirees and retirees). The sample includes all the observations between 55 and 70 years old.

Source: MCVL, own calculations.

Figure A2. Probability of death within five years by age



Note: Shaded areas show 95% confidence interval, dots represent averages over bins of 3 months and the polynomial fit is of order 1. The sample includes all the observations between 55 and 70 years old. And I control for month of birth.

Source: MCVL, own calculation.

Table A4. Baseline covariates test age 60

Variable	Treatment discontinuity	Variable	Treatment discontinuity
Birth region		**Nationality**	
Andalucía	-0.0045 (0.0022)*	*Spain*	0.0001 (0.0002)
Aragón	0.0005 (0.0013)	*Germany*	0.0003 (0.0003)
Catalunya	-0.0015 (0.0015)	*Argentina*	0.0003 (0.0002)
C de Madrid	-0.0009 (0.0013)	*Bulgaria*	-0.0000 (0.0001)
C Valenciana	0.0042 (0.0018)**	*China*	-0.0004 (0.0003)
Galicia	0.0007 (0.0015)	*Colombia*	0.0002 (0.0002)
Castilla y León	-0.0017 (0.0019)	*Cuba*	0.0001 (0.0002)
País Vasco	0.0000 (0.0013)	*Dominican Republic*	0.0001 (0.0004)
Canarias	0.0015 (0.0010)	*Ecuador*	0.0000 (0.0002)
La Rioja	0.0002 (0.0005)	*France*	0.0001 (0.0003)
R de Murcia	0.0013 (0.0009)	*Italy*	-0.0005 (0.0003)
Castilla la Mancha	0.0001 (0.0016)	*Morocco*	0.0001 (0.0002)
Islas Baleares	0.0006 (0.0006)	*Peru*	0.0000 (0.0002)
Extremadura	0.0007 (0.0013)	*Poland*	-0.0001 (0.0003)
P de Asturias	-0.0004 (0.0008)	*United Kingdom*	0.0002 (0.0004)
Navarra	0.0000 (0.0006)	*Romania*	-0.0001 (0.0003)
Cantabria	0.0006 (0.0007)	*Ukraine*	0.0000 (0.0002)
		UE15	0.0001 (0.0002)
Gender		*UE new entries*	-0.0001 (0.0001)
Females	0.0024 (0.0026)	*Other EU countries*	-0.0000 (0.0002)
		Centre and South America	-0.0001 (0.0003)
		Other African countries	-0.0003 (0.0002)*
Educational level		*Other Asian and Pacific countries*	-0.0001 (0.0001)
No education	0.0046 (0.0030)	*Other regions*	0.0000 (0.0001)
Between 1 and 12 years of schooling	-0.0009 (0.0014)	*Bolivia*	0.0002 (0.0002)
More than 12 years of schooling	-0.0017 (0.0014)	*Brazil*	-0.0000 (0.0001)
N	126,043	*N*	126,022
Individuals	60,020	*Individuals*	60,008

* Significant at 10%.
** Significant at 5%.
*** Significant at 1%.

Note: standard errors are in parenthesis and are clustered at individual-level, each estimate comes from a different regression following equation (2) and all identification strategies include a dummy for eligibility age, a linear age trend centred at the threshold, and the chosen bandwidth detailed in Section 6. The sample includes all the observations within the chosen bandwidth.

Source: MCVL, own calculations.

Table A5. Baseline covariates test age 65

Variable	Treatment discontinuity	Variable	Treatment discontinuity
Birth region		**Nationality**	
Andalucía	-0.0084 (0.0026)***	*Spain*	0.0000 (0.0003)
Aragón	0.0014 (0.0014)	*Germany*	0.0002 (0.0002)
Catalunya	0.0039 (0.0017)**	*Argentina*	0.0002 (0.0001)
C de Madrid	0.0012 (0.0015)	*Bulgaria*	0.0001 (0.0000)**
C Valenciana	0.0003 (0.0020)	*China*	-0.0002 (0.0002)
Galicia	0.0004 (0.0017)	*Colombia*	-0.0002 (0.0002)
Castilla y León	0.0025 (0.0023)	*Cuba*	-0.0001 (0.0001)
País Vasco	0.0030 (0.0014)*	*Dominican Republic*	-0.0001 (0.0002)
Canarias	0.0023 (0.0011)**	*Ecuador*	0.0000 (0.0002)
La Rioja	0.0002 (0.0006)	*France*	-0.0002 (0.0003)
R de Murcia	0.0008 (0.0010)	*Italy*	-0.0002 (0.0002)
Castilla la Mancha	-0.0042 (0.0019)**	*Morocco*	-0.0001 (0.0002)
Islas Baleares	0.0008 (0.0006)	*Peru*	-0.0001 (0.0001)
Extremadura	-0.0019 (0.0014)	*Poland*	-0.0002 (0.0002)
P de Asturias	-0.0009 (0.0009)	*United Kingdom*	0.0003 (0.0003)
Navarra	-0.0007 (0.0008)	*Romania*	0.0003 (0.0001)**
Cantabria	0.0001 (0.008)	*Ukraine*	0.0000 (0.0001)
		UE15	0.0000 (0.0002)
Gender		*UE new entries*	0.0001 (0.0001)
Females	-0.0173 (0.0030)***	*Other EU countries*	0.0000 (0.0001)
		Centre and South America	-0.0001 (0.0002)
		Other African countries	0.0001 (0.0001)
Educational level		*Other Asian and Pacific countries*	0.0002 (0.0001)
No education	0.0037 (0.0033)	*Other regions*	0.0002 (0.0001)
Between 1 and 12 years of schooling	0.0005 (0.0015)	*Bolivia*	0.0000 (0.0000)
More than 12 years of schooling	0.0008 (0.0015)	*Brazil*	0.0000 (0.0000)
N	98,093	*N*	98,079
Individuals	46,723	*Individuals*	46,716

* Significant at 10%.
** Significant at 5%.
*** Significant at 1%.

Note: standard errors are in parenthesis and are clustered at individual-level, each estimate comes from a different regression following equation (2) and all identification strategies include a dummy for eligibility age, a linear age trend centred at the threshold and the optimal bandwidth detailed in Section 6. The sample includes all the observations within the chosen bandwidth.

Source: MCVL, own calculations.

Table A6. Heterogenous first-stage estimates

	At age 60	At age 65
Panel A. Baseline results		
Treatment effect	0.069 (0.005)***	0.146 (0.005)***
N (Individuals)	126,043 (85,200)	98,093 (66,183)
Panel B. Gender		
Males	0.071 (0.007)**	0.139 (0.005)**
N (Individuals)	126,043 (85,200)	98,093 (66,183)
Females	0.006 (0.009)***	0.168 (0.010)***
N (Individuals)	40,861 (27,997)	25,192 (17,442)
Panel C. Educational level		
No education	0.060 (0.007)***	0.142 (0.006)***
N (Individuals)	75,737 (52,351)	63,773 (43,817)
Primary education	0.088 (0.010)***	0.145 (0.009)***
N (Individuals)	37,195 (26,239)	25,888 (18,211)
Higher education	0.063 (0.015)***	0.178 (0.019)***
N (Individuals)	13,111 (9,298)	8,432 (5,926)
Panel D. Occupational strain		
Low physical strain	0.059 (0.011)***	0.185 (0.015)***
N (Individuals)	24,314 (17,362)	13,715 (9,793)
Medium physical strain	0.063 (0.009)***	0.153 (0.007)***
N (Individuals)	52,784 (38,930)	45,963 (33,508)
High physical strain	0.090 (0.011)***	0.120 (0.011)***
N (Individuals)	30,275 (22,086)	17,662 (12,888)
Low psychological strain	0.096 (0.017)***	0.146 (0.020)***
N (Individuals)	12,344 (9,442)	6,681 (5,157)
Medium psychological strain	0.031 (0.011)***	0.175 (0.014)***
N (Individuals)	27,845 (20,608)	16,243 (11,890)
High psychological strain	0.080 (0.007)***	0.145 (0.006)***
N (Individuals)	67,184 (48,043)	54,416 (38,935)
Panel E. Nationality		
Only Spanish	0.070 (0.005)***	0.149 (0.047)***
N (Individuals)	122,823 (82,735)	96,909 (65,288)

* Significant at 10%.
** Significant at 5%.
** Significant at 1%.

Note: standard errors are in parenthesis and are clustered at individual-level, each estimate comes from a different regression following equation (1) and all identification strategies include a linear age trend and the optimal bandwidth detailed in Section 6. The sample includes all the observations within the chosen bandwidth. Source: MCVL, own calculations.

Table A7. Robustness check first-stage estimates

	At age 60	At age 65		At age 60	At age 65
Panel A. No controls			**Panel E. Sample selection**		
Treatment effect	0.069 (0.005)***	0.146 (0.005)***	I. Retirement without unemployed	0.056 (0.004)***	0.118 (0.006)***
			N (individuals)	126,043 (85,200)	98,093 (66,183)
Panel B. Covariates					
Gender	0.069 (0.005)***	0.147 (0.005)***	II. RGSS and RESS	0.051 (0.004)***	0.195 (0.004)***
Year	0.069 (0.005)***	0.146 (0.005)***	N (individuals)	190,684 (127,680)	154,537 (103,627)
Nationality	0.068 (0.005)***	0.147 (0.005)***			
Educational level	0.068 (0.005)***	0.146 (0.005)***	**Panel F. Nationality**		
			Only Spanish	0.070 (0.005)***	0.149 (0.047)***
Panel C. Functional form			N (Individuals)	122,823 (82,735)	96,909 (65,288)
Quadratic age trend	-0.310 (0.132)**	0.075 (0.050)			
			Panel G. Other discontinuities		
N	126,043	98,093	Age 57.5	0.004 (0.005)	
Individuals	85,200	66,183	N (individuals)	138,892 (93,902)	
Panel D. Bandwidth choice			Age 62.5	-0.007 (0.006)	
BW 0.9	0.035 (0.008)***	0.089 (0.007)***	N (individuals)	114,360 (76,830)	
N (individuals)	62,849 (62,776)	49,012 (48,948)			
			Age 67.5	-0.001 (0.003)	
BW 3.6	0.104 (0.004)***	0.184 (0.004)***	N (individuals)	81,264 (54,614)	
N (individuals)	246,152 (120,033)	190,174 (91,637)			

* Significant at 10%.
** Significant at 5%.
** Significant at 1%.

Note: standard errors are in parenthesis and are clustered at individual-level, each estimate comes from a different regression following equation (1) and all identification strategies include a linear age trend and the optimal bandwidth detailed in Section 6. The sample includes all the observations within the chosen bandwidth. Source: MCVL, own calculations.