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Abstract

This study examines how knowledge about institutional settings and their reform affects the effectiveness of those reforms. We examine this question in the context of social security, the largest social insurance program in Europe, by exploiting time and cross-country variation in pension regulations in seven European countries. We show that many individuals are not well informed about the pension rules applicable to them and that individuals with lower education and lower numeracy skills fail to update their knowledge when affected by pension reforms. Moreover, the effect of pension reforms on individuals' labour supply decisions is driven by well-informed individuals. This is the first study to separate information gathering from labour supply decision making, thus providing a causal link between the knowledge of pension rules and individuals' labour supply behaviour. Pension policies could potentially be more effective if individuals were adequately informed.

Keywords: Expectations, Retirement age, Pension Reforms, SHARE

JEL Classification: J26, H55

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1 Introduction

When institutional settings are changed, the common assumption is that those affected by the changes are well informed and react accordingly to the new incentives. However, this outcome requires that people affected by the new rules are aware of the change and update their knowledge and related expectations accordingly. The general underlying question is: How does knowledge about institutional settings and their reform affect the effectiveness of those reforms?

We examine this issue empirically in the context of pension reforms and how they affect labour market decisions. Driven by demographic pressure, many countries have reformed their pension systems in recent decades. These reforms changed the rules that apply to individuals and, thus, the incentives for retiring. Standard models of labour supply and retirement assume that individuals decide between working and retiring based on their labour-leisure preferences and the financial incentives embedded in the pension system. The implicit assumption is that decision makers have full knowledge of these incentives, and they will immediately update their information set when a change in pension rules is legislated. But do workers actually have accurate information about pension rules? And how important is workers' knowledge of pension rules in shaping their retirement decisions?

This paper investigates how individuals adjust their expectations about pension eligibility age and their labour market behaviour in response to new pension rules. We exploit the variation in rules regarding the pension eligibility ages that were reformed in many European countries in recent years. More in detail, this study exploits time and cross-country variation in pension regulations by using longitudinal data on pension age expectations and the labour market behaviour of older Europeans. Individual-level survey data is matched with external policy data on pension eligibility ages and their reform. We find that more than half of the individuals in our sample do not know their pension eligibility age, meaning that these individuals do not have the necessary information to correctly quantify their prospective pensions. Furthermore, we estimate that a one-year legislated increase in the pension eligibility age leads individuals to update their expected eligibility age by 2-3 months on average, depending on whether they are eligible for the statutory or early pension. Pension knowledge - or lack thereof - is heterogeneous across different groups of respondents: Individuals with higher education, higher cognitive levels, and ex ante correct beliefs of their pension age update their expectations more when the rules are changed. In a second step, we show that due to this inaccurate knowledge, not all individuals are equally responsive to changes in pension incentives in terms of labour market behaviour. Indeed, we find that our instrumental variable model - where identification stems from individuals who updated their expectations in response to a pension reform - delivers coefficients that are substantially larger than the average effect that we find in a reduced-form model of pension reforms on labour supply. This finding is true for several labour outcomes, including retirement, working hours and expectations about the probability of working past age 63. This finding implies that pension reforms could be more effective in delaying retirement if individuals were better informed about the rules applicable to them.

Calculating prospective pension income is a complicated task. The measures of pension incentives that have been typically used by economists interested in studying older workers' labour supply elasticities involve the trade-off between what could be earned in terms of labour and pension income by postponing retirement and what would be lost in terms of the present value of future pension benefits. These calculations involve knowledge of complex institutional details and expectations about future income and taxation.[1] Things are complicated further if pensions rules change due to reforms. Individuals who are not well informed might fail to adjust to the new setting. Furthermore, continuous changes in pension rules might affect individuals' trust that future governments will stick to the new rules. This, in turn, might affect how individuals form expectations and the extent to which people are informed about new policies.

The lack of information about the rules that apply in a specific setting can have important consequences for expectation formation and related behaviours. In our context, if individuals do not know the pension rules applicable to them, they might mis-estimate the age at which they can draw their pensions or the amount of pension benefits they will receive. As a consequence, they might

[1] Several pathways leading to retirement should be taken into consideration. Examples are retirement through an old-age pension or a pension for individuals with a long contribution history, unemployment and disability. Many details are required to calculate pension incentives for each of these pathways, for instance, eligibility age, number of years of contributions required to be eligible, taxes on pension income and the pension benefit formula defined in the law. The trade-off between retiring or continue working further involves knowledge of the expected income in the case of prolonged work, net of taxes and contributions. Finally, different type of workers might be subject to different rules. See, for example, Coile and Gruber (2000) for details.

fail to adjust their saving behaviour or labour supply decisions. Ultimately, individuals' limited or incorrect knowledge of institutions and their reforms might undermine the policies' effectiveness.[2] Last but not least, misinformation might alter support to critical political decisions.[3]

We examine pension eligibility age expectations and labour market behaviour in Europe based on panel data from the Survey of Health Aging and Retirement in Europe (SHARE). We match the SHARE data with hand-collected policy data on pension reforms. Overall, we have a sample size of around 20,000 individuals within seven countries that experienced at least one pension reform that modifies retirement eligibility ages from 2004 to 2015.[4] Our identification strategy is based on the fact that, due to the timing and scope of the reforms, not all individuals are treated, that is, experience a reform that changes the retirement rules applicable to them. Furthermore, affected individuals are treated at different intensities because pension reforms are usually introduced gradually, mostly based on individuals' birth cohort, and differentiated by gender. More specifically, SHARE respondents are asked at what age they expect to start collecting their pension payments for the first time. We interpret this more generally as knowledge of pension rules because eligibility ages are the most salient element of pension regulations on which the calculation of retirement incentives is based. By comparing changes in eligibility ages according to legislation and changes in expected eligibility ages, we can estimate to what extent individuals adjust their expectations regarding public pension eligibility ages when these are changed exogenously by a pension reform. We can control for individual fixed effects because we observe changes in expectations over time. In a second step, we study how expectations shape actual labour market behaviour based on individuals' labour force status at each point in time.

The econometric challenge of studying how individuals' knowledge of pension rules shapes their labour force participation is reverse causation: well-informed individuals might take certain labour supply decisions in reaction to changes in pension incentives, and workers who wish to retire might

[2]The recent wave of pension reforms in many countries has had the explicit main purpose of increasing the average age at which individuals exit the labour market. While the literature shows that these reforms effectively encourage individuals to delay their retirement, it is unclear to what extent these effects are mitigated by incorrect knowledge of the new pension rules. Indeed, in most OECD countries, the average age of labour force exits is still well below the statutory pension eligibility age (see OECD, 2017).

[3]Fornero and Lo Prete (2019), for instance, show that the probability of an incumbent party becoming reelected after a major pension reform is higher if individuals are financially literate. They take this as evidence that public support for pension reforms is higher if individuals are well informed.

[4]The countries we cover are Austria, Belgium, Denmark, Germany, Italy, the Netherlands, and Spain.

acquire more information about pension rules. Therefore, by regressing labour force participation on a measure of pension knowledge, one would not be able to separate information gathering from labour-supply decision making. Furthermore, pension knowledge might be endogenous to individuals' unobserved characteristics. We solve the identification issue posed by the reverse causation by using the applicable statutory eligibility age as an instrument for the expected eligibility age. To the best of our knowledge, this is the first study that can show the causal link between individuals' pension knowledge and their labour supply decisions.

We contribute to the literature in several ways. First, we speak to the public finance literature that has shown the important role played by information in behavioural responses to financial incentives. Most studies in this literature consist of field experiments that have analysed the effect of an information treatment on outcomes such as, for instance, take-up of social safety net programs like the Supplemental Nutrition Assistance Program (Finkelstein and Notowidigdo, 2019), social benefits such as the Earned Income Tax Credit (Bhargava and Manoli, 2015; Chetty and Saez, 2013; Jones, 2010), indebtedness of cardholders (Seira et al., 2017) and retirement (Liebman and Luttmer, 2015). A smaller literature exploits policy changes, namely the introduction of social security statements, to analyse the effect of information provision on labour supply (Mastrobuoni, 2011), savings (Dolls et al., 2018), and disability insurance application (Armour, 2018). Chetty et al. (2013) use a different approach by proxying for Earned Income Tax Credit knowledge using the fraction of individuals who manipulate reported income to maximise their tax refund in a ZIP Code. These studies find mixed results on the impact of access to information, depending on the outcome, type of information, and population considered (Armour, 2018). Unlike the above-mentioned studies, we have a direct measure of knowledge in the setting of social security, the largest social insurance program in Europe. Moreover, we use yet a different strategy by exploiting pension reforms, which are exogenous to individuals' pension knowledge, as a shock to their information set. This strategy allows us to identify individuals who actually do update their expectations and to directly relate changes in knowledge to labour market behaviour.

The second strand of literature consists of studies that analyse the effects of changes in the financial incentives to retire on labour market behaviour. These works use plausibly exogenous changes to the pension rules to identify the causal behavioural impacts by exploiting the fact that pension reforms often hit individuals that differ in observable characteristics such as birth cohort or gender at different intensities (see, among others, Atalay and Barrett, 2015; Hanel and Riphahn, 2012; Krueger and Pischke, 1992; Lalive and Staubli, 2015; Mastrobuoni, 2009; Staubli and Zweimüller, 2013). These studies identify an average behavioural response in the affected population but do not analyse the heterogeneity of this result to individuals' knowledge of pension reforms. We extend this literature in that respect and show that previous studies that estimated individuals' labour supply elasticities to pension incentives found a lower bound of the true effect.

Finally, we contribute to the literature dealing with financial and pension literacy and its role in economic decisions. Gustman and Steinmeier (2001, 2004) compare measures of knowledge about future social security and pension benefits with their true counterparts and document a general presence of misinformation or lack of information about retirement benefits. A related, limited number of studies document how expectations about future retirement age and replacement rates are updated when individuals are hit by reforms that change eligibility ages or benefit calculations. Most studies find limited expectations revision and substantial heterogeneity, such that the most vulnerable individuals fail to fully revise their expectations (Bottazzi et al., 2006; Coppola and Wilke, 2014; Michaud and Van Soest, 2008), while Okumura and Usui (2014) find for Japan that individuals update their expectation by almost the same amount as the increase in the pensionable age.

A study somewhat closer to ours is Chan and Stevens (2008). In this work, the authors compare individuals' self-report of their pension entitlements with employer reports that represent the true pension values and construct summary measures of individuals' pension knowledge. They show that the labour response to true pension incentives is fully driven by well-informed individuals, while ill-informed individuals only respond to their own incorrect beliefs. However, the authors admit to not being able to disentangle information gathering and pension decisions, meaning that it remains unclear whether there is a causal effect of information on labour supply decisions or, rather, information gathering and retirement decision-making are jointly determined. In contrast, we estimate the causal link between individuals' pension knowledge and retirement decisions.

Our results have important policy implications, especially in times of rapidly ageing societies. We provide evidence that many older individuals in Europe have only a partial understanding of the applicable pension rules. Moreover, the behavioural response to pension reforms in terms of individual labour supply behaviour is driven by well-informed individuals. If everyone were fully informed, recent pension reforms would be more effective in their purpose of delaying individuals' retirement. In that respect, we provide further evidence for the role of financial and pension literacy at the individual and at the macroeconomic level. Furthermore, we believe that our results can be generalised to other public policy domains, especially the tax code, which can be very complicated. Individuals need to be well informed to respond to incentives set within these systems.

The paper is structured as follows. In Section 2, we set the stage of our study by providing an overview of pension systems and pension reforms in Europe. Section 3 presents the survey and policy data and explains how the two are matched. In Section 4, we present our econometric strategy and in Section 5, our results regarding individuals' knowledge and how this knowledge shapes individuals' labour supply responses. Section 6 concludes with a discussion of the policy implications of our results.

2 Pension reforms and identification strategy

Up to the 1990s, pension coverage in many European countries was characterised by both increasing generosity and increasing duration of pension receipt, leading to a sustainability crisis of these systems. Many European governments have therefore reformed their pension systems with the aim of returning to their financial sustainability. These reforms included creating stricter links between contributions and benefits, reducing or completely abolishing early retirement pathways, increasing eligibility ages, and introducing or developing occupational pensions and encouraging private savings for retirement.

A straightforward way to reduce pension expenditure is to decrease the dependency ratio. To reach this goal, many countries increased pension eligibility ages with the aim of keeping individuals in the labour force for longer periods and thus reducing the number of pensioners while increasing the number of contribution payers. Unlike reducing replacement rates that may affect the pension adequacy for retirees, an increase in the eligibility age does not reduce pension income for those who are able to work longer, therefore making it an attractive option for policy makers.

In this study, we focus on pension reforms that increased either the early or the statutory eligibility age or both. We consider pension reforms in Austria, Belgium, Denmark, Germany, Italy, the Netherlands and Spain. Nearly all the countries we consider distinguish between two eligibility concepts: the statutory eligibility age (SEA) and the early eligibility age (EEA). Broadly, the EEA is defined as the age at which early retirement through a social security program is possible, (mostly) with reduced benefits and conditional on a relatively long contribution history, and without being conditioned on health or a specific occupation. SEA is instead the age at which an individual is eligible for full, public, old-age pension benefits. A (often relatively short) contribution history may still be required for claiming benefits.

Table A.1 in the Appendix lists the pension reforms between 2004 and 2015 that we consider in our analysis. All pension reforms considered have in common that they modified either SEA or EEA, as indicated in the last column of Table A.1. While most countries experienced at least one change of both eligibility ages, Austria only made changes to the EEA, and the Netherlands only made changes to the SEA. The table also shows the date when the reforms were announced (i.e. passed into law) and the date when the legislated changes started taking effect. Usually, implementation happens with some lag with respect to the announcement date. People on the verge of retirement are generally unaffected by the reforms, giving individuals time to adjust their expectations and behaviour. Therefore, our treatment definition is based on the announcement date of the reforms, as this is the relevant date to study how individuals' expectations and behaviour change in response to changes in pension rules.

Figures 1 to 4 help visualise the reform elements that are relevant to our analysis. Figures 1 and 2 show the statutory eligibility age of men and women, respectively, by year and for some representative cohorts. Similarly, Figures 3 and 4 show early eligibility ages. Red vertical bars indicate the month and year of (the announcement of) the pension reforms.[5] These figures show the large variability across countries in terms of reform years, eligibility ages and size of the legislated changes.

A common characteristic of most pension reforms is the gradual introduction of changes to eligibility ages, typically depending on the birth cohort. This is clearly displayed in the figures that show how adjacent and otherwise similar cohorts are treated at different intensities. Variation is often also present at the gender level and less frequently at the occupation level. Our analysis exploits the variation between countries, over time, and between birth cohorts, gender and occupational groups to estimate how these reforms affect pension eligibility age expectations and labour market and retirement behaviour. Therefore, in a first step, we estimate the effect of the pension reforms on expectations about pension eligibility age. As common in the literature, we think of pension reforms as exogenous events. Even though they can be anticipated by political and public discussions, the timing and the details of their implementation are uncertain until the new rules are passed into law.

In a second step, we estimate the effect of expectations on labour market behaviour. We will study several labour market outcomes, including retirement decisions. A simple regression of labour supply decisions on pension knowledge would, however, suffer from a reverse causality problem: different knowledge of pension rules might induce systematically different labour supply responses, but at the same time, individuals who are close to retirement might acquire more information on pension rules. This makes the identification of the causal effect of knowledge on behaviour hard to identify. However, pension reforms that modify eligibility ages act as an exogenous shock to the individuals' information set so that their pension knowledge changes due to reasons that are unrelated to individuals' labour preferences. For this reason, we will utilise the statutory eligibility age as an instrument for the expected eligibility age. We will discuss the estimation strategy in detail in Section 4.

[5] Sometimes, a reform is signalled, but no change in eligibility age is displayed. In this case, the reform only affected contribution year requirements.

3 The data

3.1 Survey data

For the empirical analysis, we use data from the Survey of Health, Aging and Retirement in Europe (SHARE)[6] combined with hand-collected data on the pension reforms in the respective countries. SHARE is a longitudinal, cross-national European survey. It includes micro data on health, socioeconomic status, and social and family networks of a representative sample of individuals (and spouses) aged 50 and above. Interviews are conducted approximately every two years. Questions are asked in the native language and follow a generic questionnaire such that they are comparable across countries. Data collection began in 2004, with 12 countries included in the first wave. Data for the seventh wave were collected in 2017 and contain information from all 28 European countries. The third and seventh waves of SHARE, also known as SHARELIFE, are different from the regular panel waves as they focus on retrospective questions about the respondents' childhood and their employment, fertility, marital and health histories. Most of our analyses are based on data from the regular waves, that is, waves 1, 2, 4, 5 and 6, because these surveys include questions about retirement knowledge and current labour market status. Additionally, we make use of the Job Episode Panel, a generated data set that organises the information contained in Wave 3 and 7 of SHARE to provide a retrospective long panel on respondents' labour market status (see Brugiavini et al., 2019)).

Eligibility age expectations. In regular waves of SHARE, all respondents - irrespective of their current labour market status - are asked to which type of pension they will be entitled, if any, from a list of possibilities. They can choose all that apply, under the condition that they are not yet receiving those pensions. The list includes public old-age pension, public early retirement or pre-retirement pension, public disability insurance or sickness/invalidity/incapacity pension, private (occupational) old-age pension, private (occupational) early retirement pension. The categories may differ from country to country due to different institutional frameworks. If respondents claim to be eligible for any of these pensions, they are further asked: *"At what age do you yourself expect to start collecting*

[6] See Börsch-Supan (2017a), Börsch-Supan (2017b), Börsch-Supan (2017c), Börsch-Supan (2017d), Börsch-Supan (2017e), Börsch-Supan (2017f), Börsch-Supan (2017g).

this pension payment for the first time?" Importantly, this question is asked separately for each type of pension. Moreover, it is nicely formulated for our purposes because it focuses on the collection of a specific pension. Thus, it allows us to capture individual's knowledge of the eligibility rules rather than individual preferences about when to stop working. Instead, most other surveys elicit the age at which respondents expect to retire or inquire about the probability to work past a certain age, which might capture a mix of preferences and knowledge.[7] Thus, due to the very specific phrasing of this question, we interpret it as capturing the eligibility age expectations and thus reflecting individuals' knowledge about the pension rules applicable to them.

Labour market outcomes. We analyse the effect of pension knowledge on several labour supply outcomes. SHARE asks respondents to indicate their current employment situation. They can choose between six options: retired, employed or self-employed, unemployed, permanently sick or disabled, homemaker, and other. We construct dummy variables indicating the status of unemployed and disabled based on the answer to this question.

We also analyse the effect of changes in eligibility age expectations on hours of work. SHARE asks respondents how many hours a week they usually work in their job. Based on this question, we construct an indicator variable of part-time work, corresponding to fewer than 30 weekly hours of work. Moreover, we analyse how individuals' expectations about future labour supply change when they update their eligibility age expectations upwards. Specifically, SHARE asks respondents, *"Thinking about your work generally and not just your present job, what are the chances that you will be working full-time after you reach age 63?"* We construct an indicator equal to one if individuals report a probability strictly larger than zero and zero else.[8]

Finally, we analyse how changes in knowledge about eligibility age are related to retirement decisions. To do this, we need exact information on whether individuals retired and when. By combining the information in the regular waves of SHARE and SHARELIFE, we can observe individuals' complete labour market history until the last wave they appear in SHARE. If individuals

[7] For example, a question in the Health and Retirement Study (HRS) asks: *"Thinking about work generally and not just your present job, what do you think are the chances that you will be working full-time after you reach 62/65?"*

[8] Around 35% of the sample report a probability equal to zero.

retire between waves, they are asked to report the retirement year, from which we can derive their retirement age. We use this information to construct six dummy variables indicating whether the individual has retired by age 60, 61, 62, 63, 64 and 65. These variables allow us to construct six models of the probability of retirement before each age in the range of 60 to 65.

Sample selection. We choose countries for which at least two regular waves of SHARE data are available, as we are interested in changes in individuals' eligibility age expectations and labour market behaviour. Among these, we select countries with at least one reform affecting the pension eligibility age during our observation period, leaving us with seven countries: Austria, Belgium, Denmark, Germany, Italy, the Netherlands and Spain.[9] Furthermore, we select individuals who are not older than 63 at the first interview to not have a selected group of individuals with a high taste for work in the sample. Finally, the final sample sizes are determined by the availability of information on individuals' contribution history to match the eligibility ages applicable at each point in time and on their eligibility age expectations.

Our analyses require the definition of two different samples. The first one (Sample A) is used in the analysis of the effect of pension reforms on expected eligibility ages (Section 5.2) and the analysis of the effect of expected eligibility age on labour supply (Section 5.3). The analysis of the effect of expected eligibility age on retirement (Section 5.4) requires a different sample (Sample B) because, by construction, individuals who already receive a pension at the time of the interview do not receive the question about the expected eligibility age. Therefore, the variable 'expected eligibility age' is missing by construction for most retired individuals.[10] Because of this, Sample A includes only individuals who do not receive a public pension yet, while Sample B includes all individuals for whom we can determine retirement status and age at retirement.

As shown in Table 1, Panel (i), Sample A amounts to around 20,000 observations, corresponding to more than 8,000 individuals, observed for a maximum of five waves. The average observation period

[9] We exclude France because we do not have enough information in the SHARE data set to precisely assign the eligibility ages. There are many exceptions to the general pension scheme in France that depend on rather detailed workers' occupation and career characteristics, which we are not able to capture with the information available in the survey.

[10] Notice that receiving a pension and being retired are two different concepts. In Sample A, for example, some individuals define themselves as retired, even though they do not receive a pension within the first-pillar yet. In Table 1, we categorise these individuals as 'out of the labour force', together with homemakers.

is 2.5 waves. Among those who claim to be eligible for a public pension that they are not receiving yet, 56% are women, 79% are married, and they have, on average, around two children. Regarding their labour force status, 78% are employed, 9% are out of the labour force,[11] 7% are unemployed, 6% are permanently sick or disabled. Of those still working, 22% hold a part-time job.

For Sample B, we report in Panel (ii) the percentage of respondents who retired before ages 60 to 65, respectively. The sample size becomes smaller because we need to observe individuals at least until age x to know whether they retired before that same age. As expected, the probability of retirement increases with age.

3.2 Policy data

The crucial policy variable in this study is the age at which an individual becomes eligible to receive a public pension. For this purpose, we supplement the SHARE data with hand-collected data on the reforms of the public pension systems of all the countries included in the analysis between 2004 and 2015. Specifically, we assign the statutory and the early eligibility age applicable to each individual in the SHARE data set at each point in time based on the rules in place. Both SEA and EEA depend first of all on individuals' birth cohort, which represents the crucial variable to link individuals in SHARE with their specific eligibility age. Depending on the rules in each country, additional individual characteristics are used to merge SEA and EEA, specifically gender, years of contributions to the pension system, unemployment spells and work sector classification.[12]

One important variable for the assignment of the eligibility age that deserves more explanation is the indicator for the acquired years of contribution. In particular, the eligibility to an early retirement pathway usually hinges on a minimum number of contribution years. When assessing at what age the contribution requirement is fulfilled, we use the information on the accumulated contribution years at that point in time and add the potential further years of contributions until the respective

[11] Out of the labour force is defined as being either retired and not receiving a public pension or a homemaker.

[12] This was only the case if data collected in SHARE were sufficient to identify these additional requirements. More detailed data on the specific job, such as special cases for substitute periods or the hazardousness of the job, are not available in SHARE and therefore could not be considered. This limitation is only relevant for EEA, as SEA requirements are generally much more straightforward.

eligibility age. For the future contribution periods, we assume that individuals will continue working with no interruptions or unemployment spells until pension eligibility. Because individuals may have imprecise knowledge of the contribution years they paid into the social security system, we run robustness checks where we exclude individuals who declare a number of contribution years that would place them at the threshold between SEA or EEA assignment.[13]

Because eligibility ages are not always full years - especially when reforms increase eligibility ages gradually based on birth cohorts - we measure SEA and EEA in months. Given that we know both the year and the month of birth of SHARE respondents, we can precisely determine when an individual becomes eligible at the monthly level.

Another key aspect of our work is that, when in the presence of pension reforms affecting eligibility rules, we assign the new eligibility ages based on the time of the announcement of the new rules, that is, when the rules become public knowledge, rather than based on the time of their implementation. Indeed, most empirical works ignore the fact that policies are frequently signed into law well before they are implemented. An exception in the context of health care policies is Alpert (2016), who stresses the importance of defining the treatment depending on the announcement date instead of the implementation date to avoid the bias caused by anticipatory effects. In light of this, we define the announcement date as the date when the new rules were officially passed into law. Based on the announcement date and the respondents' interview date, we can precisely assess whether an individual is affected by the pension reform or not at the time of the interview.

4 Econometric strategy

4.1 The effect of reforms on eligibility age expectations

The first step of our analysis consists of estimating the extent to which individuals adjust their expectations regarding their public pension eligibility age when pension reforms change this age. Accordingly, we estimate the following baseline econometric model:

[13] In some countries, the concept of early pension does not exist within the first pillar. This is, for example, the case of the Netherlands, where early retirement is possible only within the occupational scheme.

$$expEA_{i,t} = \alpha_0 + \beta EA_{i,t} + \sum_{j=1}^{3} \beta_j a_{i,t}^j + \delta_t + \mu_i + \epsilon_{i,t} \quad (1)$$

where $expEA_{i,t}$ is individual i's expectation about pension eligibility in year t and $EA_{i,t}$ is the eligibility age of individual i in year t, as established by pension rules in individual i's country. EA will alternatively stand for statutory eligibility age SEA or early eligibility age EEA. Both $expEA_{i,t}$ and $EA_{i,t}$ are measured in months. $a_{i,t}$ is a cubic of age, δ_t is a full set of year dummies, μ_i are individual fixed effects, α_0 is a constant, and $\epsilon_{i,t}$ represents unobservable characteristics of individual i in year t.

EA varies across countries as well as over time due to pension reforms. Time-invariant individual-specific observable (for instance, country and birth cohort) and unobservable characteristics that might be correlated with individuals' eligibility age are absorbed by the individual fixed effects μ_i.[14] Time fixed effects are included to control for unobserved common shocks across countries; this is important given that the data span covers the financial crisis period. Furthermore, controlling for age is important because knowledge of pension rules might improve as workers approach retirement. Therefore, we introduce a cubic of age.[15] Finally, throughout the analysis, we will use cluster-robust standard errors to allow for clustering and heteroskedasticity at the individual level.

It is important to emphasise that we interpret the expected eligibility age as knowledge of pension rules in general, given that the eligibility age is the most salient element of pension regulations. We make this assumption because the calculation of pension benefits and retirement incentives is based on the eligibility ages, in addition, of course, to the specific details of each country's pension formula. If an individual ignores the correct statutory or early eligibility age, there is little hope she will be able to compute other more complicated incentive measures. More in general, the eligibility ages are a measure of the generosity of pension systems, as an increase in eligibility ages correspond to a reduction in pension generosity.

While Model (1) is interesting per se, it also represents the first stage of our instrumental variable

[14] We run a Hausman test to decide between random and fixed effects. We rejected the null hypothesis that individual errors μ_i are not correlated with the regressors; therefore, we chose a fixed effects model.

[15] Results are robust to different functional form specifications of age (results available upon request).

analyses of the effect of reforms on the labour market and retirement behaviour.

4.2 The effect of reforms on the labour market and retirement behaviour

The second step of our analysis consists of estimating how individuals adjust their labour market outcomes and retirement behaviour in response to changes in pension eligibility. Due to the structure of the data, we need two different models - one to study labour market outcomes that precede retirement and the second to study retirement.

The first econometric model is the following:

$$Y_{i,t} = \alpha_0 + \zeta expEA_{i,t} + \eta_1 DP_{c,t} + \eta_2 UP_{c,t} + \sum_{j=1}^{3} \theta_j a^j_{i,t} + \delta_t + \mu_i + \sigma_{i,t} \tag{2}$$

where Y is, alternatively: a dummy indicating individual i's labour force status (unemployed, permanently sick or disabled, working part-time) or a dummy indicating whether the individual has a positive expectation of working past age 63. $expEA_{i,t}$ is individual i's expectation about pension eligibility in year t, measured in months. δ_t is a full set of year dummies; μ_i are individual fixed effects, α_0 is a constant, and $\sigma_{i,t}$ represents unobservable characteristics of individual i in year t.

We are interested in these outcomes because an increase in pension eligibility ages might induce individuals to seek benefits from other social security programs, such as unemployment or disability, that effectively would provide an alternative pathway to retirement.[16] To avoid this sort of program substitution, changes in pension generosity are often accompanied by a tightening of unemployment and disability access rules. Therefore, when analysing the effect of pension changes on unemployment and disability, it is important to control for changes in the generosity of such alternative programs. In the following regressions, we will always control for each country's yearly per-head total expenditure on disability and unemployment programs, $DP_{c,t}$ and $UP_{c,t}$ respectively.[17]

[16] Evidence of this is found, for instance, by Duggan et al. (2007), who showed that a reform that reduced generosity of the social security in the U.S. led to increased enrollment in the social security disability insurance. Similarly, Atalay and Barrett (2015) find that an Australian reform that increased the eligibility age for women in Australia led to increased enrollment in other social insurance programs.

[17] These measures come from the OECD Social and Welfare Statistics data (OECD, 2020), which include internationally comparable statistics on, among others, public and mandatory social expenditure on disability and unemployment programs.

As explained in Section 2, a simple regression of labour supply decisions on pension knowledge would suffer from a reverse causality problem. For this reason, we instrument $expEA$ with the statutory eligibility age EA. We also use a fixed-effects model to control for individual-specific and time-invariant unobserved characteristics that might be correlated with pension knowledge and other observed characteristics. Time fixed effects control for unobserved common shocks. Finally, a cubic polynomial of age controls for age trends in labour supply decisions.

The following assumptions must be fulfilled for the instrumental variable approach to be valid: First, we show a strong effect of pension eligibility rule changes on changes in individuals' expected SEA (see below). We also formally test for relevance of the instrument. In all models we present, the robust Wald F-statistic is above the Stock-Yogo weak identification critical value.

A second identification assumption is that changes in pension knowledge are the only channel through which pension reforms affect individuals' labour supply decisions. This assumption might not hold in the presence of leisure complementarities among spouses. The economic literature is rather inconclusive on this subject, perhaps because different pension systems have different implications on each spouse's incentives to retire.[18] Nevertheless, we run robustness regressions where we include the spouse's work status as a control variable.

A third identification assumption is monotonicity. Failure of this assumption can be safely ruled out, as there appear to be no good reasons why someone who would not update an expectation in case of reform would instead systematically do so in case of no reform.

The coefficient of interest, ζ, represents the effect of an increase in the eligibility age on the labour supply decision of compliers, that is, the individuals who actually update their eligibility age expectations because of pension reforms. The coefficient does not capture the effect on individuals who do not update their expectation when hit by a reform, perhaps because they are uninformed or do not fully comprehend it. Therefore, we expect the effect in the subsample of compliers to be stronger than the effect that we would find in a reduced-form version of the model, where statutory eligibility

[18] For instance, Baker (2002) and Atalay et al. (2019) find evidence of such spillover effects in Canada and Australia, respectively; Stancanelli (2017) finds small spillover effects in France; Selin (2017) finds no evidence of spillover effects in Sweden.

changes enter the model directly, without being funnelled through individuals' expectations. In other words, the labour supply response usually studied in the literature is dampened by individuals who are not fully aware of the pension rules. When only aware individuals are considered, the behavioural response to pension changes is likely larger. We will examine this in the empirical section below.

To analyse the retirement decisions, we need to develop a different econometric strategy. The reason is that retirement is a one-time event, and, by construction, once a respondent retires with a public pension, she is not asked anymore at what age she expects to draw her pension for the first time. Therefore, we create a sample composed of individuals who responded to the expectation question at least two times combined with information on the exact retirement age. We construct a measure of the change in expectations between the first and last time an individual is interviewed about EA expectations. As this change might be endogenous to retirement decisions, we instrument it with the corresponding change of the institutional EA according to the pension reforms. The coefficient of interest measures how a change in expected eligibility age affects the decision to retire before a certain age.

The econometric model to study retirement decisions is the following:

$$\begin{aligned} Y_i = \alpha_0 + \gamma_1 \Delta(expEA)_{i,21} + \gamma_2 expEA_{i,1} + \gamma_3 EA_{i,1} + \gamma_3 age_{i,1} + \gamma_4 age_{i,2} \\ + \gamma_5 coh_i + \gamma_6 X_i + \omega_i \end{aligned} \tag{3}$$

The outcome variable, Y_i, is a dummy indicating whether the individual has retired strictly before each age from 60 to 65, meaning that we will estimate six different models. The variable $\Delta(expEA)_{i,21}$ measures the difference in expected EA between the last time (indexed as 2) and the first time (indexed as 1) the individual responds to the eligibility age expectation question. We include a quadratic polynomial of respondents' age at their first and last interview ($age_{i,1}$ and $age_{i,2}$, respectively). Furthermore, we control for their year of birth (coh_i). By controlling for birth year together with age at the time of the first and last interview, we implicitly control for calendar year at the time of the two interviews.

We cannot include country dummies together with individual's cohort and age at the interview because cohort, year and country explain most of the variation in the EA. Nevertheless, the inclusion of expectations in the first interview, $expEA_{i,1}$, controls for the fact that individuals have heterogeneous initial knowledge, and the inclusion of the EA at the first interview, $EA_{i,1}$, controls for different baseline eligibility ages across countries. Finally, $X_{i,t}$ includes several other controls, such as gender, education, marital status and number of children, because we cannot include individual fixed effects in these models.

For the same reasons explained above, the change in expectations might be endogenous to retirement decisions. Therefore, we instrument $\Delta(expEA)_{i,21}$ with the true change in EA between the last and first interview. In all models shown, the robust Wald F-statistic is above the Stock-Yogo weak identification critical value, indicating the relevance of the instrument.

5 Results

This section provides descriptive evidence on legislated and expected eligibility ages in our sample and on their development across countries and years. Then, we present results on the estimated effect of pension reforms on eligibility age expectations. Finally, we show the effect of changes in expected eligibility age on several labour market outcomes and retirement behaviour. We also describe and perform robustness and sensitivity checks.

5.1 Descriptive evidence

Table 1 shows the average eligibility age in our sample, which amounts to around 765 months (or around 63.8 years). This average, however, masks the variability of SEA across countries and cohorts, which is fundamental to our empirical analysis. Therefore, in Figure 5 and Figure 6, we show, for men and women respectively, the cohort evolution of eligibility ages according to law and of eligibility age expectations by country. The graphs separately depict the evolution of statutory and early eligibility ages.

These figures reveal a few interesting facts. First, the younger the cohort, the higher the eligibility age. This finding is consistent with Figures 1 to 4, which show that the eligibility age increases established by pension reforms are generally implemented gradually, depending on the birth cohort. As expected, the development of individuals' expected eligibility ages follows the development of legislated eligibility ages. However, in some countries - for instance, Denmark and the Netherlands - expectations are almost perfectly aligned with the legislated eligibility ages, while in other countries, expectations are further away from those values. In most cases, on average, individuals underestimate their statutory eligibility age, while the error direction is less clear when it comes to early eligibility ages.

5.2 The effect of reforms on eligibility age expectations

In Table 2, Column 1, we present the results on the effect of changes in EA on individuals' expectations in the full sample, where EA is alternatively SEA or EEA (Model 1). As explained above, we defined the treatment based on the announcement date.[19] Because individuals might respond differently to increases in the early and the statutory eligibility age and because individuals eligible for early retirement might differ systematically from individuals eligible for the statutory pensions, we separately analyse these in Columns 2 and 3, respectively. Individuals who have a very long contribution history and are eligible for early retirement might have started working at earlier ages and thus have a lower education level. At the same time, all other conditions equal, they might have had less-interrupted careers than individuals with a lower number of contribution years.

All eligibility measures are expressed in months; therefore, a 0.175 coefficient (Table 2, Column 1) means that for every month increase in EA, expected EA increases on average by around 5.3 days or, alternatively, for a one-year increase, expected EA increases by around 2.1 months. A one-year increase in SEA leads to a 3.3-month increase in expected SEA (Table 2, Column 2). Instead, a one-year

[19] In unreported results, we show that using the implementation date to define the treatment would lead to coefficients that are smaller in magnitude. This confirms that using the implementation date, as opposed to the announcement date, would lead to biased results and, in our case, to an underestimation of the reforms' effect.

increase in EEA leads to a 2-month increase in expected EEA (Table 2, Column 3).[20] Overall, the adjustment of expectations about pension eligibility age seems to be modest on average.

One potential issue with our data is that individuals' eligibility ages might be non-full years (for instance, 65 years and 6 months, or 786 months), whereas SHARE respondents, due to the design of the survey instrument, can only answer to the expectation question with full rounded years. It is unclear, though, what the direction of their rounding is: whether they systematically round up or down, or rather they round to the closest integer. Therefore, in Table A.2, we check the sensitivity of our results by repeating the analysis with, alternatively, rounded down EA (Column 1), rounded up EA (Column 2), and EA rounded to the nearest integer (Column 3). Results show that the coefficient is barely affected by the assumptions we make on the rounding direction. In Column 4, we restrict the sample to changes in EA equal or bigger than one full year. In this case, we get a sizable and statistically significant coefficient, even though smaller than that of Table 2.[21]

While eligibility age expectations surely reflect incorrect knowledge for individuals who report an expected EA that is lower than the applicable EA according to legislation, some individuals might report an expected eligibility age that is higher than their current and future (reformed) legal eligibility age. This expectation might reflect incorrect knowledge, but it could also reflect preferences or the need for later retirement. For these individuals, the reform is not salient, and a lack of update of expectations in the face of reform does not necessarily imply a lack of knowledge. For this reason, we check the robustness of the results and exclude individuals who report at their first interview an expected EA higher than the reformed EA. Results in Table A.3 show that coefficients of interest are barely affected.

Finally, in Table A.4, we gradually introduce several time-varying control variables to check the robustness of our results to changes in individuals' characteristics that are not absorbed by the fixed effect, such as marital status, health, income decile and wealth decile.[22] Results in Table A.4 show

[20]The reason why the sample in Column 1 is bigger than the sum of the samples of Column 2 and 3 is that we exclude Austria from the SEA sample and the Netherlands from the EEA sample, as there were no corresponding reforms of these eligibility ages in Austria and the Netherlands in the period considered.

[21]Because the result of Column 4, Table A.2, is based on a subsample of the sample used in Table 2, the two results are not strictly comparable.

[22]Health status is self-assessed and measured on a scale from 1 (excellent) to 5 (poor). Income and wealth deciles are country and wave specific.

that our baseline specification is robust to the introduction of these variables.

5.2.1 Heterogeneity analysis

To dig deeper, we study the heterogeneity in the adaptation in eligibility age expectations across different groups. First, we split the sample by high and low educated individuals. Individuals with an education level above the median ISCED category level are considered highly educated, and vice versa.[23] The median is calculated at the country and cohort level. Table 3, Columns 1 and 2, shows that the changes in eligibility age expectations are stronger for highly educated individuals. While less well-educated individuals adjust their expectations by 1.8 months for every year increase in the legal eligibility age, the adjustment is 2.4 months for highly educated individuals. The difference between the two coefficients is not statistically significant. If, however, we compare the bottom and top education terciles, we find a 9-percentage point higher adjustment for the top tercile, and the difference among the two coefficients is statistically significant at the 5% level.[24] Next, we construct a variable indicating an expectation error. By expectation error, we mean the difference in the legislated eligibility age and the expected eligibility age at the first interview; we interpret this as individuals' baseline knowledge level. We split individuals based on whether they reported the correct eligibility age applicable to them (Column 3) or not (Column 4) in the first interview. Individuals who are well informed about their pension age at the time of the first interview are very responsive to changes in the legislated eligibility ages - they increase their expectation by 5.4 months for every year increase in the eligibility age. In contrast to this, individuals who report an expected eligibility age that does not correspond to the legislation in place are largely unresponsive to changes in the pension rules - they only adjust their expectation by 0.8 months. The two coefficients are statistically different at the 1% level.

Finally, we study the heterogeneity of the result with respect to several cognitive measures. In SHARE, cognitive status is measured using simple tests of memory, verbal fluency, and numeracy

[23] The education definition is based on the International Standard Classification of Education (ISCED) 1997 categories to have comparability across countries.

[24] Unreported results, available upon request.

that are comparable with similar tests implemented in the Health and Retirement Study (HRS) and the English Longitudinal Study of Ageing (ELSA). These tests follow a protocol aimed at minimising the potential influences of the interviewer and the interview process.

The test of memory consists of verbal registration and recall of a list of 10 words. The respondent hears the complete list only once, and the test is carried out twice, immediately after the encoding phase (immediate recall) and at the end of the cognitive function module (delayed recall). The total scores of both tests correspond to the number of words that the respondent recalls. We make use of the delayed recall, as it shows more variability in the data. The test of verbal fluency consists of counting how many distinct elements from a particular category (real or mythical members of the animal kingdom) the respondent can name in a one-minute interval. Finally, the test of numeracy consists of a few questions involving simple arithmetical calculations based on real-life situations. Respondents who correctly answer the first question are asked a more difficult one, while those who make a mistake are asked an easier one, and the resulting total score ranges from 0 to 4.

Our results are presented in Table 4, where we split the sample according to the median of each cognitive measure, with values above the median indicating higher cognitive levels.[25] The median is defined at the country and cohort level to avoid the risk that some countries or cohorts are all clustered above or below the median.

We can observe that for all three cognition measures, the direction of the effect is as expected: individuals with higher cognition levels adjust their expectations more than individuals with lower cognition levels. Only the comparison of individuals with lower and higher numeracy (Columns 1 and 2) returns a statistically significant difference in the coefficients (at the 5% level). This result is not surprising, given the strong correlation between education and numeracy.

Based on these results, we cannot confirm the findings of Gustman et al. (2012), who sought to determine whether knowledge of pensions and Social Security plays an intermediary role in linking numeracy to wealth. The authors, using HRS data, find that numeracy and other measures of cognition (similar or equal to the one used in this study) are not significant determinants of

[25] As recall and verbal fluency are asked at each interview and might possibly be affected by retirement, we fix them at their first interview value.

knowledge of pensions and Social Security. In our setting, where we study the extent to which individuals update their knowledge in the wake of pension reforms, we do find an important role for education and numeracy. Individuals with higher education and numeracy levels and those with ex ante better knowledge of the pension rules applicable to them are more likely to adjust eligibility age expectations upwards after a pension reform that affected them.

5.3 The effect of expected eligibility age on labour supply

In the previous subsection, we have shown that individuals display only partial adjustment of expectations to new pension rules. The extent of the adjustment displays substantial heterogeneity across certain groups of individuals. If some individuals do not or only partially update their expectations because they do not know about pension reforms or do not understand how they will personally be affected, they will not respond to pension changes in the way that economic theory would predict. Therefore, we are interested in investigating how labour supply responses depend on the level of individual pension knowledge.

We first analyse the effect of changes in eligibility age expectations on unemployment and disability. Second, we analyse the effect of changes in pension knowledge on hours of work, using an indicator variable for part-time work. In this analysis, we include only employed individuals to capture only the effect at the intensive margin on working hours. Finally, we analyse how individuals' expectations about the probability of working past age 63 change when they update their eligibility expectations upwards (see Section 3.1 for the variable description).

Our results are displayed in Table 5 for both genders and separately by gender in Table 6. In Table 5, we first show results for the full sample (Panel *(i)*), then separately for the sample of individuals eligible for the statutory pension (Panel *(ii)*) and for the early pension (Panel *(iii)*).

Overall, we observe in the full sample that a one month increase in expected EA leads to a reduction of 0.5 percentage points (pps), or -2.7%, in the probability of working part-time, and a 1.2pps, or 1.8%, increase in the probability of reporting a positive likelihood of working past age 63.[26]

[26]Because this question is asked only to individuals younger than 61 and was not asked in wave 1 and only to baseline interviews in wave 6, the sample size is considerably smaller.

We do not find any significant effect of increases in the expected eligibility age on unemployment or disability.

The picture changes slightly depending on whether we analyse individuals eligible for statutory or early pension. On the one hand (Panel *(ii)*), we find a 0.2pps increase in the probability of being unemployed. On the other hand, we observe a 0.6pps decrease in the probability of being unemployed for those eligible for early pension (Panel *(iii)*). Thus, while individuals seem to use unemployment as a route to retirement in the case of an increase in the statutory eligibility age, the opposite seems to be the case for increases in the early eligibility age. This might indicate that individuals who were using unemployment as a route to early retirement are surprised by the increase in early eligibility age and are thus forced out of unemployment when unemployment benefits are exhausted.

The analysis by gender also reveals some interesting facts. In particular, the effect on working hours appears to be completely driven by women, who may compensate for the reduction in social security wealth by working more at the intensive margin. Additionally, while we do not find an increase in unemployment in the full sample, there is a significant increase among women and no effect among men.

Because the exclusion restriction might not hold in the presence of leisure complementarities between spouses, we run a robustness check (Table A.5 in the Appendix) where we include the work status of the spouse as a control variable for the subsample of married individuals. When compared to the baseline results for the subsample of married individuals, results remain largely unchanged. Finally, in Table A.6, we test the robustness of our results to assigned eligibility age by excluding observations of individuals who declare a number of contribution years that would place them at the threshold between SEA or EEA assignment. In particular, we exclude individuals whose potential SEA and EEA are within 12 months from each other in absolute value. We find that our results are robust to the assigned eligibility age.[27]

As explained above, by estimating a local average treatment effect (LATE), these results represent

[27] An example will clarify this exercise. Suppose an individual declares a number of contribution years such that, if she continues to work, she will be able to draw her pension at the early eligibility age of 64, while the statutory eligibility age is 65. As 64 and 65 are within 12 months distance, we exclude this individual from the robustness analysis.

the labour response to pension reforms among the compliers, that is, individuals who updated their eligibility age expectations because of pension reforms. In Table A.7 in the appendix, we use EA in the main regression (reduced from estimates). Interestingly, all coefficients are smaller - in some cases even of one order of magnitude - than in the IV regression. Thus, the average effect of pension reforms on labour market outcomes is smaller than the effect among those who are informed about how the new rules apply to them.

While we cannot exactly say what the labour supply response of individuals who are uninformed about pension reforms would be if they were well-informed about such reforms (unless we assume a constant causal effect), we can nevertheless conclude that reduced-form models of retirement produce an estimate of the labour supply response in the population that is an average response of informed and uninformed individuals. If everyone were correctly updating their expectations, the estimated labour supply response in the reduced form would most likely be larger.

5.4 The effect of eligibility age expectations on retirement decisions

Our results on early retirement are displayed in Table 7. Here we show the probability of being retired (strictly) before each age included in the age range 60 to 65.[28] We do not find any statistically significant effect for the probability of retiring before age 60 (Column 1). At the same time, we find that an increase in expectations of one month has a statistically significant effect on the probability of retiring before each age between 61 and 65 (Columns 2 to 6), of -0.5, -0.6, -0.7, -1.2 and -1.2 pps, respectively. This outcome amounts to a reduction in the probability of retirement before the respective ages of 2.4%, 2.1%, 1.9%, 2.6% and 2.5%, for every one-month increase in expectations.

In Tables 8 and 9, we separately look at men and women. Overall, we find that women are much more responsive to pension reforms than men. While the reduction for men reaches 1.6% in terms of the probability of retiring before age 61, women experience up to a 4% reduction in the probability of retiring before age 64.

[28] Because we can only study retirement before a certain age if we observe the individual at least until that age, in each model, we restrict the sample to individuals who were older than the respective age when observed for the last time. This explains the shrinking sample size from Column 1 to Column 6 of Table 7.

We perform a series of robustness checks similar to the previous sections. In Table A.8, we include the work status of the spouse at the first and last interview as a control variable for the subsample of married individuals. Again, when compared to the baseline results for the subsample of married individuals, results remain largely unchanged. In Table A.9, we exclude observations of individuals who declare a number of contribution years that would place them at the threshold between SEA or EEA assignment from the sample. Results are robust to the assigned eligibility age.[29]

Finally, as in the previous section, we compare the IV results with those obtained from a reduced-form regression model. These are displayed in Table A.10 in the appendix. Consistent with what we have shown in the previous section, the estimated effects in the reduced-form models are up to one order of magnitude lower than in the IV case. Thus, a change in the eligibility age on the labour force participation is much smaller on average than when estimating the effect among those individuals who are well informed about the new rules.

As a final step, we would like to propose a thought experiment about what would happen to labour market outcomes if everyone were well informed about the new pension rules and adjusted expected eligibility ages and labour market behaviour accordingly. As shown above, the change in the probability of retirement before age 65 amounts to 0.186 pps in the reduced-form model and 1.2 pps in the IV model. Furthermore, the observed average probability of retirement before age 65 in our sample is 47.73%. Given that the average increase in the pension eligibility age in our sample is about 9.95 months, we can obtain the counterfactual probability of retirement before age 65 in case of no reforms, which amounts to 49.58%. If we are willing to assume a constant causal effect, we can also derive the probability of retirement before age 65 if everyone correctly updated their expectations. This amounts to a probability of 37.64%, that is, a probability 10.09 pps (or 21%) lower than the corresponding observed probability (47.73%).

As seen in Section 5.2.1, however, individuals who do not adjust their expectations are different in observable characteristics from individuals who update their expectations. They have lower education, lower cognitive abilities, and are less well informed about their pension age even before

[29]In unreported results, we also exclude from the sample one country at a time to check the robustness of the results to country exclusion, and we find that no single country seems to be driving the results.

the reforms. They might differ in other, unobservable characteristics. Therefore, it is hard to infer what the labour market response of those individuals would be if they were well informed. Nevertheless, at the very least, our results document that a considerable number of individuals are not making an informed choice when making plans for their retirement. This can be detrimental if the labour market and saving choices turn out to be sub-optimal and there is not sufficient time to make adjustments.

6 Discussion and conclusion

Based on data from seven European countries, we show that many individuals are not well informed about the pension rules that apply to them. After pension reforms, not all individuals update their expectations about their prospective pension eligibility age. In particular, those with lower education, lower numeracy and less ex-ante knowledge of the pension rules update their beliefs less.

Moreover, individuals who update their pension expectations more are more likely to adjust their labour market behaviour. Specifically, we see evidence of later labour market exit, an increase in the probability of working full-time, and some program substitution, namely an increase in the likelihood of claiming unemployment benefits. All margins we observe are stronger for women than for men.

Accordingly, we show that reduced-form estimations of pension rules on retirement behaviour significantly underestimate labour supply elasticity because only knowledgeable individuals react to the reforms. On the contrary, individuals with wrong expectations are responsive to their perceived incentives - as measured by expected pension eligibility age - rather than to actual retirement incentives. In this respect, our results are consistent with Chan and Stevens (2008), with the important difference that we can causally identify the relationship between knowledge and labour market behaviour.

Importantly, we show that the individuals who fail to update their expectations about eligibility ages are potentially the most financially fragile because low education and low cognitive abilities are also often associated with less financial resources (Banks, 2010; Christelis et al., 2010). For these individuals, lack of information about pension regulations and their reform, and the resulting ill-informed labour supply decisions, might be especially detrimental. The crucial policy consequence is that lack of information or incomplete understanding of pension policies might undermine their effectiveness and have undesired effects.

The solution to this might not be straightforward, though. Informing individuals about the pension rules that apply to them might be a cost-effective policy to help people plan for their retirement and make appropriate choices. However, the literature that has studied the effects of giving information treatments to individuals, or the recent introduction of pension letters in a few countries, has not reached an agreement on the effectiveness of such information policies. More research is needed about how to successfully convey this type of information.

Figures 5 and 6 show that in some countries, individuals appear much better informed than in other countries. Several reasons might explain these patterns. Some countries have experienced many pension reforms in the last decades, which might have increased uncertainty about the pension rules. Furthermore, continuous policy changes might decrease trust that future governments will stick to the new rules, which in turn might affect individuals' expectations formation and the extent to which people keep informed about new policies. Furthermore, some countries have much more complicated pension rules and offer several potential pathways to exit the labour force. Finally, the extent to which governments inform their citizens varies considerably by country. In the time span considered in this analysis, Denmark, France, Germany and the Netherlands already provided online or offline pension statements with individual-specific information about eligibility age, contributions made, predicted pension benefits under different scenarios, and so on, depending on the country considered. On the contrary, Italy started providing individual pension information only in 2016, and Spain does not yet offer this type of information. While explaining these country differences in pension knowledge has not been the purpose of this study, it would be an interesting avenue for future research.

Table 1: Descriptive statistics

Variable	**Mean**	**Std. Dev.**	**Min.**	**Max.**	**N**
Age	56.01	4.08	39	70	20609
Female	0.54	0.5	0	1	20609
Working	0.78	0.41	0	1	20312
Out of the labour force	0.09	0.29	0	1	20312
Unemployed	0.07	0.25	0	1	20312
Permanently sick or disabled	0.06	0.24	0	1	20312
Part-time job	0.22	0.41	0	1	16605
Married	0.79	0.41	0	1	20590
Number of children	2.04	1.22	0	12	20599
Exp. EA (months)	768.86	32.18	600	900	20609
EA (months)	765.19	29.31	638	986	20609

Notes: This table shows the mean, standard deviation, maximum and minimum values, and number of observations for a selection of variables, computed on a sample that includes seven European countries (Austria, Belgium, Denmark, Germany, Italy, the Netherlands and Spain), over the period 2004-2015.

Table 2: Expectations adjustment

VARIABLES	(1) Exp. EA	(2) Exp. SEA	(3) Exp. EEA
EA	0.175***		
	(0.0169)		
SEA		0.271***	
		(0.0392)	
EEA			0.170***
			(0.0316)
Observations	20,609	9,861	8,304
R^2	0.086	0.141	0.062
Number of panels	8,289	3,933	3,481
IND FE	YES	YES	YES
YEAR FE	YES	YES	YES
AGE	YES	YES	YES

Notes: This table reports results from Model (1). In Column (1), regression is on the full sample, and the outcome variable eligibility age (EA) is either the statutory eligibility age (SEA) or the early eligibility age (EEA). In Column (2), the regression is on the subsample of those eligible at the statutory age; the outcome variable is SEA. In Column (3), the regression is on the subsample of those eligible at the early age, and the outcome variable is EEA. Austria is excluded from the SEA sample and the Netherlands from the EEA sample. Regressions include individual fixed effects, year dummies and a cubic of age. Standard errors are clustered at the individual level and are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 3: Heterogeneity over education and baseline pension knowledge

VARIABLES	(1) Education Low	(2) Education High	(3) Expectation error err=0	(4) Expectation error $\|err\| > 0$
EA	0.152***	0.204***	0.449***	0.0652***
	(0.0230)	(0.0259)	(0.0247)	(0.0217)
Observations	12,720	7,586	9,266	11,343
R^2	0.079	0.100	0.225	0.057
Number of panels	5,140	3,027	3,591	4,698
IND FE	YES	YES	YES	YES
YEAR FE	YES	YES	YES	YES
AGE	YES	YES	YES	YES

Notes: This table reports results from Model (1). The outcome variable is expected EA (eligibility age). The sample is split by low and high education (Columns (1) and (2)), defined as an education level below or above the country-cohort median education level, respectively, and by ex ante beliefs (Columns (3) and (4)), defined as the difference between expected EA and EA in the first observation year. Regressions include individual fixed effects, year dummies and a cubic of age. Standard errors are clustered at the individual level and are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 4: Heterogeneity over cognitive levels

VARIABLES	(1) Numeracy Low	(2) Numeracy High	(3) Verbal fluency Low	(4) Verbal fluency High	(5) Words recall Low	(6) Words recall High
EA	0.145***	0.233***	0.151***	0.196***	0.169***	0.181***
	(0.0203)	(0.0321)	(0.0252)	(0.0234)	(0.0240)	(0.0238)
Observations	13,416	6,295	9,873	10,067	12,054	7,949
R^2	0.081	0.093	0.081	0.094	0.079	0.100
Number of panels	5,439	2,528	3,984	4,025	4,839	3,197
IND FE	YES	YES	YES	YES	YES	YES
YEAR FE	YES	YES	YES	YES	YES	YES
AGE	YES	YES	YES	YES	YES	YES

Notes: This table reports results from Model (1). The outcome variable is expected EA (eligibility age). The sample is split by different cognitive levels: low and high numeracy (Columns (1) and (2)); low and high verbal fluency (Columns (3) and (4)); low and high words recall (Columns (5) and (6)). Low (high) cognition is defined as having received a score below (above) the corresponding median country-cohort test score. Regressions include individual fixed effects, year dummies and a cubic of age. Standard errors are clustered at the individual level and are reported in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 5: Labour force status, IV regression

VARIABLES	(1) Unemployed	(2) Permanently sick or disabled	(3) Part-time 30	(4) High probability of working after 63
	(i) Full sample			
Exp. EA	0.000548	0.000117	-0.00499**	0.0120***
	(0.000868)	(0.000498)	(0.00203)	(0.00419)
Observations	17,881	17,881	10,514	4,206
Number of panels	7,238	7,238	4,311	2,098
	(ii) Eligible to statutory age			
Exp. SEA	0.00223*	-0.000727	-0.00696**	0.0124**
	(0.00130)	(0.000504)	(0.00352)	(0.00572)
Observations	8,173	8,173	5,130	1,888
Number of panels	3,274	3,274	2,055	943
	(iii) Eligible to early age			
Exp. EEA	-0.00634***	0.00140	-0.00644	0.0216
	(0.00243)	(0.00129)	(0.00494)	(0.0143)
Observations	7,599	7,599	4,125	1,515
Number of panels	3,200	3,200	1,790	754
IND FE	YES	YES	YES	YES
YEAR FE	YES	YES	YES	YES
AGE	YES	YES	YES	YES

Notes: This table reports results from Model (2). The outcome variables in Columns (1) and (2) are indicators of individuals' unemployment and disability status. The outcome variable in Column (3) is a dummy equal to 1 if the individual holds a part-time job. The outcome variable in Column (4) is a dummy equal to 1 if the individual reports a chance of working past age 63 strictly larger than zero, based on the question: *"Thinking about your work generally and not just your present job, what are the chances that you will be working full-time after you reach age 63?"* Regressions include individual fixed effects, year dummies and a cubic of age. Standard errors are clustered at the individual level and are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 6: Labour force status by gender, IV regression

VARIABLES	(1) Unemployed	(2) Permanently sick or disabled	(3) Part-time 30	(4) High probability of working after 63
	(i) Full sample, men			
Exp. EA	-0.00147	-1.12e-05	-0.00281	0.0112*
	(0.00134)	(0.000736)	(0.00178)	(0.00626)
Observations	8,677	8,677	5,036	1,963
Number of panels	3,532	3,532	2,077	980
	(ii) Full sample, women			
Exp. EA	0.00249*	0.000201	-0.00677*	0.0126**
	(0.00128)	(0.000689)	(0.00368)	(0.00549)
Observations	9,204	9,204	5,478	2,243
Number of panels	3,706	3,706	2,234	1,118
IND FE	YES	YES	YES	YES
YEAR FE	YES	YES	YES	YES
AGE	YES	YES	YES	YES

Notes: This table reports results from Model (2). The outcome variables in Columns (1) and (2) are indicators of individuals' unemployment and disability status. The outcome variable in Column (3) is a dummy equal to 1 if the individual holds a part-time job. The outcome variable in Column (4) is a dummy equal to 1 if the individual reports a chance of working past age 63 strictly larger than zero, based on the question: *"Thinking about your work generally and not just your present job, what are the chances that you will be working full-time after you reach age 63?"* Regressions include individual fixed effects, year dummies and a cubic of age. Standard errors are clustered at the individual level and are reported in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 7: Retirement probability, IV regression

VARIABLES	(1) Retired before 60	(2) Retired before 61	(3) Retired before 62	(4) Retired before 63	(5) Retired before 64	(6) Retired before 65
Exp. EA change	-9.34e-05	-0.00515***	-0.00587***	-0.00699***	-0.0116***	-0.0120***
	(0.000801)	(0.00104)	(0.00133)	(0.00180)	(0.00275)	(0.00313)
Observations	5,272	4,638	4,096	3,551	3,029	2,535
AGE	YES	YES	YES	YES	YES	YES
BIRTH COHORT	YES	YES	YES	YES	YES	YES
CONTROL VARIABLES	YES	YES	YES	YES	YES	YES

Notes: This table reports results from Model (3). The outcome variables are dummies indicating whether the individual has retired strictly before each age from 60 (Column (1)) to 65 (Column (6)). Regressions include birth cohort, a quadratic of age at first and last interview, gender, education, marital status and number of children. Robust standard errors are reported in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 8: Retirement probability, IV regression, males

VARIABLES	(1) Retired before 60	(2) Retired before 61	(3) Retired before 62	(4) Retired before 63	(5) Retired before 64	(6) Retired before 65
Exp. EA change	0.00118	-0.00321**	-0.00374**	-0.00429*	-0.00576**	-0.00690**
	(0.00134)	(0.00157)	(0.00181)	(0.00237)	(0.00289)	(0.00337)
Observations	2,632	2,317	2,062	1,787	1,532	1,287
AGE	YES	YES	YES	YES	YES	YES
BIRTH COHORT	YES	YES	YES	YES	YES	YES
CONTROL VARIABLES	YES	YES	YES	YES	YES	YES

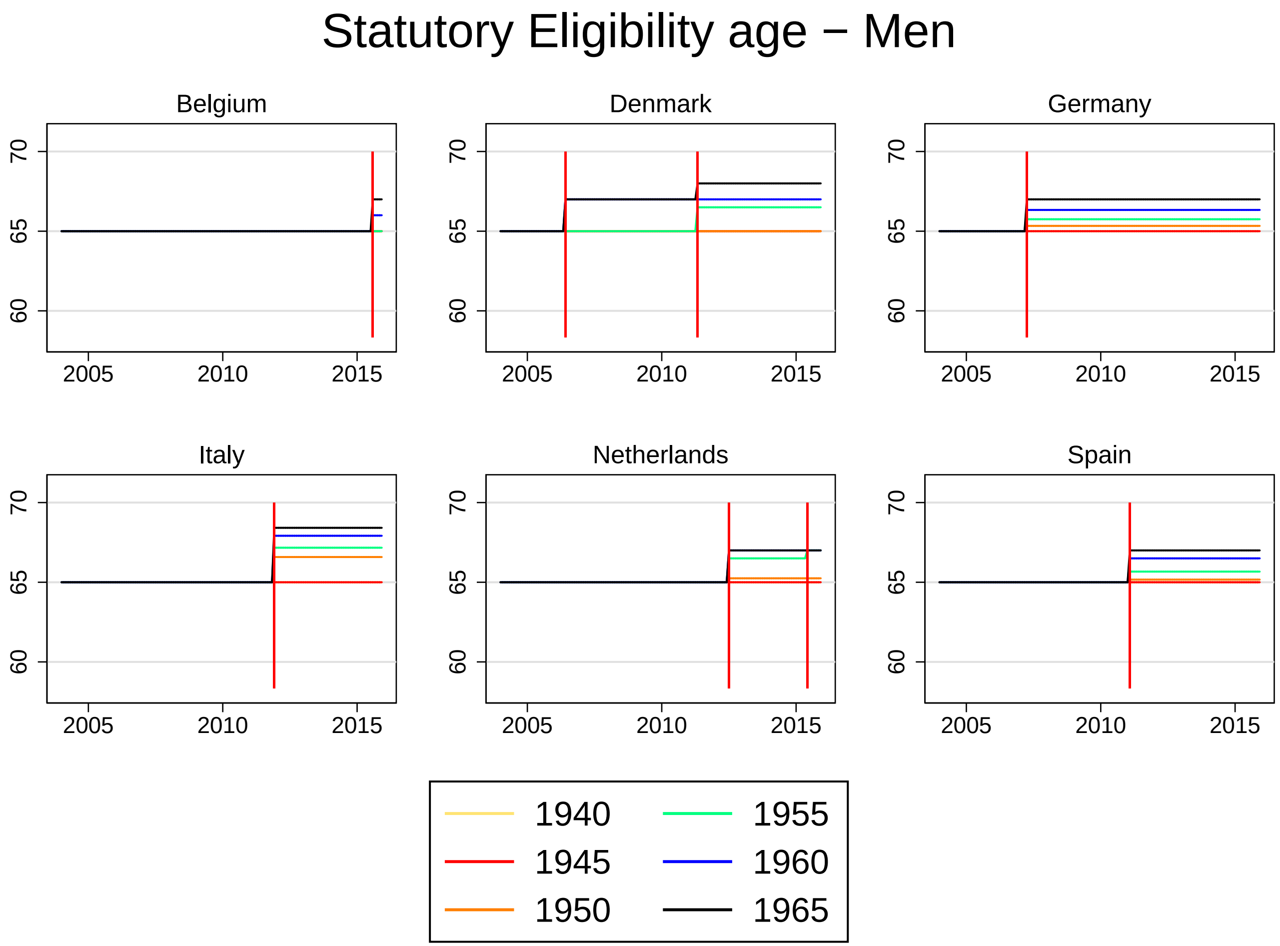
Notes: This table reports results from Model (3). The outcome variables are dummies indicating whether the individual has retired strictly before each age from 60 (Column (1)) to 65 (Column (6)). Regressions include birth cohort, a quadratic of age at first and last interview, gender, education, marital status and number of children. Robust standard errors are reported in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 9: Retirement probability, IV regression, females

VARIABLES	(1) Retired before 60	(2) Retired before 61	(3) Retired before 62	(4) Retired before 63	(5) Retired before 64	(6) Retired before 65
Exp. EA change	-0.00112	-0.00666***	-0.00754***	-0.00952***	-0.0176***	-0.0185***
	(0.000875)	(0.00132)	(0.00192)	(0.00283)	(0.00552)	(0.00618)
Observations	2,640	2,321	2,034	1,764	1,497	1,248
AGE	YES	YES	YES	YES	YES	YES
BIRTH COHORT	YES	YES	YES	YES	YES	YES
CONTROL VARIABLES	YES	YES	YES	YES	YES	YES

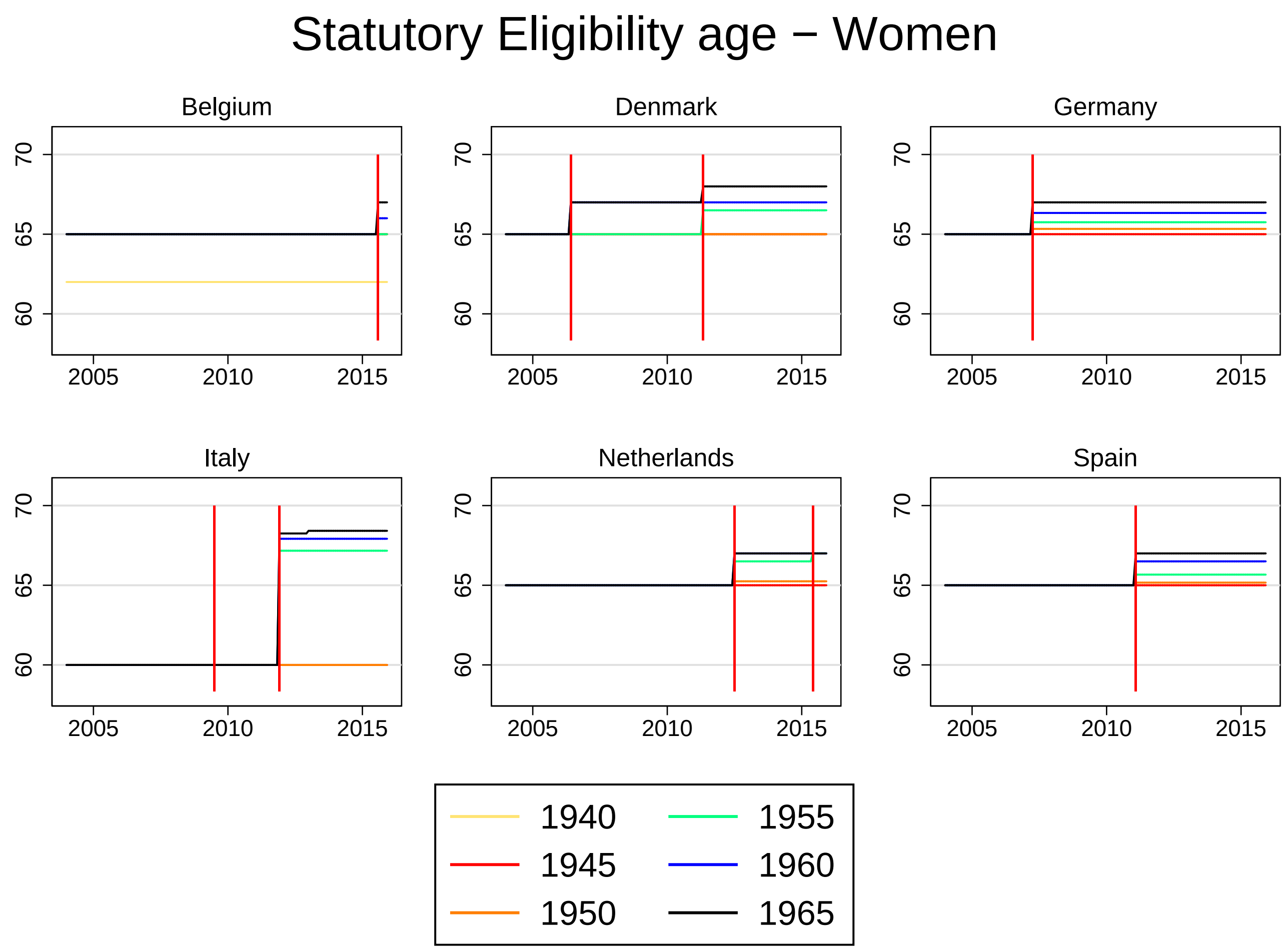
Notes: This table reports results from Model (3). The outcome variables are dummies indicating whether the individual has retired strictly before each age from 60 (Column (1)) to 65 (Column (6)). Regressions include birth cohort, a quadratic of age at first and last interview, gender, education, marital status and number of children. Robust standard errors are reported in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Figure 1: Statutory eligibility age by year and cohort, men



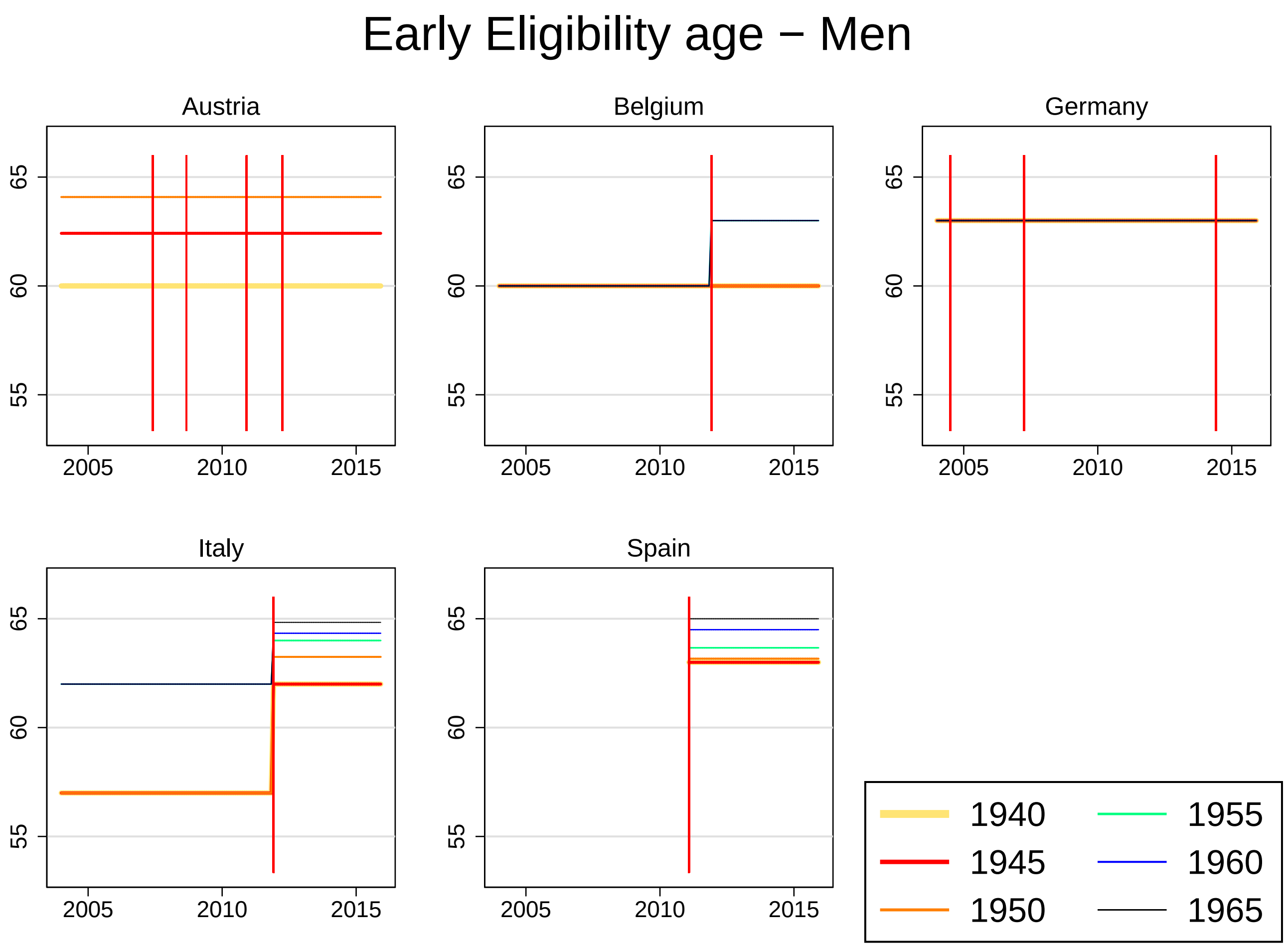
Notes: This graph shows, for each country, the development by year (X-axis) of men's statutory eligibility age (Y-axis), for selected cohorts. Red vertical lines indicate reform years.

Figure 2: Statutory eligibility age by year and cohort, women



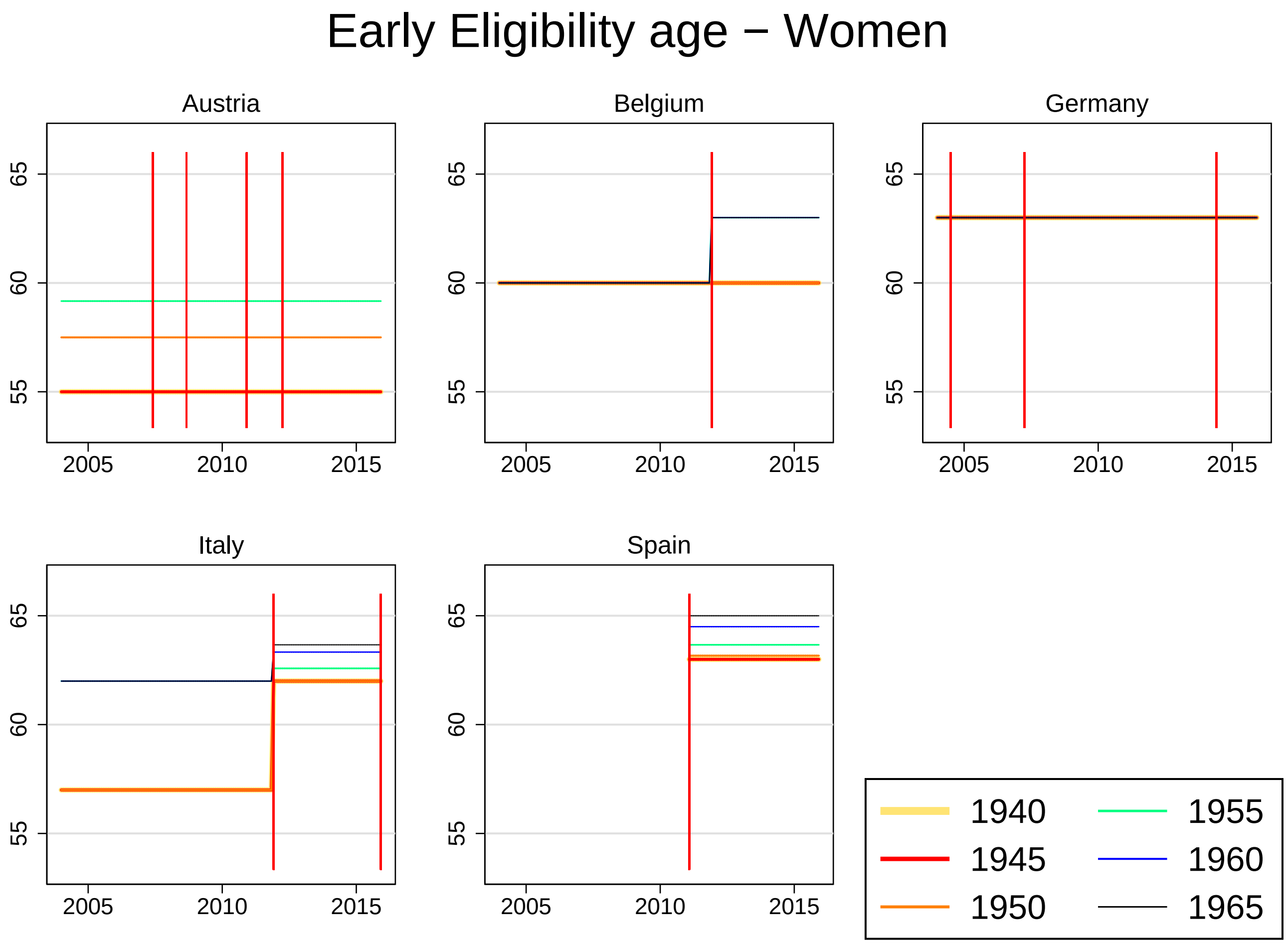
Notes: This graph shows, for each country, the development by year (X-axis) of women's statutory eligibility age (Y-axis), for selected cohorts. Red vertical lines indicate reform years.

Figure 3: Early eligibility age by year and cohort, men



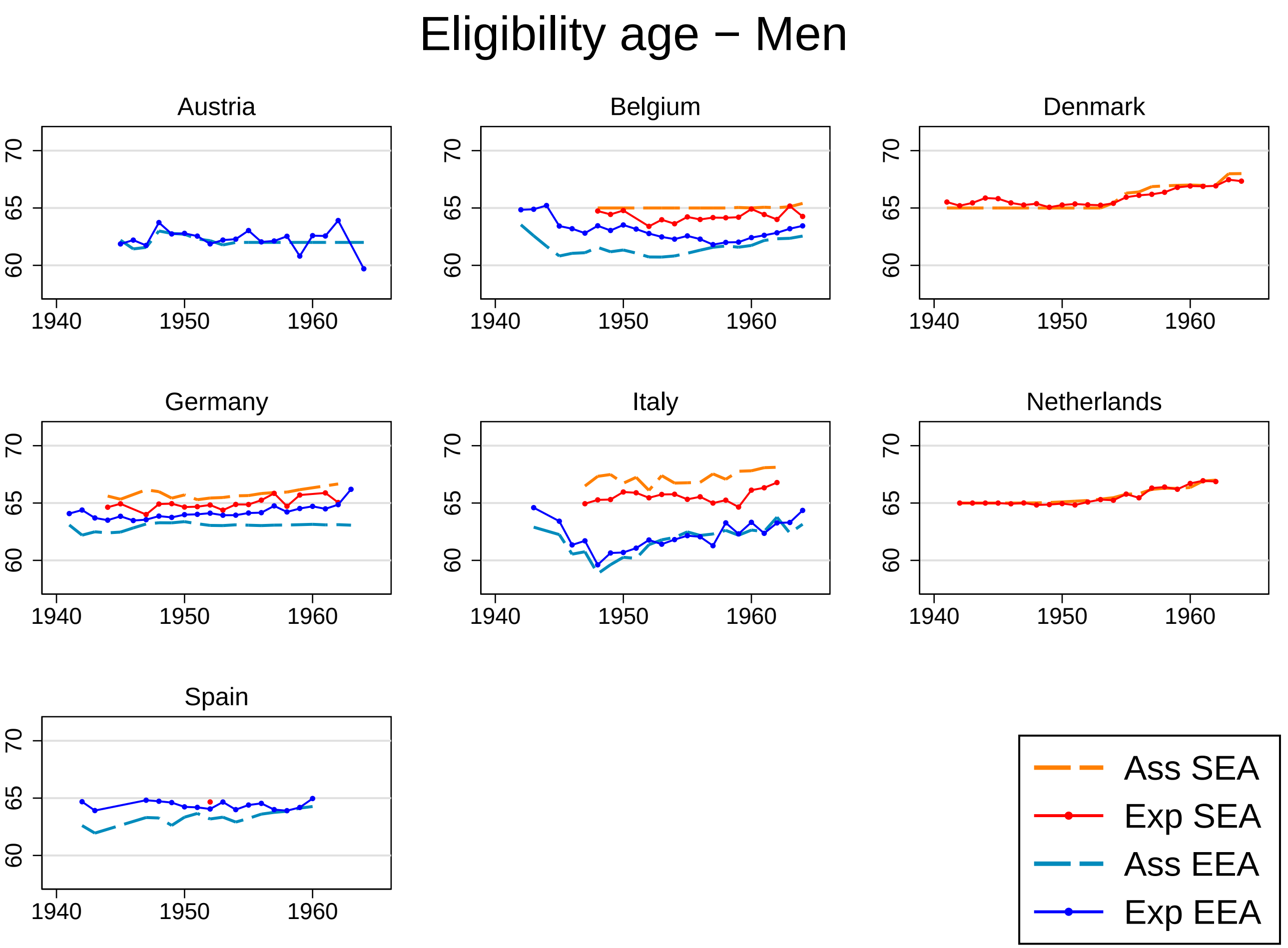
Notes: This graph shows, for each country, the development by year (X-axis) of men's early eligibility age (Y-axis), for selected cohorts. Red vertical lines indicate reform years.

Figure 4: Early eligibility age by year and cohort, women



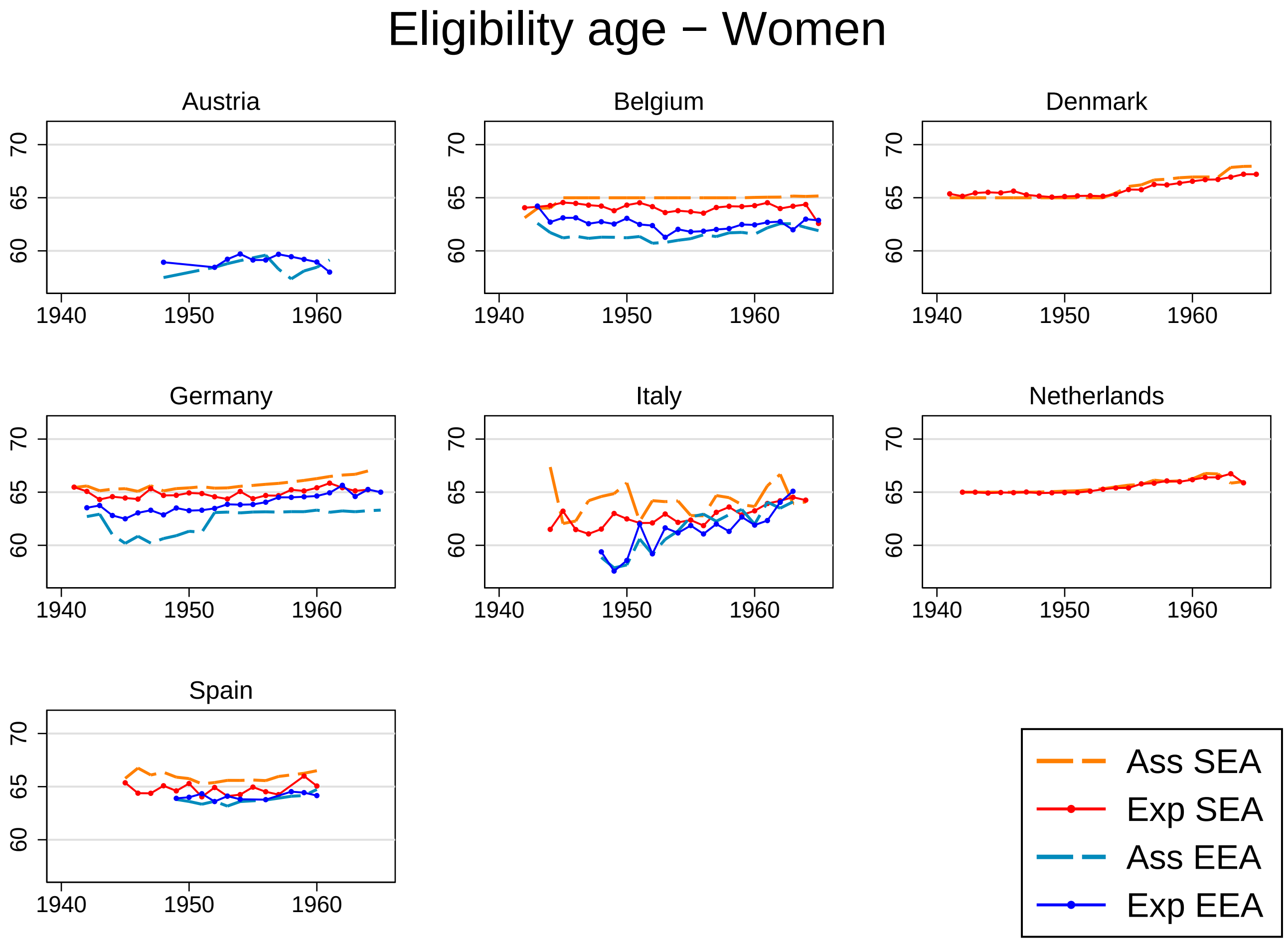
Notes: This graph shows, for each country, the development by year (X-axis) of women's early eligibility age (Y-axis), for selected cohorts. Red vertical lines indicate reform years.

Figure 5: Assigned and expected eligibility age by cohort, men



Notes: This graph shows, for each country, the birth cohort (X-axis) development of men's expected SEA and EEA (Y-axis) by treatment status.

Figure 6: Assigned and expected eligibility age by cohort, women



Notes: This graph shows, for each country, the birth cohort (X-axis) development of women's expected SEA and EEA (Y-axis) by treatment status.

A Appendix

Table A.1: Overview of pension reforms changing eligibility ages

Country	Name	Announced	Implemented	SEA/ EEA
Austria	67. ASVG Novelle (Sozialrechts-Änderungsgesetz 2007 & Sozialversicherungs-Änderungsgesetz (SRÄG) 2007)	05/2007	01/2008	EEA
	Sozialrechts-Änderungsgesetz 2008	09/2008	10/2008	EEA
	Budgetbegleitgesetz	12/2010	01/2011	EEA
	Zweites Stabilitätsgesetz	04/2012	01/2013	EEA
Belgium	Loi portant des dispositions diverses	12/2011	01/2012	EEA
	Loi visant à relever l'âge légal de la pension de retraite et portant modification des conditions d'accès à la pension de retraite anticipée et de l'âge minimum de la pension de survie	08/2015	08/2015	SEA
Denmark	Velfærdsreform	06/2006	*late 2006-07*	SEA
	Tilbagetrækningsreformen	05/2011	01/2014	SEA
Germany	Rentenversicherungs-Nachhaltigkeitsgesetz	07/2004	01/2005	EEA
	Rentenversicherungs-Altersgrenzenanpassungsgesetz	04/2007	01/2008	EEA & SEA
	Rentenversicherungs-Leistungsverbesserungsgesetz	06/2014	01/2015	EEA
Italy	Decreto-Legge 78-2009 & Legge 102/2009	07/2009	01/ 2010	SEA
	Decreto Salva Italia & Riforma Fornero	12/2011	01/ 2012	EEA & SEA
	Legge di stabilità 2016	12/2015	01/2016	EEA

Country	Name	Announced	Implemented	SEA/ EEA
Netherlands	Decision of Senate (made the proposal of the spring accord official)	07/2012	01/2013	SEA
	Adjustement II	03/2015	01/2016	SEA
Spain	Ley 27/2011, de 1 de agosto, sobre actualizacion, adecuacion y modernizacion del sistema de Seguridad Social	08/2011	01/2013	EEA & SEA

Notes: This table shows an overview by country of the pension reforms included in the analysis and their announcement and implementation dates. Data collected by the authors.

Table A.2: Sensitivity analysis

VARIABLES	(1) Exp. EA	(2) Exp. EA	(3) Exp. EA	(4) Exp. EA
EA rounded down	0.179***			
	(0.0174)			
EA rounded up		0.167***		
		(0.0161)		
EA rounded			0.172***	
			(0.0168)	
EA				0.134***
				(0.0205)
Observations	20,609	20,609	20,609	8,209
R^2	0.086	0.086	0.086	0.136
Number of panels	8,289	8,289	8,289	3,102
IND FE	YES	YES	YES	YES
YEAR FE	YES	YES	YES	YES
AGE	YES	YES	YES	YES

Notes: This table reports results from Model (1). The outcome variable is rounded down expected SEA (statutory eligibility age), rounded up SEA (Column 2), SEA rounded to the nearest integer (Column 3). In Column 4, the sample is restricted to changes in SEA equal or bigger than one full year. Regressions include individual fixed effects, year dummies and a cubic of age. Standard errors are clustered at the individual level and are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A.3: Robustness to reforms' saliency

VARIABLES	(1) Exp. EA	(2) Exp. SEA	(3) Exp. EEA
EA	0.171***		
	(0.0175)		
SEA		0.279***	
		(0.0362)	
EEA			0.168***
			(0.0377)
Observations	16,167	9,201	4,872
R^2	0.172	0.186	0.201
Number of panels	6,402	3,660	2,013
IND FE	YES	YES	YES
YEAR FE	YES	YES	YES
AGE	YES	YES	YES

Notes: This table reports results from Model (1). In Column (1), regression is on the full sample, and the outcome variable eligibility age (EA) is either the statutory eligibility age (SEA) or the early eligibility age (EEA). In Column (2), the regression is on the subsample of those eligible at the statutory age, and the outcome variable is SEA. In Column (3), the regression is on the subsample of those eligible at the early age, and the outcome variable is EEA. Austria is excluded from the SEA sample and the Netherlands from the EEA sample. Regressions include individual fixed effects, year dummies and a cubic of age. Standard errors are clustered at the individual level and are reported in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table A.4: Controls

VARIABLES	(1) Exp. EA	(2) Exp. EA	(3) Exp. EA	(4) Exp. EA	(5) Exp. EA
		(0.0169)	(0.0169)	(0.0169)	(0.0169)
EA	0.175***	0.176***	0.176***	0.176***	0.176***
	(0.0144)	(0.0144)	(0.0144)	(0.0144)	(0.0144)
Marital status		0.317	0.309	0.275	0.274
		(0.344)	(0.344)	(0.346)	(0.346)
Health status			-0.428*	-0.431*	-0.431*
			(0.258)	(0.258)	(0.258)
Income decile				-0.0630	-0.0626
				(0.0963)	(0.0968)
Total net wealth decile					-0.00705
					(0.119)
Observations	20,609	20,588	20,582	20,582	20,582
R^2	0.086	0.086	0.087	0.087	0.087
Number of panels	8,289	8,279	8,277	8,277	8,277
IND FE	YES	YES	YES	YES	YES
YEAR FE	YES	YES	YES	YES	YES
AGE	YES	YES	YES	YES	YES

Notes: This table reports results from Model (1), with sequentially included control variables. The outcome variable is expected SEA (statutory eligibility age). Marital status is a dummy equal to one if the individual is married. Health status is self-assessed and measured on a scale from 1 (excellent) to 5 (poor). Income and wealth deciles are country and wave specific. Regressions include individual fixed effects, year dummies and a cubic of age. Standard errors are clustered at the individual level and are reported in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table A.5: Robustness to the working status of the spouse

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Unemployed		Permanently sick or disabled		Part-time		High probability of working after 63	
Exp. EA	0.000646	0.000630	-7.67e-05	-8.14e-05	-0.00374	-0.00377	0.0147**	0.0147**
	(0.000972)	(0.000973)	(0.000535)	(0.000536)	(0.00242)	(0.00242)	(0.00575)	(0.00576)
Observations	11,957	11,957	11,957	11,957	7,206	7,206	3,206	3,206
Number of panels	4,910	4,910	4,910	4,910	2,995	2,995	1,599	1,599
IND FE	YES	YES	YES	YES	YES	YES	YES	YES
YEAR FE	YES	YES	YES	YES	YES	YES	YES	YES
AGE	YES	YES	YES	YES	YES	YES	YES	YES
SPOUSE WORKING STATUS	YES	NO	YES	NO	YES	NO	YES	NO

Notes: This table reports results from Model (2) for the subsample of married individuals. The outcome variable in Columns (1) and (2) are indicators of individuals' unemployment; the outcome variable in Columns (3) and (4) are indicators of disability status. The outcome variable in Columns (5) and (6) is a dummy equal to 1 if the individual holds a part-time job. The outcome variable in Columns (7) and (8) is a dummy equal to 1 if the individual reports a chance of working past age 63 strictly larger than zero, based on the question: *"Thinking about your work generally and not just your present job, what are the chances that you will be working full-time after you reach age 63?"* Regressions include individual fixed effects, year dummies and a cubic of age. Standard errors are clustered at the individual level and are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A.6: Robustness to the assigned eligibility age

VARIABLES	(1) Unemployed	(2) Permanently sick or disabled	(3) Part-time 30	(4) High probability of working after 63
		(i) Full sample		
Exp. EA	0.000146	0.000173	-0.00345	0.0169***
	(0.000921)	(0.000510)	(0.00215)	(0.00641)
Observations	16,420	16,420	9,671	3,797
Number of panels	6,694	6,694	3,984	1,894
		(ii) Eligible to statutory age		
Exp. SEA	0.00205	-0.000616	-0.00675*	0.0165**
	(0.00132)	(0.000540)	(0.00397)	(0.00839)
Observations	7,935	7,935	4,983	1,866
Number of panels	3,169	3,169	1,988	932
		(iii) Eligible to early age		
Exp. EEA	-0.00683***	0.00149	-0.00375	0.0204
	(0.00248)	(0.00126)	(0.00347)	(0.0130)
Observations	6,875	6,875	3,746	1,324
Number of panels	2,918	2,918	1,634	659
IND FE	YES	YES	YES	YES
YEAR FE	YES	YES	YES	YES
AGE	YES	YES	YES	YES

Notes: This table reports results from Model (2). The outcome variables in Columns (1) and (2) are indicators of individuals' unemployment and disability status. The outcome variable in Column (3) is a dummy equal to 1 if the individual holds a part-time job. The outcome variable in Column (4) is a dummy equal to 1 if the individual reports a chance of working past age 63 strictly larger than zero, based on the question: *"Thinking about your work generally and not just your present job, what are the chances that you will be working full-time after you reach age 63?"* Regressions include individual fixed effects, year dummies and a cubic of age. Standard errors are clustered at the individual level and are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A.7: Labour force status, reduced form

VARIABLES	(1) Unemployed	(2) Permanently sick or disabled	(3) Part-time 30	(4) High probability of working after 63
	(i) Full sample			
Exp. EA	9.67e-05	2.07e-05	-0.000776***	0.00180***
	(0.000154)	(8.80e-05)	(0.000287)	(0.000545)
Observations	17,881	17,881	10,514	4,206
Number of panels	7,238	7,238	4,311	2,098
	(ii) Eligible to statutory age			
Exp. SEA	0.000630*	-0.000205	-0.00158**	0.00307***
	(0.000366)	(0.000140)	(0.000665)	(0.00111)
Observations	8,173	8,173	5,130	1,888
Number of panels	3,274	3,274	2,055	943
	(iii) Eligible to early age			
Exp. EEA	-0.00105***	0.000231	-0.000761*	0.00287***
	(0.000298)	(0.000216)	(0.000455)	(0.00108)
Observations	7,599	7,599	4,125	1,515
Number of panels	3,200	3,200	1,790	754
IND FE	YES	YES	YES	YES
YEAR FE	YES	YES	YES	YES
AGE	YES	YES	YES	YES

Notes: This table reports results from Model (2). The outcome variables in Columns (1) and (2) are indicators of individuals' unemployment and disability status. The outcome variable in Column (3) is a dummy equal to 1 if the individual holds a part-time job. The outcome variable in Column (4) is a dummy equal to 1 if the individual reports a chance of working past age 63 strictly larger than zero, based on the question: *"Thinking about your work generally and not just your present job, what are the chances that you will be working full-time after you reach age 63?"* Regressions include individual fixed effects, year dummies and a cubic of age. Standard errors are clustered at the individual level and are reported in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table A.8: Robustness to the working status of spouse

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Retired before 60		Retired before 61		Retired before 62	
Exp. EA change	-0.000138	-0.000150	-0.00451***	-0.00452***	-0.00423**	-0.00427**
	(0.00104)	(0.00103)	(0.00138)	(0.00137)	(0.00173)	(0.00172)
Observations	3,213	3,213	2,809	2,809	2,472	2,472
AGE	YES	YES	YES	YES	YES	YES
BIRTH COHORT	YES	YES	YES	YES	YES	YES
CONTROL VARIABLES	YES	YES	YES	YES	YES	YES
SPOUSE WORK. STATUS	YES	NO	YES	NO	YES	NO

Table A.9: *continued*

	(7)	(8)	(9)	(10)	(11)	(12)
VARIABLES	Retired before 63		Retired before 64		Retired before 65	
Exp. EA change	-0.00438*	-0.00449**	-0.00754**	-0.00805**	-0.00755**	-0.00788**
	(0.00225)	(0.00224)	(0.00352)	(0.00347)	(0.00373)	(0.00368)
Observations	2,136	2,136	1,803	1,803	1,504	1,504
AGE	YES	YES	YES	YES	YES	YES
BIRTH COHORT	YES	YES	YES	YES	YES	YES
CONTROL VARIABLES	YES	YES	YES	YES	YES	YES
SPOUSE WORK. STATUS	YES	NO	YES	NO	YES	NO

Notes: This table reports results from Model (3) for the subsample of married individuals. The outcome variables are dummies indicating whether the individual has retired strictly before each age from 60 (Column (1) and (2)) to 65 (Column (11) and (12)). Regressions include birth cohort, a quadratic of age at first and last interview, gender, education, marital status and number of children. Robust standard errors are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A.9: Retirement probability, robustness to the assigned eligibility age

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Retired before 60	Retired before 61	Retired before 62	Retired before 63	Retired before 64	Retired before 65
Exp. EA change	-0.000515	-0.00536***	-0.00635***	-0.00741***	-0.0127***	-0.0134***
	(0.000875)	(0.00115)	(0.00148)	(0.00199)	(0.00317)	(0.00363)
Observations	4,611	4,026	3,536	3,048	2,575	2,119
AGE	YES	YES	YES	YES	YES	YES
BIRTH COHORT	YES	YES	YES	YES	YES	YES
CONTROL VARIABLES	YES	YES	YES	YES	YES	YES

Notes: This table reports results from Model (3). The outcome variables are dummies indicating whether the individual has retired strictly before each age from 60 (Column (1)) to 65 (Column (6)). Regressions include birth cohort, a quadratic of age at first and last interview, gender, education, marital status and number of children. Robust standard errors are reported in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table A.10: Retirement probability, reduced form

VARIABLES	(1) Retired before 60	(2) Retired before 61	(3) Retired before 62	(4) Retired before 63	(5) Retired before 64	(6) Retired before 65
EA change	-2.84e-05	-0.00144***	-0.00142***	-0.00139***	-0.00201***	-0.00186***
	(0.000244)	(0.000318)	(0.000352)	(0.000375)	(0.000445)	(0.000473)
	(0.000221)	(0.000285)	(0.000318)	(0.000337)	(0.000382)	(0.000410)
Observations	5,272	4,638	4,096	3,551	3,029	2,535
AGE	YES	YES	YES	YES	YES	YES
BIRTH COHORT	YES	YES	YES	YES	YES	YES
CONTROL VARIABLES	YES	YES	YES	YES	YES	YES

Notes: This table reports results from Model (3). The outcome variables are dummies indicating whether the individual has retired strictly before each age from 60 (Column (1)) to 65 (Column (6)). Regressions include birth cohort, a quadratic of age at first and last interview, gender, education, marital status and number of children. Robust standard errors are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

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