Policy Uncertainty, Misinformation, and Retirement Age Reform

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This study examines the impact of *Statutory Retirement Age* (SRA) reforms on individual behavior and welfare in the presence of policy uncertainty and misinformation. We develop a structural life-cycle model in which individuals are uncertain about the future evolution of the SRA and misinformed about its mechanism. We derive individuals' expectations and information on the SRA from self-elicited belief data using the German Socio-Economic Panel Innovation Sample (SOEP-IS). The model accounts for key life-cycle savings and old-age labor supply determinants, such as human capital accumulation, involuntary job loss, health status, and family dynamics. We estimate the model using decision data from the core sample of the SOEP. We design counterfactual simulations to assess the effects of SRA reforms and illustrate the trade-offs of several implementation strategies.

JEL Codes D15, D83, I38, J11, J26

Contents

1. Introduction

Aging populations are straining social security systems across the world, continuously prompting governments to reform pension systems. Since the immediate effects of such reforms often only emerge at the end of one's working life, behavioral reactions critically depend on the beliefs that people form about them. We study how subjective pension policy beliefs affect behavior directly and how they moderate the effects of policy reform. We distinguish between *policy misinformation* — systematic misperception about existing policy features — and *policy uncertainty* — individuals' subjective beliefs about how policy parameters will evolve. While misinformation could be the result of either a lack of salience or of (potentially rational) inattention (Bordalo et al., 2022; Gabaix, 2019), policy uncertainty is the unavoidable unpredictability of the future policy environment (Koşar and O'Dea, 2023). To quantify subjective belief evolution, we collect survey evidence and study how subjective policy beliefs evolve over the life cycle. Then, we formalize belief updating in a tractable way to match key features of the survey data and to study the interaction of beliefs with policy reform in a comprehensive life-cycle framework.

The policy we focus on is the *Statutory Retirement Age* (SRA), which is the German reference year for retirement and pension claiming. Unlike some other jurisdictions, the SRA in Germany is not a strict constraint for the majority of people. Under relatively mild conditions, early retirement is possible at a cost of 3.6 percent of pension per year of early retirement, the *Early Retirement Penalty* (ERP). In other words, for someone wishing to retire before the SRA, the SRA determines how many years of early retirement they must "purchase," while the ERP sets the price. Following Germany's 2007 reform that gradually raised the SRA to 67 years, further increases are frequently debated in public, making its future evolution uncertain, but the number itself very salient. That is why subjective probabilistic expectations of the headline SRA are our measure of policy uncertainty. While several details about the SRA mechanism could be unclear in principle, we argue that knowing the ERP is of first-order importance. The ERP is arguably much less salient than the SRA and it has never been changed since its introduction in 1992. While researchers do not all agree if it is actuarially fair (cf. Börsch-Supan et al., 2016), there is no *public* debate about changing it, which previous research has shown to be critical for the formation of policy reform expectations (Ciani et al., 2023). For these reasons, we use the ERP to model misinformation, but we abstract from expectations about its future changes.

To quantify subjective beliefs, we include a questionnaire in the German *Socio-Economic Panel Innovation Sample* (SOEP-IS, Richter and Schupp, 2015), which is a rich and representative panel survey of the German population. In this questionnaire, we elicit probabilistic policy beliefs about the SRA and the ERP (cf. Manski, 2004). We use these data to predict the policy beliefs for the much larger SOEP-Core household survey, on which we estimate our model. The model is a classic life-cycle model of retirement (Rust, 1987; French, 2005), which features men and women, who make decisions about labor supply, savings, and retirement age over their life cycle. Life-cycle reactions to pension age reforms are typically second-order effects that depend largely on the direct reform effect on retirement timing. The timing of retirement has many important determinants (Blundell et al., 2016), which have been studied in the literature and which we model to avoid misattributing observed behavior to policy beliefs. We allow for stochastic factors such as declining health (Blundell et al., 2023) and longevity risk, declining wages Fan et al. (2024), joint leisure with retired partners (Carta and De Philippis, 2024), age-dependent probabilities losing or finding a job (Rabaté, 2019; Rabaté et al., 2024), all of which are estimated outside the model. We further include important institutional peculiarities such as alternative paths to retirement based on diasbility or long working lives.

Our survey evidence shows that respondents on average expect further increases in the SRA, with younger respondents expecting stronger increases over their lifetime than older ones. Forecast uncertainty is lower for older respondents, consistent with gradual resolution of policy uncertainty. We model expectations with a simple nonstationary, autoregressive process, which is similar to Hentall-MacCuish (2025). This functional form matches the desired features of the data, while remaining computationally tractable in the context of a dynamic markov decision process model, which only only allows for limited history-dependence.[1]. Unlike Hentall-MacCuish (2025), we estimate the parameters of the process purely from subjective expectation data rather than past reform frequencies. Our survey further reveals that a majority of people strongly overestimate the ERP. In our model, we classify people into "informed" and "uninformed", where informed people know the true ERP and uninformed people hold the belief of an average person classified as uninformed in the data. This is similar to the approach of Bairoliya and McKiernan (2025). However, in contrast to their data, misinformation rates in survey responses decline over the life cycle, suggesting that people learn about the retirement system as they age. In our policy simulations, we account for this with a random state-dependent information updating process, which we estimate from the survey data.

With the estimated model, we can simulate the reactions to counterfactual policy reform and observe how they differ from a model without policy uncertainty. We simulate life cycles of 30-year-old agents, starting with a current SRA of 67 years, and consider gradual SRA increases to 68, 69, and 70 years. Results show that while both models produce similar reactions at the margin of retirement timing, which are in line with the findings of studies that evaluate past reforms[2], life cycle-reactions are considerably smaller when policy uncertainty is accounted for. This happens for two reasons. First, agents in the no-increase baseline expect increases in the SRA even when they do not happen and prepare for them by saving and working more. Second, although policy and expectations gradually converge, particularly younger agents in the counterfactual retain uncertainty over their lives and optimize for a mix of possible outcomes, which attenuates their response.

This finding represents an important contribution to a large literature which evaluates responses to pension reform through the lense of forward-looking life-cycle models (e.g., Haan and Prowse, 2014; Iskhakov and Keane, 2021; van der Klaauw and Wolpin, 2008). Earlier studies have recognized that whether pension reform is anticipated or not significantly affects responses (Burtless, 1986). Our results complement the findings of Bairoliya and McKiernan (2025) and de Bresser (2024), who show that the inclusion of subjective expectations can attenuate pension reform effects. In both studies, biased subjective survival expectations are a main driver, although in case of Bairoliya and McKiernan (2025), biased beliefs about the ERP also play a role. We show that uncertainty about the retirement age is an additional mechanism which produces reform effect attenuation.

We then simulate the effects of 'policy belief management policies', specifically (i) early SRA announcement with credible commitment and (ii) a de-biasing reform that eliminates misinfor-

[1] We discuss consequences and potential alternatives to this approach in Section **??**

[2] For example, Dolls and Krolage (2023) estimates a similar effect size of around 0.4 years of retirement age reduction after per year of decrease in the SRA for a recent German reform. Mastrobuoni (2009); **?** produce similar estimates for reforms in France and the United States.

mation. For the expectation management reforms, we assume that the actual SRA is increased to 69 years. *Announcement timing.* We compare a baseline in which the SRA is announced at 63 years - the earliest possible time at which agents can retire in the model - to scenarios in which the SRA is announced at 55, 45, or 35 years. Note that this means that the timing of announcement presents a negative shock to agents' expected lifetime income who were continuously downward revising their expectations before the announcement. As soon as the SRA is announced, agents start to increase savings, so that they can retire earlier than they would in a late-announcement scenario. *De-biasing.* We compare the baseline with misinformation and random updating to a counterfactual scenario in which everyone is informed from the start. Since agents already in the baseline expect to retire early on average, de-biasing implies an increase in lifetime income, which agents spread over the life cycle by saving less, working less, and eventually retiring earlier. Also, compared to the baseline, retirement behavior of the debiased agents in the counterfactual is a much smoother function of their age. In the baseline, retirement behavior exhibits the classical spike at the SRA, which the empirical literature across different countries has documented extensively (cf. Lumsdaine et al., 1996; Rust, 1997, for an early discussion of the phenomenon in the US). This is due to the fact that even close to retirement, close to half of agents are still uninformed, implying they hold early retirement to be almost prohibitively expensive.

A growing literature has emerged that explores the implications of objective policy uncertainty and biased beliefs. Cottle Hunt (2021); Caliendo et al. (2019); Kitao (2018) assume scenarios with probability distributions over future policy parameters to quantify welfare cost of uncertainty about timing and design of inevitable retirement reform.[3] We contribute by showing that despite the undoubtedly negative effect on welfare, efforts to correct misbeliefs or eliminating policy uncertainty may conflict with policy goals about the type of behavior that policymakers wish to stimulate. Furthermore, we join Hentall-MacCuish (2025) and Bairoliya and McKiernan (2025) in offering a subjective-belief-based complementary explanation for the bunching of retirement decisions around the SRA, which the literature has recently attributed chiefly to reference-dependent preferences (Gruber et al., 2022; Lalive et al., 2023; Seibold, 2021).

The rest of the paper is structured as follows. In Section 2, we outline the most important features of the German retirement system and describe our data. Section 3 describes the policy beliefs, how they are treated in our model, and how we estimate them. In Section 4, we explain our life-cycle model. In Section 5, we lay down our estimation methods and estimation results. In Chapter 6, we present our counterfactual policy simulations. Section 7 concludes.

2. Institutional Background and Data

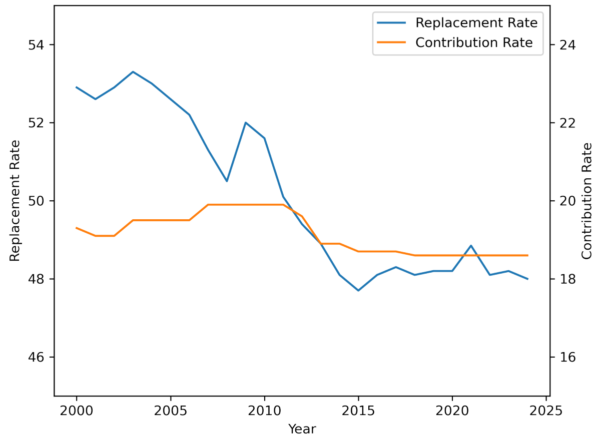
2.1. Public Pension Insurance in Germany

Germany has a pay-as-you-go pension system, which is financed by flat-rate contributions from employees and employers. The pension system is mandatory for nearly all employees and, as of 2023, covers 87 percent of the working population (70 percent of people aged 15-64). The most important exceptions are self-employed or marginally employed workers, civil servants, and military personnel.

[3] Luttmer and Samwick (2018) quantifies welfare effects of subjective pension policy uncertainty with a survey experiment.

Public pensions in 2023 provided a replacement rate of 48 percent according to the definition of the German Public Pension Insurance (around 44 percent according to that of the OECD). Pension size depends on work experience and labor earnings history. The pension formula is not inherently redistributive, so replacement rates are similar across income groups[4]. While replacement rates have fallen in recent years, contribution rates have been stable at around 19 percent (cf. figure 1). Both are linked to demographic change, so without further reform, replacement rates are expected to fall, while contribution rates are expected to rise.

Figure 1: Replacement Rate and Contribution Rate



Notes: Contribution rates are a percent of gross wages, half of which is owed respectively by employer and employee. The replacement rate is defined as the ratio GI/GP, where GI is the gross pension which a worker after 45 years of working at the average wage would get and GP is the average gross income of all insured workers.

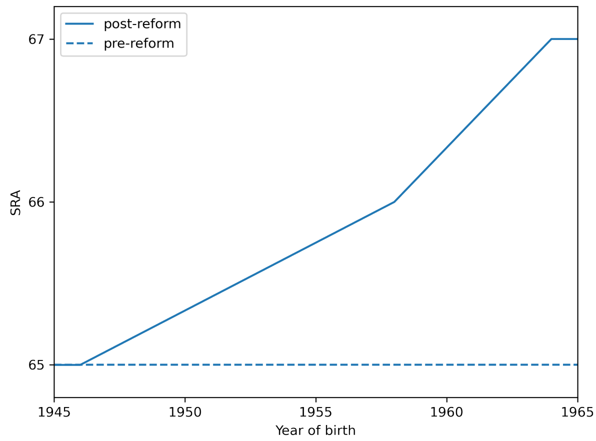
Source: German Pension Insurance (DRV)

The *statutory retirement age* (SRA), similar to the *full retirement age* of the American social security system, is a key policy parameter in the German pension system. The current SRA is a function of birth year and stands at 67 years for everyone born after 1964 (cf. Figure 2). Given certain requirements, claiming a pension is possible up to four years before this age,[5] but no earlier than 63 years. Early retirement comes at a penalty of 3.6 percent of the pension value per year of early retirement, or 0.3 percent per month. In 2023, one in three old-age pensions was claimed before the applicable SRA. On average, pensions that were claimed early were claimed 30 months in advance, implying an average penalty size of 9 percent. In addition, people who have contributed for 45 years can retire two years before the SRA without penalty.

[4]This holds until a cap of roughly twice the average wage, beyond which no contributions have to be made and no claims are accumulated

[5]A claimant needs to have 35 years of *credited periods*. In addition to years of work, these include unpaid childcare and elderly care, as well as short-term unemployment and sickness.

Figure 2: 2007 reform of the Statutory Retirement Age



To offset the erosion of replacement rates and the rise in contribution rates brought about by demographic change, there is a public debate about further increases in the SRA. For example, the German Council of Economic Experts recommends a continued increase in the SRA by 0.5 years every 10 years (Grimm et al., 2023). This would imply an SRA of 68 years for the birth cohort of 1984 and of 69 years for the 2004 cohort.

2.2. Data

When deciding how to respond to retirement policy reform, life-cycle savings and labor supply as well as retirement timing are to some extent substitutes for households. Household retirement plans depend on many factors, including financial assets and employment history, but also personal aspects such as health and family circumstances. Therefore, studying household responses to retirement policy reform in a comprehensive framework requires abundant micro-level data.

We use data from the German Socio-Economic Panel (SOEP), a rich and representative household panel survey(Goebel et al., 2019), because it provides detailed information on all these factors. The SOEP includes a wide range of variables covering both individual and household characteristics. Its panel structure allows us to track individuals over time and analyze dynamic joint distributions of labor supply decisions and covariates. This makes the dataset well-suited for structural policy analysis. We link the dataset with administrative pension data to get more precise data on retirement timing(**?**).

We generate the model estimation sample from the SOEP-Core, the main household panel dataset. We limit the analysis to the years 2013-2020. Other sample restrictions stem from model restrictions, such as not being allowed to work after a certain age, and from data availability. In addition, we create several auxiliary samples from the SOEP core for the estimation of some processes that we estimate outside the model, such as the evolution of health over the life-cycle. We do not estimate these on the structural estimation sample because data availability requirements differ.

We use subjective expectations data from a survey we included in the SOEP Innovation Sample (SOEP-IS), which allows researchers to submit their own questions. In the 2022 wave, we included various questions on social insurance uncertainty. From this survey, we use the data on respondent SRA uncertainty and planned retirement age. See appendix A.3 for the exact wording of the questions.

Aside from SOEP data, we rely on very few outside data sources. CPI data and population mortality data come from the German Federal Statistical Office. Furthermore, we use some estimates from the literature where our data cannot identify certain parameters.

3. Policy Beliefs

In this chapter, we describe the elicitation and formalization of subjective policy beliefs. The policy belief we focus on in this study is the *Statutory Retirement Age* (SRA), which is very well suited for quantitative belief elicitation. It is one number that holds for most of the working-age population. We argue that it is very salient[6], part of the public debate, and it is clear to the individual what behavior is supposed to prescribe. People should form expectations about it. However, it is not clear that people understand to what extent the SRA is a binding prescription and to what extent it is mere guidance. That is why we allow for misinformation about the fact that at a relatively small *Early Retirement Penalty* (ERP), most people can actually retire before they reach the SRA. Börsch-Supan et al. (2016) simulates that varying that penalty in a rational, full information model has very large effects on actual retirement ages. On average, people want to retire (weakly) before SRA; later retirement is very rare. Therefore, the interaction of SRA and ERP belief is crucial to understand expectations about own retirement.

While actual pension size is just as relevant for household retirement planning, it is less suited for our purposes. With respect to policy expectations, it is unclear what potential reforms would look like. Recent reforms have added or amended factors in the pension value growth formula, but eliciting expectations about these types of reforms would be challenging. [7] On the other hand, people could be misinformed about the current size of the pension to which they are entitled.[8] In annual letters, the German Pension Insurance informs insurees about the pension they can expect if they continue to earn their current wage until retirement. This information has been found to influence behavior (Dolls et al., 2018) and is important for individuals to form expectations over, but it is difficult to connect it to a specific policy environment in a structural model. That is why we abstract from beliefs about these policies in this project.

3.1. Policy Uncertainty and the Statutory Retirement Age

We elicit probabilistic expectations of the SRA at the time respondents expect to retire (see A.3 for question wording). The results are twofold. First, respondents expect further increases in the SRA. The younger respondents are, the higher the SRA they expect. Second, the further away respondents are from expected retirement, the larger the uncertainty. Figure **??** illustrates these findings. In other words, uncertainty increases with age; policy and expectation

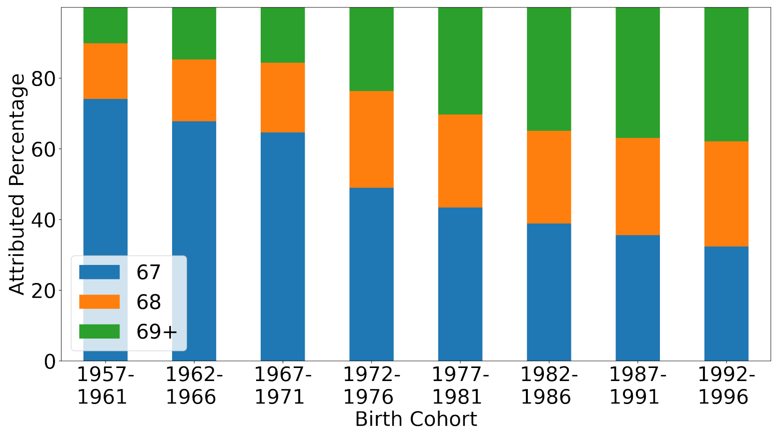
[6]See Seibold (2021) for a discussion about how it is framed in German public discourse and by the German pension insurance

[7]The key policy parameter in the public debate about pension size, the replacement rate, carries limited information for the individual because it only describes a stylized worker.

[8]For the US Social Security system, it has been a long established fact that people are, in fact, misinformed about their claims(Bernheim, 1987; Gustman and Steinmeier, 2005).

converge over time. In the model, we implement uncertainty about the future SRA in a simple and computationally tractable way while retaining these key features.

Figure 3: Subjective Distributions over Future SRAs



Note: Respondent expected SRA age at the time they retire. Seeappendix A.3 for question wording.

In particular, agents of age t expect the SRA to evolve according to a random walk with drift:

$$SRA_{t+1} = \alpha + SRA_t + \upsilon_{t+1} \tag{1}$$

where υ_t is i.i.d. normally distributed with mean zero and constant variance σ^2_{SRA}.[9] This formalization is similar to objective policy uncertainty in Hentall-MacCuish (2025), except that we allow for negative and non-integer shocks, to account for people born before 1964 to whom a non-integer SRA currently applies. As a result, at any time t before retirement, agents' expectations and associated uncertainty about the SRA at time $T > t$ are given by

$$SRA_T \sim N(SRA_t + (T-t)\alpha, (T-t)\sigma^2) \tag{2}$$

Although this model captures the key features of our survey data, it is rather simple and abstracts entirely from the determinants of expectation formations aside from current policy. One alternative would be to model reform expectations as a function of previous experience (Malmendier and Nagel, 2016; Kuchler and Zafar, 2019), but such reforms are rare and allowing for too much history-dependence in a dynamic programming model quickly becomes computationally untractable.[10]

[9] For the numerical model, we discretize the policy process into step sizes of quarter years. The retirement age bounds that we defined together with the i.i.d. assumption of υ_t result in a simple Markov process that depends only on the current SRA as its state.

[10] Another alternative would be to model people's expectations about factors underlying pension policy, chiefly the evolution of demographic change, and assuming some mapping from these factors to policy, as is done in Cottle Hunt (2021). Doing so based on subjective expectations would require a lot more survey data, and some strong assumptions about agent understanding of political economy, which is why we leave it a a venue for future research.

Table 1: Expectation process parameter estimates

Parameter Name	Parameter	Estimate
Drift	α	0.041
		(0.0014)
Variance of belief process	σ^2_{SRA}	0.0641
		(0.0273)

Notes: Standard errors in parentheses.

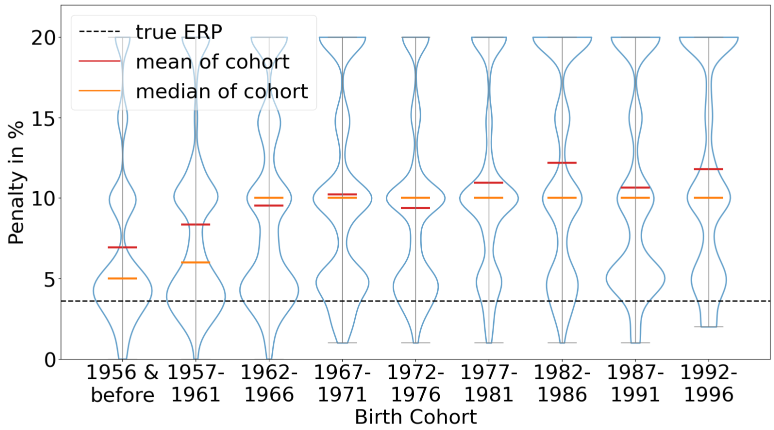
Table (1) reports our estimate for the random walk of our policy belief process. As a benchmark, the implied expected SRA increase of 0.41 years every ten years is close to the German Council of Economic Advisors recommendation, which is 0.5 years every ten years (Grimm et al., 2023). We find considerable heterogeneity in policy expectations across individuals. However, this heterogeneity cannot be explained sex and education, the two factors that are time-invariant in our model. Therefore, we do not take expectation heterogeneity into account in our simulations and assign to every individual the same expectation process as a function of age and current SRA.

3.2. Misinformation and the Early Retirement Penalty

We further elicit probabilistic beliefs of the current ERP(see A.3 for question wording). Figure 4 illustrates respondents' point estimates. Except for respondents in their 60s, the average belief about this number is around 12 percent across ages, while in reality, it is only 3.6 percent. This misinformation may significantly distort people's reasoning about retirement and how they react to reforms. While it may be too much to expect people to know the exact Early Retirement Penalty, knowing its magnitude is crucial for everyone who considers early retirement. At its true size, early retirement is a viable option for many[11]. By contrast, at the average reported ERP size of around 12 percent, early retirement would be prohibitively expensive for most people.

[11] In fact, many economists argue that 3.6 percent is too low and that the actuarily fair size should be 5-7 percent. Börsch-Supan et al. (2016).

Figure 4: Belief about Current ERP



Notes: Respondents' beliefs about the current ERP. distributions censored above at 20 percent. See appendix A.3 for question wording.

For these reasons, we classify people into informed and uninformed in the model, as Bairoliya and McKiernan (2025) do[12] Unlike their data, however, our survey results show that misinformation rates decline notably over the life-cycle. It appears that when it starts being most relevant to them, people become informed about the ERP. This can be interpreted as evidence in favor of rational attention models (**?**Hentall-MacCuish, 2025), or it may be that a lack of salience, e.g., due to social networks in which few people are already retired, causes this lack of knowledge among younger people. In our counterfactual model simulations, we are agnostic about the process of information acquisition. A simple type-specific Markov process governs transitions from being uninformed to being informed, which we estimate from age-type specific choice shares in the survey data.

4. Model

The model is a classic consumption-saving and labor supply life-cycle model in the tradition of French (2005). Agents make discrete employment and continuous consumption-savings decisions from age 30 until their stochastic death. They maximize the discounted sum of expected utilities over their whole life subject to an inter-temporal budget constraint. Upon death, agents bequeath all remaining assets.

We model men and women who completed either a high or low education, determining four exogenous types $\tau \in \{men, women\} \times \{high, low\}$ in the model. Wealth inequality arises through heterogeneity in initial endowments and due to type-specific income and endogenous investments in work experience e_t. Income uncertainty arises from transitory wage shocks, stochastic job offers, and destruction o_t. A modeled approximation of the German tax and transfer system partially offsets these risks. Additionally, the model includes Markov processes capturing the arrival, departure, and retirement of partners p_t and the evolution of an individual's health over the life cycle[13]. Additionally, we track the two policy states, SRA_t and i_t,

[12]We classify as informed a respondent who answered "5" or less to the question eliciting beliefs about the current ERP. We chose the threshold so respondents whose answers were below it were as close as possible to the true ERP.

[13]The empirical parametrization of the Markov processes for job offers and destruction, partners, health, and

described in Section (3). An overview of the states, decisions, and their notation can be found in the appendix A.1.

The model tracks states and decisions annually, assuming they remain constant within each year. At the start of each period, the agent fully observes their state x_t, and the value of the decision problem is denoted by $V(x_t)$. It represents the sum of discounted expected utilities from future periods, given the agent's current state x_t. It is the solution to the Bellman equation:

$$V(x_t) = \max_{0 \leq c_t \leq a_t, d_t} u(c_t, d_t, x_t) + \beta \, \mathrm{E}\left[V(x_{t+1} | c_t, d_t, x_t)\right] \tag{3}$$

where c_t and d_t denote the consumption- and labor supply decisions, respectively. Assets at the beginning of the period, denoted by a_t, are part of the state vector x_t. The Bellman equation allows us to solve the problem via backward induction and obtain the optimal consumption and value functions conditional on state and labor-supply decisions. We employ the DC-EGM method by Iskhakov et al. (2017), which avoids computationally expensive root-finding procedures (Carroll, 2006). The remainder of this section describes the modeling of decisions and utility, the agent's income, the tax and transfer system, and the additional Markov processes.

4.1. Decisions and Utility

At every age $t \in \{30, ..., 100\}$ or until their stochastic deaths, agents choose continuous consumption c_t and discrete labor supply d_t to maximize the sum of discounted expected utility.

Labor supply $d_t \in \mathcal{D} = \{0, 1, 2, 3\}$ can take values of retirement ($d_t = 0$), unemployment ($d_t = 1$), part-time ($d_t = 2$), and full-time work ($d_t = 3$). Full-time work increases an agent's experience stock by one year, while part-time work increases it by half.[14]. During their working life, agents can decide to work part- or full-time if they have a job offer o_t in the current period. Otherwise, they must choose unemployment. The law of motion of o_t is described in Appendix (A.4.2). Retirement can be chosen up to four years before the statutory retirement age (SRA) but no earlier than age 63, following a simplified version of the current German law. To simplify further, we restrict decisions so that retirement is absorbing and from age 72 everyone must be retired.

Agents may consume $c_t \in \mathcal{C}_t = [0, a_t]$ any amount up to their assets at the beginning of the period, a_t. As a result, borrowing is not allowed, and there is no explicit consumption floor in the model. However, we assume that the welfare state always provides a basic level of income (see Section (4.2)), ensuring agents can always afford a positive level of consumption.

Utility. In each period they are alive, agents derive flow utility based on their choices and state:

$$u(c_t, d_t, x_t) = \frac{\left(\frac{c_t}{n_t(x_t)} L_t(x_t, d_t)\right)^{1-\mu} - 1}{1 - \mu} + \epsilon_t(d_t) \tag{4}$$

where $n_t(x_t)$ is the consumption equivalence scale, calculated as the square root of the household size.[15] The term $L_t(x_t, d_t) \in [0, 1]$ captures the reduction in consumption utility relative

death can be found in the Appendix.

[14]We use a projection of the experience stock to the interval $[0, 1]$, following Iskhakov and Keane (2021)

[15]Note that while the partner state is stochastic, conditional on partner presence, age, sex, and education, the number of children is deterministic and might take fractional values.

to the retirement baseline. Its functional form is given by:

$$L_t(x_t, d_t) = \begin{cases} 1, & \text{if } d_t = 0 \\ exp\Big\{ - Z_L(x_t, d_t)'\kappa_{d_t} \Big\}, & \text{if } d_t > 0 \end{cases} \tag{5}$$

where $Z_L(x_t, d_t)$ is a vector of choice-specific characteristics that depend on the current state, such as the number of children, education, and sex. The vector κ_{d_t} is the collection of corresponding choice-specific disutility parameters. The transposed vector multiplication leads to a sum of characteristic times parameter entry.

The model features choice-specific utility shocks $\epsilon_t(d_t)$, which follow an i.i.d. extreme value distribution with mean zero and scale σ_u. Extreme-value shocks are widely used in studies using discrete choice models McFadden (1973). They capture unexplained choice behavior and improve the computational feasibility of these models (Adda et al., 2017; Iskhakov and Keane, 2021). Apart from computational reasons, we include them to reflect empirical evidence showing that many retirement decisions result from idiosyncratic shocks (Caliendo et al., 2023).

Upon death or reaching the terminal age of 100, individuals bequeath their remaining wealth and derive utility from it, represented by the following bequest utility:

$$u_b(a_T) = \vartheta \frac{a_T^{1-\mu}}{1-\mu} \tag{6}$$

where ϑ measures the intensity of the bequest motive. A strong bequest motive is a simple way to model the gradual dissaving behavior observed among retirees (Ameriks et al., 2020; De Nardi et al., 2010).

4.2. Income and Budget

At the end of each period, assets saved for future periods generate income at a risk-free interest rate of r. Assets evolve according to the following intertemporal budget equation:

$$a_{t+1} = (1 + r)(a_t - c_t) + Y_t(d_t, x_t), \tag{7}$$

where Y_t represents total household income, which consists of own income y_t (from work or pension), potential partner income y_t^p, household level benefits $B(\cdot)$ and taxes $T(\cdot)$:

$$Y_t(x_t, d_t) = y_t(x_t, d_t) + y_t^p(x_t) + B(x_t, d_t) - T(x_t, d_t). \tag{8}$$

If the agent works, she receives an hourly wage based on accumulated work experience e_t, and an i.i.d. normally distributed shock $\zeta \sim N(0, \sigma^2_{w,\tau})$. Part- or full-time income is then the product of hourly wage and the type-specific average annual hours. Returns to experience also vary by type τ.

$$y_t(x_t, d_t) = w_t(x_t)\, hrs(x_t, d_t), \text{ for } d_t \in \{2, 3\}. \tag{9}$$

The wage given by

$$\ln w_t(x_t) = \gamma_{0,\tau} + \gamma_{1,\tau} \ln (e_t + 1) + \zeta_t. \tag{10}$$

When retired, agents receive a pension that increases with work experience. In Germany, Pensions depend on three factors: The pension points track the contributions over the working life, the pension-point value assigns a monetary value to the stock of pension points, and the deduction factor reduces the pension in case of early retirement. As contributions are a fraction of wages, each year of experience has a different type-specific effect on the stock of pension points. We, therefore, construct a function, mapping the state of an agent into pension points $PP(x_t)$. Appendix (A.5.1) details how we construct this function. The pension income of an agent who retires at the SRA is then given by: for

$$y_t(x_t, 0) = PP(x_t) * PPV. \tag{11}$$

If an agent retires before the SRA at age t^R, she incurs a permanent pension reduction, denoted by ERP:

$$y_t(x_t, 0) = PP(x_t) * PPV \tag{12}$$

$$* (1 - ERP)(SRA_{t^R} - t^R)\mathbb{1}(SRA_{t^R} > t^R)). \tag{13}$$

In our model, agents can be misinformed about the ERP when constructing their expectations. Dependent on on the informed state i_t, the agent expects the following ERP:

$$ERP = \begin{cases} E\tilde{R}P, & \text{if } i_t = 0 \\ 0.036, & \text{if } i_t = 1. \end{cases} \tag{14}$$

where $E\tilde{R}P$ is the expectation of uninformed agents. Appendix (A.5.1) also documents how we can track the deduction of pensions due to early retirement with the experience stock. Therefore, we do not need to track t^R.

Partner income $y_t^p(x_t)$ deterministically depends on the agent's state. For model sparsity, we do not track any state variables, e.g., experience for the partner. In particular, the partner's income depends on the agent's age, education, and sex. We do not model any uncertainty in the partner's income; all income uncertainty arises from the agent's income. Details on the approximation of partner income can be found in appendix A.6.

Household-level benefits account for the presence of a partner, the agent's own labor supply decision, and the wages of both spouses. Benefits also provide transfers based on the number of children in the household, proxied by age, education, and partner state. Child benefits vary depending on whether the agent is unemployed or working. If the spouse's wage exceeds the minimum level of social security payments, the household relies entirely on that salary.

We implement a simplified tax system with income brackets, which captures the progressivity of the German tax system and the structure of social security contributions. Notably, it features joint taxation for couples. Unemployed agents are exempt from taxes or contributions, while retired agents pay taxes but only reduced contributions. Working individuals are subject to full taxation and contributions.

5. Estimation

There are three sets of parameters that need to be determined for our counterfactual policy simulations. The first set is calibrated using external data sources and established literature estimates. This set includes policy parameters that are assumed to remain constant within the model (e.g., tax brackets), as well as standard parameters such as the interest rate r, the discount factor β, and the inter-temporal elasticity of substitution μ. The interest rate is set to $r = 0.04$, the discount factor $\beta = 0.97$, and the inter-temporal elasticity of substitution $\mu = 1.5$.

The second set of parameters is estimated in a first step on data, outside of the model. The estimates and corresponding estimation strategies are detailed in the appendix. The set includes transition probabilities for partner status (A.4.1), health and mortality (A.4.3), and job destruction (A.4.2). Additionally, it comprises wage parameters, such as the return to experience and the variance of income shocks (A.5.2). As described in Section 3, we also estimate the policy belief and misinformation parameters separately and use them to parameterize the model.

We obtain the third set of deep structural parameters governing the labor supply decision by estimating the model with maximum likelihood following Rust (1994). In the following, we describe the estimation procedure, report the estimates of the structural parameters, and show how our model fits the data.

5.1. Structural Estimation

Identification. We estimate two kinds of parameters in the model with maximum likelihood. First, we estimate the structural disutility parameters governing the consumption utility reduction of each choice in comparison with retirement (equation 5). A higher disutility parameter implies a greater reduction in consumption utility for a given choice. Identification relies on the direct effect of these parameters on the choice probabilities through the utility function, independent of the financial incentives of these choices that generate utility via consumption.

Second, we estimate the parameters determining the probabilities of a job offer for unemployed individuals. Since job offers are not fully observed, job offer probabilities must be estimated jointly with utility parameters and inside the model. Conditional on the utility parameters, job offer probabilities are identified by the observed decisions of the unemployed, which they directly impact.

Likelihood. Formally, we can derive the likelihood function as follows: Let $\mathcal{M}$ denote the dataset of observed states and choices. It contains for each individual i at time t their labor supply decision d_{it} and their observed states. In the following, we denote an agent's state, excluding the taste shock's realization, by x_{it}. As the choice-specific taste shocks $\epsilon_{it}(d_{it})$ are assumed to be i.i.d. extreme value distributed and enter the utility function additive separable, the choice probabilities have a closed form solution. Therefore, the probability to observe choice d_{it} under a fully observed x_{it}, is given by:

$$P(d_{it}|x_{it}) = \frac{\exp V(d_{it}|x_{it})}{\sum_{d \in \mathcal{D}} \exp V(d|x_{it})}$$

However, we do not observe two states or only partially observe them. In particular, we do not observe the job offer state if an individual stays unemployed or retires after being unemployed in the previous year. If she starts working, she must have a job offer. The probability of receiving a job offer in $t+1$, if unemployed in the previous year, is dependent on the current state and given by

$$\pi(o_{t+1} = 1 | x_t, d_t = 1) = \Lambda_o\bigg(Z_o(x_t)'\phi_o\bigg) \tag{15}$$

where Λ_o denotes the logistic distribution function, $Z_o(x_t)$ are characteristics depending on the current state and ϕ_o are the corresponding parameters. The full Markov transition matrix for the job states $\pi(o_{t+1}|x_t)$ is complemented by the probabilities of job destruction if employed in the previous year. We estimate the probability of job destruction outside the model using information on (in)voluntary job loss, which we document in appendix A.4.2.

Moreover, we do not observe if agents are informed. However, with the age and education-specific shares $G(i_t|x_{it})$ of informed agents that we estimate from the Blesch et al. (2024) belief data (cf. section **??**), we can integrate this unobserved variable.

Formally, the likelihood of a structural parameter $\theta = (\kappa_d, \sigma_u, \phi_o)$ is given by:

$$\mathcal{L}(\mathcal{M}, \theta) = \Pi_{i=0}^{N}\Pi_{t=0}^{T}\Bigg(\sum_{o_t=0}^{1}\sum_{i_t=0}^{1} P(d_{it}|x_{it}, o_t, i_t\theta)\pi(o_t|x_{it-1})G(i_t|x_{it})\Bigg) \tag{16}$$

For maximizing the likelihood and obtaining our structural parameter estimates we use the standard transformation to log-likelihood and use Gabler (2022) with the limited memory Broyden–Fletcher–Goldfarb–Shanno algorithm from Virtanen et al. (2020) to maximize it. We use the algorithm's approximation of the inverse Hessian to obtain standard errors of the estimates.

5.2. Estimation Results and Model Fit

After parametrizing the model with the estimates from the literature and our first step estimation, we use maximum likelihood to estimate the disutility parameters of our model (cf. equation 5). Table (2) reports our estimates of the structural parameters. An example to facilitate parameter interpretation is that men in good health are indifferent, all other things equal, between working full-time or being retired at a 32 percent reduced level of consumption.[16]. Likewise, women in bad health are indifferent between working part-time or working full-time while consuming 15 percent less.[17]

[16] $1 - \exp(-0.3896)$
[17] $1 - \exp\left(-(1.6879 - 1.8497)\right)$

Table 2: Disutility parameters

Parameter Name	Estimates	
	Men	Women
Unemployed	1.4057	0.9600
	(0.0168)	(0.0217)
Full-time; Bad Health	1.2649	1.8497
	(0.0419)	(0.0076)
Full-time; Good Health	0.3896	1.4565
	(0.0220)	(0.0328)
Part-time; Bad Health		1.6879
		(0.0326)
Part-time; Good Health		1.2784
		(0.0192)
Children; Full-time; Low Education		0.2123
		(0.0375)
Children; Full-time; High Education		0.1197
		(0.0375)
Taste shock scale	0.4851	0.4851
	(0.0433)	(0.0433)

Notes: Maximum likelihood estimates of structural parameters. Standard errors in parentheses.

Table 3 reports logit parameters of the job offer process.(cf. A.4.2). We document a negative age trend for job offers, in line with estimates from similar contexts in the literature.

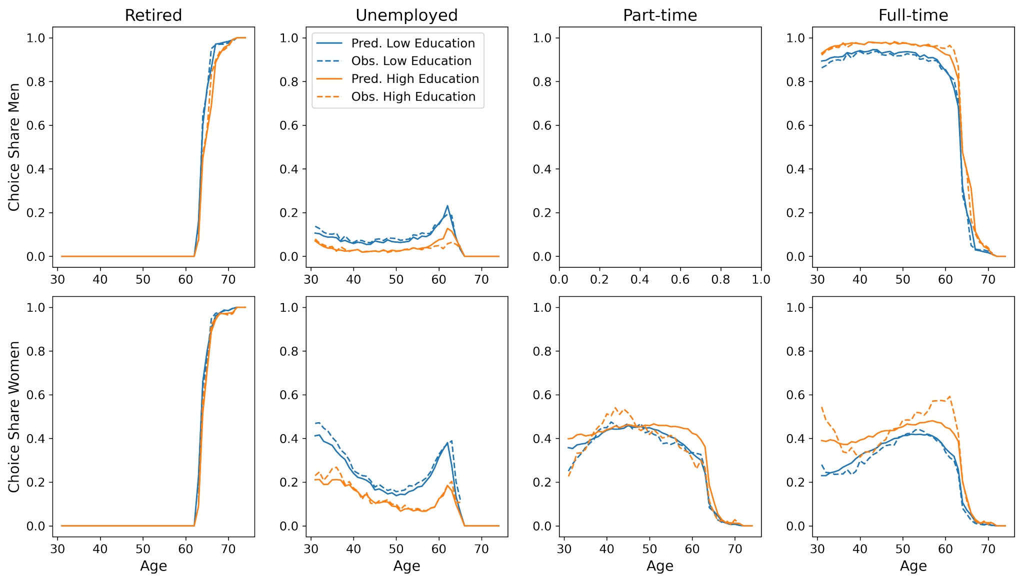
Table 3: Job offer parameters

Parameter Name	Estimates	
	Men	Women
Constant	0.7138	0.7226
	(0.0023)	(0.0366)
Age	-0.0409	-0.0586
	(0.0127)	(0.1087)
High education	-0.2733	0.5729
	(0.1113)	(0.0025)

Notes: Maximum likelihood estimates of structural parameters. Standard errors in parentheses.

Figure (5) shows the fit of our estimated model to the data for low-men (upper panel) and women (lower panel), split by education group. The figure is constructed by solving the model for the estimated parameters and assigning each observation the calculated choice probabilities. The observed choice shares are directly calculated from the observed choices, while the predicted ones are the average choice probabilities of all observations at a particular age. Our model can predict the working choice and retirement patterns of individuals of all four types in the dataset very well. If we simulate life-cycles instead and draw the initial conditions from observed distributions, choice patterns look similar. This gives credence to the results of our counterfactual policy simulations.

Figure 5: Model fit



Notes: Estimated and observed choice shares for men (top) and women (bottom).

6. Counterfactual Policy Simulations

In this section, we explain how we use the model described in section 4, which we parameterize with the estimates from section 5.2 to simulate different policy reforms. Specifically, conduct four exercises corresponding to different policies: i. further SRA increases, ii. timing of reform announcement, and iii. eliminating the ERP bias.

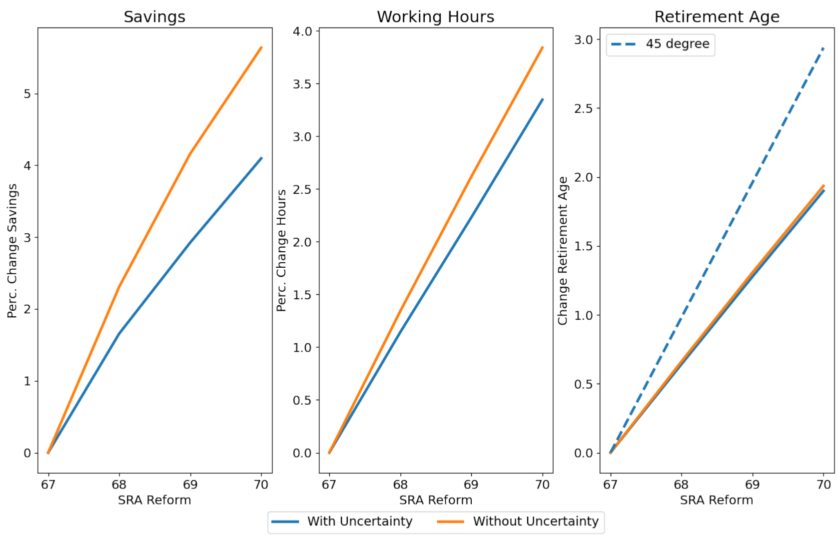
In simulation exercise i. and iii. we consider different true future policy trajectories, which we call *scenarios*. We denote true policy SRA_t^s in scenario s at time t. We quantify the effects of policy reform by considering changes in behavior and welfare. For the welfare analysis, we follow Low et al. (2010) and construct a welfare measure that describes the welfare difference as the percentage change of consumption in each period over the lifecycle that would make an agent indifferent between baseline and counterfactuals (refer to appendix A.7.1 for details).

In all of our policy simulations, agents start at age 30. We assume an initial Statutory Retirement Age $SRA_{30}^s = 67$, which is the case in Germany for everyone born after 1963 as of the 2007 reform. In the scenarios without policy commitment, agents form expectations according to equations **??**, parametrized with the estimates shown in 1. We draw initial experience and wealth from our estimation sample's observed distributions of 30-year-olds. We then draw a series of shock realizations and simulate N=100,000 life cycles for each scenario.

6.1. Policy Uncertainty and Raising the Retirement Age

The purpose of the first simulation exercise is to uncover the effects that policy uncertainty has on behavioral effects of further increases in the SRA. In this exercise, we compare a base-

Figure 6: Behvaioral Reactions to SRA increase



line of no policy change to different alternative policy trajectories. We do so for two models, i. our standard model with subjective policy uncertainty, and ii. a 'rational expectations' model in which agents are perfectly informed about the SRA that will apply to them. In the standard model, for both baseline and counterfactual, subjective beliefs are modeled and parametrized as described in Section 3.1. In the baseline, $SRA^s_{63} = 67$ for all scenarios, while in the counterfactuals $SRA^s_{63} = s$ with $s \in \{67, 67.25, ..., 69.75, 70\}$. We abstract from the timing-of-announcement effects of the policy changes by having SRA_t evolve gradually at a constant rate of α^*.

Behavioral responses are illustrated in the figure 6. We can observe that agents react to increased SRAs with a mix of behavioral responses. Roughly, in the model with uncertainty a one-year increase in the SRA induces a 1.8-percent increase in savings and a 1.1-percent increase in life-cycle annual working hours. Just as behavioral adjustment is almost linear in the SRA increase, welfare loss falls linearly as the SRA increases. For every additional year of SRA, the retirement age only increases roughly by half a year. This finding is in line with program evaluation literature. (cf. **?**Mastrobuoni, 2009).

Interestingly, in the model without uncertainty, while the effect on the margin of retirement is similar, reactions over the life-cycle are considerably stronger. Savings increase around 25 percent more, working hours by around 15 percent more. This is due to two reasons. First, in the baseline, i.e., when SRA stays at 67, the agents in the model with uncertainty initially expect further increases. Although over their lives they become more and more certain that these increases are not materializing, they have already worked and saved more compared to the baseline, in which they know that SRA will stay at 67. Second, in the counterfactual in which the SRA is increased, agents are never completely sure by how much and optimizing for a mix of different possible policy outcomes, which further attenuates the optimal response.

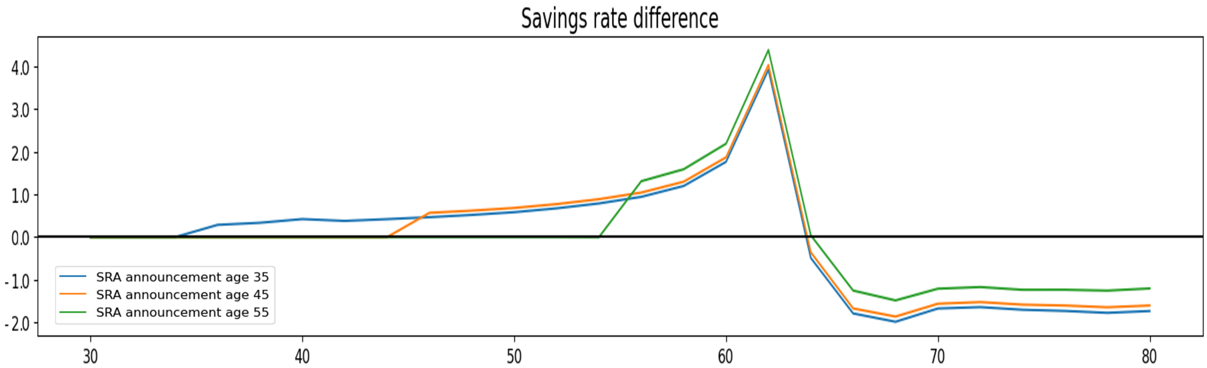
6.2. Announcement Timing

In the 2007 reform, the oldest cohort that saw their SRA increased by two full years was 43 years old at the time of the reform (cf. Figure 2). Older cohorts were subject to smaller increases in their applicable SRAs. The justification for unequal treatment is typically that the elderly should have more time to adjust to the new policy environment. However, if the goal of policy reform is to increase the effective working life, it is not clear that giving people more time to explore other margins for adjustment corresponds to the intention of the policymaker. It is, therefore, interesting to study the difference the timing of the reform announcement makes.

For this exercise, we focus on a 2-year increase in the SRA to $SRA_{63} = 69$ for all scenarios. In the baseline, this increase is announced at the latest possible point but before anyone could retire, at 63 years. In the counterfactuals, we look at different variations of *early announcement* at 55, 45 or 35 years. People have subjective expectations before and after the announcement as described in Section 3.1.[18]

We find that people react to the announcement's timing with a marked increase in savings throughout their working life and a concomitant increase in spending during retirement (cf. Figure **??**). This can be understood in the context of the findings from exercise 6.1. Since people react to a one-year increase with a less than one-year year increase in actual retirement, they save for the increase in the incurred early retirement penalty that they now expect. Interestingly, earlier announcement does not lead to a reduction in employment or to earlier retirement compared to the late-announcement baseline.

Figure 7: Effects of Announcement Timing



Notes: Effects (counterfactual - baseline) of announcing a 2-year increase in the SRA at different times in the life-cycle. In the baseline, the reform is announced at age 63; in the counterfactual, it is announced between ages 35 and 55. Savings rate is the ratio of aggregate periodic household savings and aggregate total net household income. Employment rate is the share of people in part-time or full-time employment at a given age.

6.3. Removing Early Retirement Penalty Bias

Our final simulation exercise answers the question of how differently people would behave if they were correctly informed about the size of the ERP from the start of their working lives. As in the previous exercises, the resolution age is set to 63 years and we conduct the evaluation for different values of SRA^s to uncover potential differences that depend on policy evolution relative to subjective expectations.

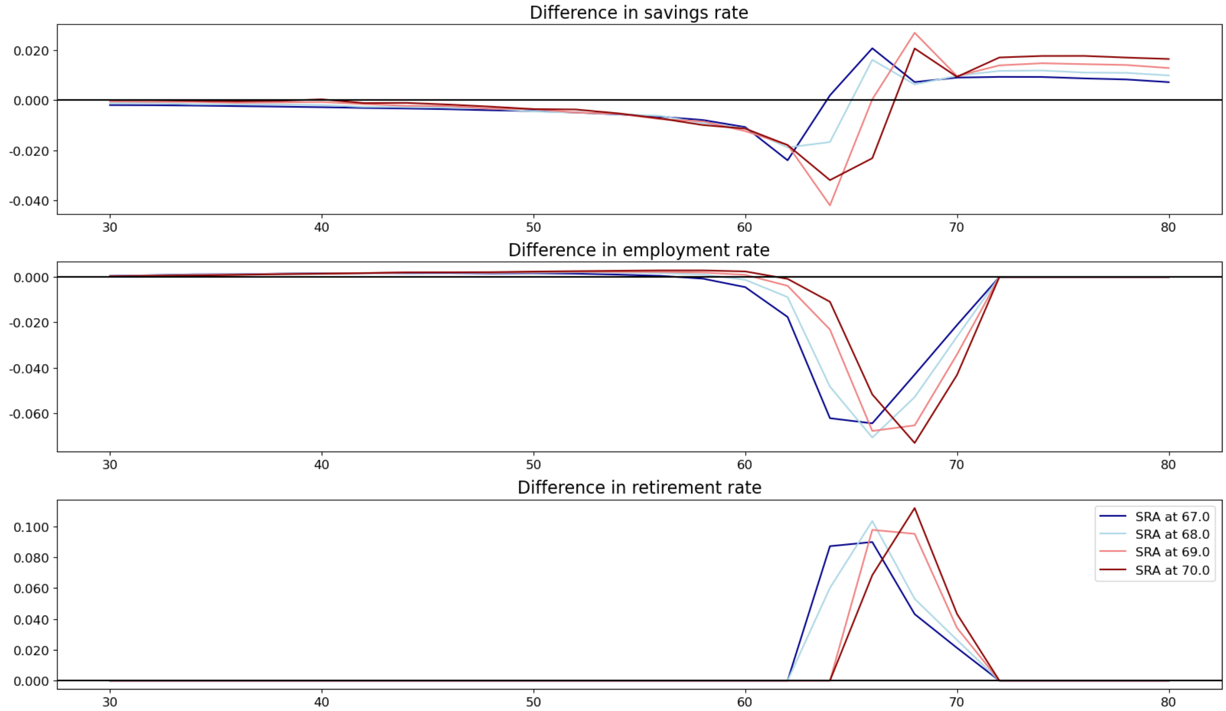
[18]Since we only have a cross-section of policy expectation data, we do not know how expectations react to policy reform. Therefore, we assume that the parameters of Equation 1 remain the same.

In the baseline, the process of learning about the true size of the ERP follows the Markov transition rates as described in Section **??**. The initial share of uninformed people at age 30 in the baseline simulation is the share predicted by that Markov process, which is around 25 percent. In the counterfactual, everyone is classified as informed from age 30, which means that no person ever transitions to uninformed because being informed is an absorbing state.

We find that removing this bias results in a considerable increase in early retirement by up to 10 percentage points compared to the biased baseline (cf. Figure 8). The old-age employment rate decreases by up to 6 percentage points, implying that transitional old-age unemployment decreases. This is accompanied by a marked decline in savings rates of 1-4 percentage points, depending on the SRA, in the years leading up to retirement. This, in turn, leads to a decrease in consumption during retirement due to higher realized early retirement penalties and lower savings.

The fact that individuals do not try to offset the reduction in income life-cycle income from earlier retirement by increasing savings and life-cycle labor supply can be understood in the context of the findings in 6.1. Since individuals even with the bias on average plan to retire early and with a penalty, de-biasing leads to an upward correction in expected retirement earnings. These expected gains can be divded into a mix of earlier retirement and higher working life consumption.

Figure 8: Effects of De-Biasing



Notes: Effects (counterfactual - baseline) of removing bias about Early Retirement Penalty (ERP) for different policy scenarios over the life cycle. Scenarios are defined by SRA at resolution. In the baseline, agents gradually learn about the true size of the ERP; in the counterfactuals, they know it from age 30. Savings rate is the ratio of aggregate periodic household savings and aggregate total net household income. Employment rate is the share of people in part-time or full-time employment at a given age.

7. Conclusion

This paper analyzes the behavioral effects and welfare costs of statutory retirement age (SRA) reforms by incorporating subjective policy beliefs into a structural life-cycle model. Using data from the German Socio-Economic Panel (SOEP) and survey-based subjective policy expectations, we estimate individual responses to policy reform under uncertainty and misinformation regarding the retirement system. Our model captures a rich set of mechanisms that influence retirement planning. These include family transitions, partner income, health and mortality, human capital accumulation, as well as job finding and destruction. It features heterogeneity along sex, education, and initial endowments. These qualities allow us to study responses to policy reform as well as the most affected groups in a comprehensive framework.

Our findings yield several insights for SRA reform. They show that neglecting policy expectations when modeling reactions to SRA reform may overestimate the reactions. They further show that eliminating uncertainty and misinformation, while welfare increasing, may have unintended behavioral effects.

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A. The appendix

A.1. Variable Overview

Variable Name	Symbol	Possible Values
Decisions		
Labor Supply	d_t	$\{0:\text{Retired}, 1:\text{Unemployed},$
		$2:\text{Part-Time}, 3:\text{Full-time}\}$
Consumption	c_t	$[0, a_t]$
Discrete states		
Age	t	$30, \ldots, 100$
Type	τ	4 Types as combination of
		Low/High Education and Men/Women
Job Offer	o_t	$\{0:$ No Offer, $1:$ Job offer$\}$
Partner State	p_t	$\{0:\text{Single}, 1:\text{Partner working age}$
		$2:\text{Partner retired}\}$
Health State	h_t	$\{0:\text{Bad Health}, 1:\text{Good Health}, 2:\text{Disabled}\}$, 3: Dead
Statutory Retirement Age	SRA_t	$\{65, 65.25, 65.50, \ldots, 72\}$
Information State	i_t	$\{0:$ Uninformed, $1:$ Informed$\}$
Continous states		
Assets	a_t	$\mathbb{R}_{\geq 0}$
Work Experience	e_t	Projection to interval $[0, 1]$
Taste Shock	$\epsilon_t(d_t)$	GEV i.i.d. taste shocks

A.2. Data and Institutional Background

A.3. Policy Beliefs

Expected Statutory Retirement Age

Under the current system, the retirement age is increased to 67. How likely do you think the following three statutory retirement ages will be at the time of your retirement? Please answer so that your three statements add up to 100%.

The possible retirement ages are ”67”, ”68”, and ”69 and above”.

Expected Retirement Age

At what age do you yourself expect to start receiving benefits from the statutory pension scheme (e.g. pension, retirement pension)?

Early Retirement Penalty

What percentage do you think the pension insurance company deducts from one's monthly pension if you retire one year before your regular retirement age?

A.4. Auxiliary Markov Processes

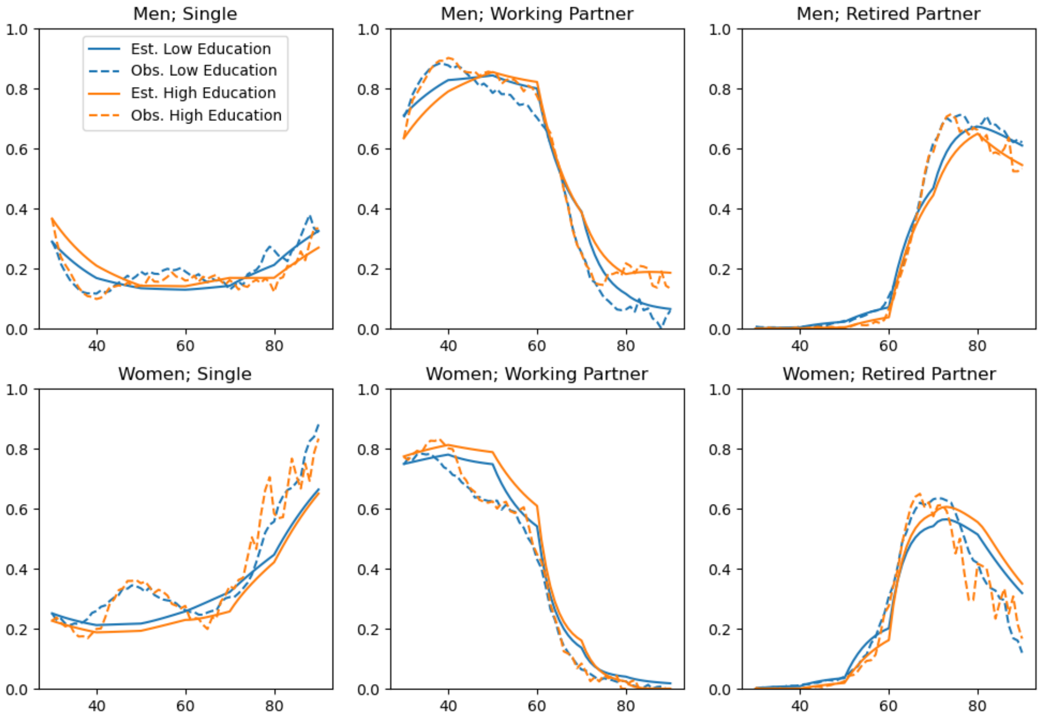
A.4.1. Partner Transitions

The partner state p_t influences utility through the consumption equivalence scaling factor and budget through partner income, taxation, and child benefits. It evolves stochastically with transition probabilities that depend on sex, education, age, and current partner state, none of which the agent can control. Formally, its transition is given by:

$$\pi(p_{t+1}|x_t) = \Lambda_p\Big(Z_p(x_t)'\,\phi_p)\Big) \tag{17}$$

where Λ_p is the three-dimensional multinominal logistic distribution function. It provides transition probabilities for the state's single, working-age partner, and retired partner. The characteristics in $Z_p(x_t)$ are, as explained earlier, the sex, education, age, and current partner states. However, we estimate the partner transitions for the four types separately. We use SOEP-Core data to estimate partner transitions. As the SOEP is a household panel, all members, including the partners, are also interviewed. We can classify them directly into retirement and working age. Simulating with our estimated transition probabilities from the initial share at age 30 of partner states in the data, we can replicate the shares in population:

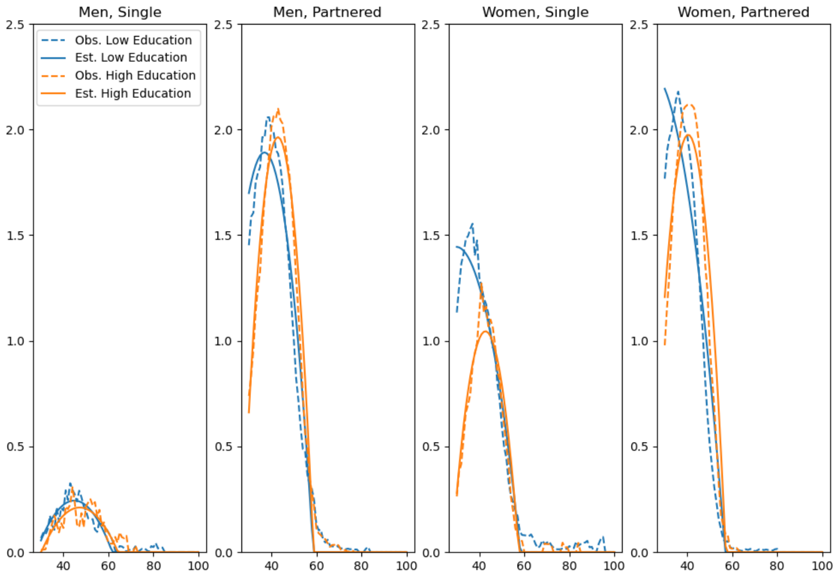
Figure 9: Shares of population in partner states



Notes: Simulated shares of individuals in each partner state from estimated transition probabilities. *Data:* SOEP-Core

The partner state, together with type (sex, education) and age, determine the number of children in the household. We use the number of children to construct the consumption equivalence scale and, if working, for additional disutility. We approximate the number of children by OLS. We provide the goodness of approximation:

Figure 10: Number of children



Notes: OLS for Number of children in the household conditional on type and partner state over the life-cycle. *Data:* SOEP-Core

A.4.2. Job-offers and Destructions

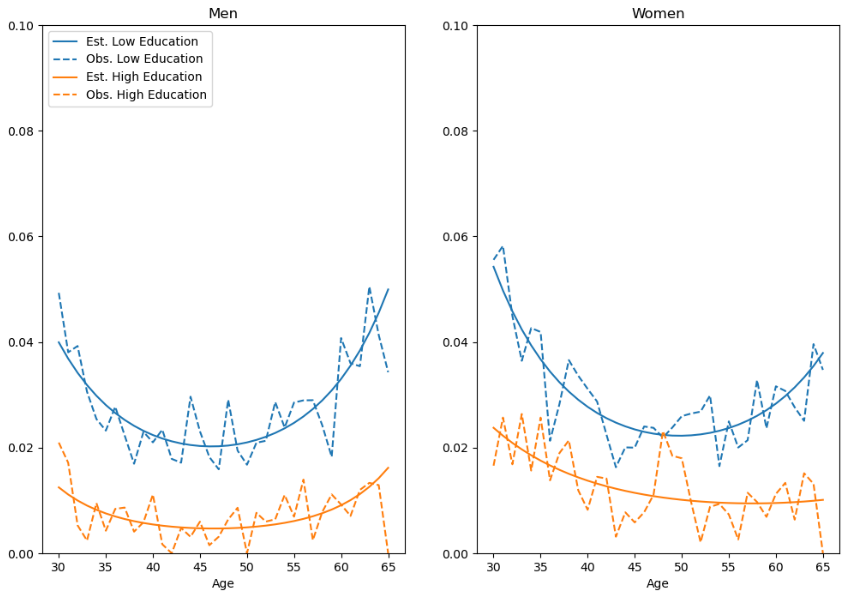
The job offer state governs the agent's ability to choose employment; the agent can choose part- or full-time if the job offer state o_t equals 1. We incorporate two processes with the job-offer state. Namely, job destruction and job offer. If the agent chooses employment in the current period, the job could be destroyed, and she has job offer state $o_{t+1} = 0$ in the next period, forcing her to choose unemployment[19]. In this case, the transition probability for the job offer state is given by:

$$\pi(o_{t+1} = 0 | x_t, d_t \in \{2, 3\}) = \Lambda_{sep}\left(Z'_{sep}\phi_{sep}\right) \tag{18}$$

where Λ_{sep} is the logistic distribution function, which predicts a job separation, conditional on education, age, and a constant. We separately estimate the probability of job separation for men and women. We estimate the probability from SOEP-Core data, where individuals are asked why they left their jobs. We only consider involuntary job loss as job separation. We restrict our sample to the start age of our model and 65 to have enough observational power. We assume that job separation rates remain constant after 65 to the age of forced retirement (72). The fit of our estimated probability can be seen in Figure 13:

[19]The agent can also choose retirement with $o_t = 0$, but we abstract from that for clarification.

Figure 11: Share of Job separations



Notes: Estimated job separation probabilities using logistic regression. Data is weighted and shares are computed using a moving average with a three-year bandwidth.

Data: SOEP-Core

The second process incorporated in the job offer state is the job offer process for unemployed agents. If the agent chooses unemployment during this period, it predicts the probability of being able to choose employment in the next period ($o_{t+1} = 1$). Why and how we estimate this process via maximum likelihood can be found in Section (5.1):

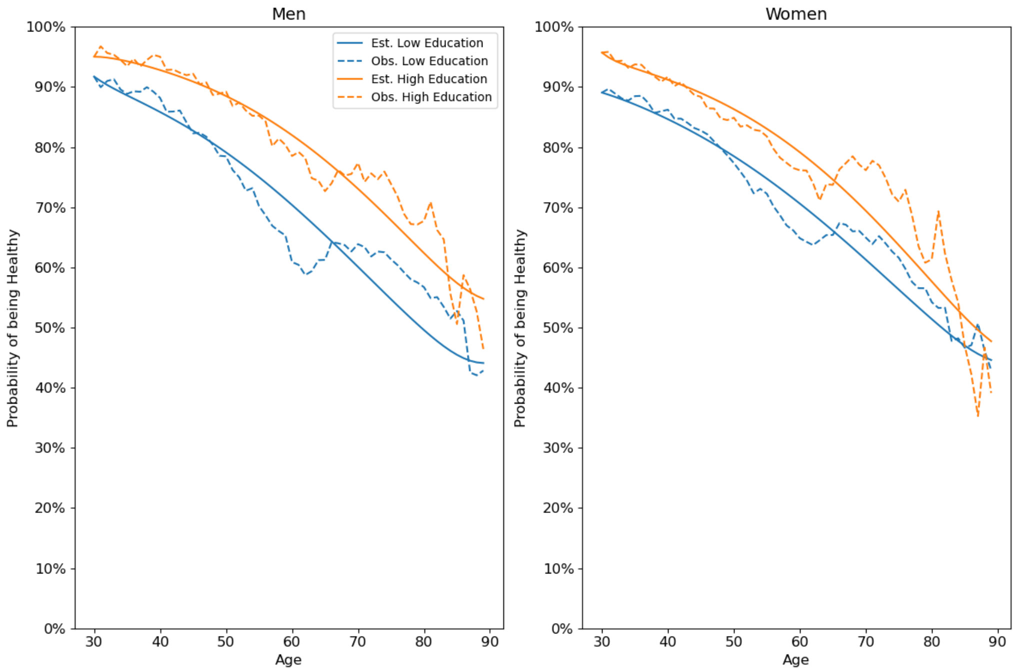
A.4.3. Health and Death

The state of health directly affects the disutility of work and the probability of survival. We, therefore, track three health states: Bad Health, Good Health, and Death. For good and bad health we use the SOEP-Core question on self-reported health, following closely Haan and Prowse (2014). We then use a logistic regression to estimate and predict the probabilities of bad (from good state to bad) and good (from bad state to good) health shocks. We use the following empirical specification:

$$\pi(h_{t+1}|x_t) = \Lambda_h\Bigg(Z_h'\phi_h\Bigg) \tag{19}$$

where Z_h includes current health state and age. Below, we document the sample fit using the predicted transition rates, and simulate with them from the initial share of healthy individuals. We fit the share of healthy individuals well:

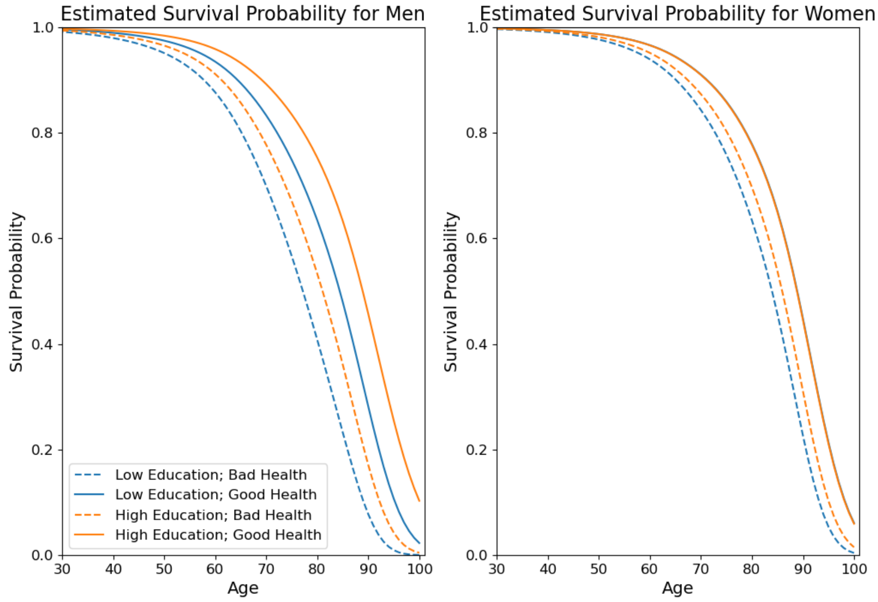
Figure 12: Share of healthy people



Notes: Predicted of healthy people in comparison to data.
Data: SOEP-Core

The third state of our health process is the state of death. In the case of death, the agent bequeathed all its wealth and received a bequest utility. The probability of dying depends on health. Therefore, we use a joint Markov process together with health. To estimate survival probabilities, we can not only rely on the SOEP. Instead, we follow Lampert et al. (2019) and use a two-step procedure: First, we generate group-specific hazard ratios with the SOEP. Second, we use the Lifetables from the German statistical office to correct and match the German mean death probability. The procedure relies on the assumption of randomness (independent of the groups we consider) that death is observed in the SOEP data. Here are the estimated survival functions over the lifetime:

Figure 13: Share of individuals alive



Notes: Estimated survival functions.
Data: SOEP-Core and Lifetables from Destatis

A.5. Modelling and Estimation of Income

A.5.1. Pension calculation

The formula for calculating pension claims in Germany consists of three parts. First is the pension point value, which we use as the population-weighted average from the 2010 pension point values for East and West Germany. Second, the pension points themself accumulated over the working life, and third, the deduction factor if the individual retired early. The second and third factors we track through the experience stock, which we will outline in this section.

Each individual receives pension points in the ratio of their yearly income compared to the overall mean wage of all working individuals. Let w_m be the mean wage, and h_t be the agent's work hours(either part- or full-time). The average (averaging over income shocks) yearly income for any experience level e_t is given by

$$exp(\gamma_{0,\tau} + \gamma_{1,\tau} \ln{(e_t + 1)}) * h_t$$

Therefore, the pension points at any age t, working h_t hours are:

$$\frac{exp(\gamma_{0,\tau} + \gamma_{1,\tau} \ln{(e_t + 1)}) * h_t}{w_m}$$

If an agent retires at age t, she has a certain number of years of experience e_t. This corresponds to working full-time hours for e_t years. Let $h_{f,\tau}$ be the type specific full-time hours and define $w_{m,\tau} = w_m / h_{f,\tau}$. We approximate the number of pension points by assuming the agent has worked e years full-time. This yields the following pension points:

$$
\begin{aligned}
PP(x_t) = & \int_0^{e_t} \frac{exp(\gamma_{0,\tau} + \gamma_{1,\tau}x + \gamma_{2,\tau}x^2) * h_{f,\tau}}{w_m} dx \\
& \frac{1}{w_{m,\tau}} \int_0^{e_t} exp(\gamma_{0,\tau}) exp(\gamma_{1,\tau}x + \gamma_{2,\tau}x^2) dx \\
& \frac{exp(\gamma_{0,\tau})}{w_{m,\tau}} \left[\frac{1}{\gamma_{1,\tau}+1} (x+1)^{\gamma_{1,\tau}+1} \right]_0^{e_t} \\
& \frac{exp(\gamma_{0,\tau})}{w_{m,\tau}(\gamma_{1,\tau}+1)} \left[(e_t+1)^{\gamma_{1,\tau}+1} - 1 \right]
\end{aligned}
$$

Therefore, we have a closed-form solution for the pension points and can calculate the monthly pension by:

$$
y_t(x_t, 0) = PP(x_t) * PPV \tag{20}
$$

The factor PPV is the pension point value, for which we use the 2020 east-west weighted average. Note that the function above is invertible. Assume that an agent retires one year early. Her pension would be given by:

$$
y_t(x_t, 0) = PP(x_t) * PPV * (1 - 0.036) \tag{21}
$$

Given the type of the agent, we can map the new pension back to the experience stock, such that the reduced pension corresponds to an unreduced pension with a new experience stock e'_t. With this method, we can track pension deductions for the experience stock without tracking the retirement age.

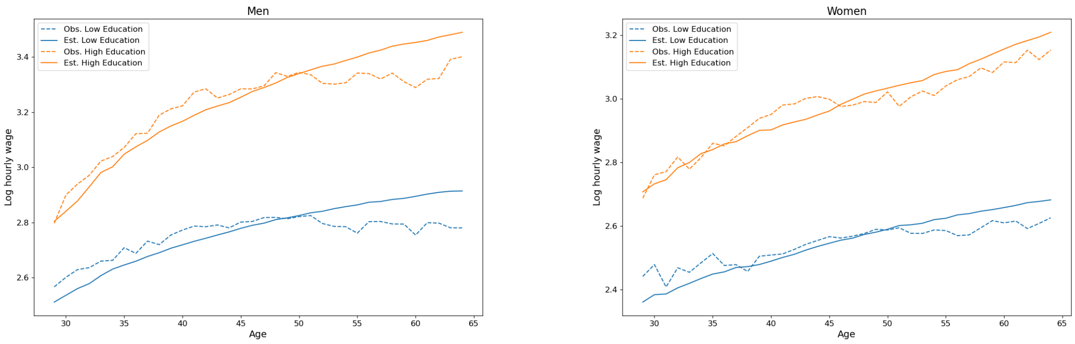
A.5.2. Wage Process

In the model, we assume that individuals can invest in their human capital by working full-time or part-time. We estimate their returns to experience with two-way fixed effects regressions using SOEP core panel data. The estimation sample is the same as the one used for the model estimation, i.e., men and women over 30 who work full- or part-time throughout the estimation period 2010-2017. Since time-fixed effects absorb the effects of aggregate income growth and inflation, all monetary quantities in the model are expressed in 2010 Euros. The returns to experience are identified as individual variations in wages over time. We estimate the following equation for each sex and education type using observations of wages and experience for each individual i and time t:

$$
log(w_{it}) = \gamma_{0,\tau} + \gamma_{1,\tau} * log(exp_{it} + 1) + \xi_i + \mu_t + \zeta_{it}. \tag{22}
$$

Our estimates of $\gamma_{0,\tau}, \gamma_{1,\tau}$, directly correspond to the parameters in equation (10). We cluster standard errors across individuals and time and estimate the wage process's variance σ_w^2. We document the fit of our estimates below:

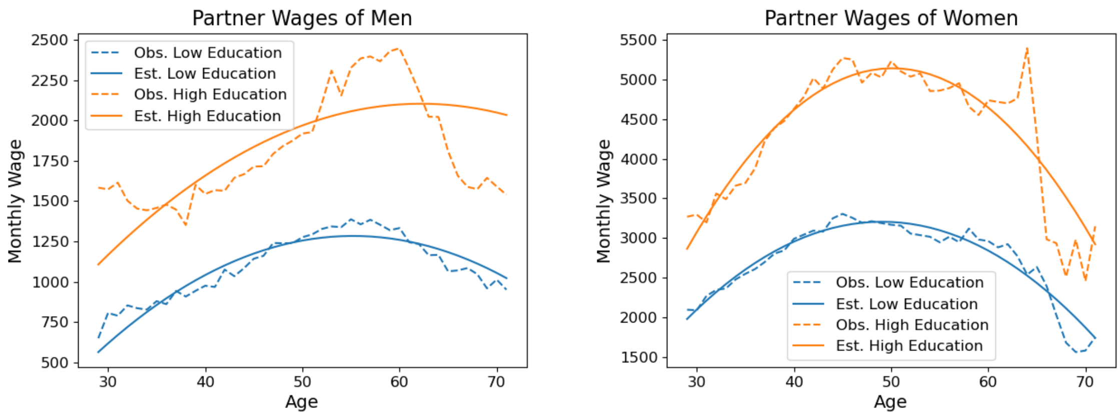
Figure 14: Wage fit



A.6. Partner Income Process

We approximate the partner's income through state variables of the agent himself. First, consider the partner state: If the agent is single, there is no partner income. When having a partner in working age life, we approximate the partner's wage by OLS of wages onto the agent's age and age squared. We assign unemployed partners a wage of zero. Therefore, the partner income is a mixture between the wages of partners and unemployed partners. We do the approximation for education and sex separately. Below, we show the fit of the

Figure 15: Wages of working age partners



Having a wage prediction over the life-cycle, we use these to approximate the partner's pension, which remains constant over retirement.

A.7. Counterfactuals

A.7.1. Welfare Measure

For the welfare analysis, we follow Low et al. (2010) who measure the welfare effects by the consumption variation that is welfare equivalent to the change from one scenario to the other. Formally, let A denote the counterfactual environment and let B denote the baseline scenario. The welfare value of scenario A is denoted by γ_A and solves $V_B(\gamma_A) = V_A(0)$, where

$$V_e(\gamma) = \mathbb{E}\left[\sum_{t=30}^{T} \beta^t u(c_t(1+\gamma), d_t, \theta, X_t)\right], \text{ for } e \in \{A, B\}. \tag{23}$$

Thus, γ_A describes the relative increase in per-period consumption to equal the average discounted utility in the counterfactual scenario [20]. Consequently, a positive value is associated with a welfare gain in the counterfactual and a negative vice versa.

[20] In this calculation, the consumption adjustment γ_A is implemented ex-post and, therefore, does not affect behavior.