# Policy Uncertainty, Misinformation, and Retirement Age Reform

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This study quantifies the impact of *Statutory Retirement Age* (SRA) reforms on individual behavior and welfare in the presence of subjective policy uncertainty and misinformation. We develop and estimate a rich structural life-cycle model with forward-looking agents and dynamic policy belief updating. In the model, individuals have probabilistic expectations about the future evolution of the SRA and are misinformed about its mechanism, the penalty for early retirement (ERP). We derive subjective policy beliefs from self-elicited survey data. The model features men and women and accounts for key determinants of retirement timing, precautionary savings, and old-age labor supply. Our results show that uncertainty and misinformation lead to both individual welfare loss and overestimation of the cost of SRA reform. However, they facilitate targeted policy implementation. Uncertainty attenuates undesired anticipatory policy responses, and misinformation ensures a stronger reaction of retirement timing to SRA increase.

**JEL Codes** D15, D83, I38, J11, J26

# Contents

# 1. Introduction

Ageing populations are straining social security systems across the world, continuously prompting governments to reform pension systems. Since the immediate effects of such reforms 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), uncertainty is the fundamental unpredictability of the future policy environment (Caplin et al., 2022; Ciani et al., 2023). To quantify subjective policy belief dynamics, we collect survey evidence and study how subjective policy beliefs evolve over the life cycle. We then 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.

Modifications of *Statutory Retirement Ages* (SRA) are among the most common types of public pension reform [1] , yet their effects on working life behavior are not very well understood. For example, consider a one-year increase the the *Statutory Retirement Age*. A forward-looking agent should respond to this first by updating her expectation about the future policy environment, then update her expectation about her own retirement timing. If she expects to follow suit and postpone her own retirement by one entire year, this reduction in pension system generosity leads to an increase in her lifetime income. Consumption smoothing behavior would then imply a reduction in her current labor supply or savings. In contrast, if she thinks that she will not be able to work longer, for instance because of health-related reasons or difficulty to find employment at high ages, the opposite may be true. Consistent with this ambiguity, recent quasi-experimental literature has found opposite-sized life-cycle reactions to SRA increases and considerable heterogeneity of responses (Carta and De Philippis, 2024; Etgeton et al., 2023).[2]

This example illustrates two things. First, extrapolating observed pension reform effects into the future is challenging because with age, the multitude of incentives that affect expected retirement timing change (Blundell et al., 2016b; Fisher et al., 2016). Koşar and O'Dea (2023) name this non-stationarity of the policy environment one of the key challenges for including subjective beliefs about late-in-life policies in structural models. [3] Comprehensive dynamic lifecycle frameworks are best suited to make counterfactual predictions about such policies. We model high-dimensional expectation formation, which can account for changes in health and labor market conditions at higher ages. Second, to predict forward-looking reform effects, it is critical to model expectations of agent behavior and policy beliefs jointly. A key insight from our analysis is that uncertainty and misinformation about features of the policy environment can lead to too little response in the present, which also means overestimation of the true wel-

[1] For example, in the 2023 version of the biennial OECD pension report, 9 out of 21 recent pension reforms in OECD countries were changes of the SRA (Scarpetta and di Noia, 2023). See also Börsch-Supan and Coile (2021) for a systematic overview of four decades of pension reforms in selected countries.

[2] Note that for elderly workers who are close to retirement, however, an increase in employment is the typically observed response. (cf. Pilipiec et al., 2021, for a literature review)

[3] This is in contrast to the macroeconomic literature, where modeling policy uncertainty is much more common, e.g. for fiscal policy (Fernández-Villaverde et al., 2015), monetary policy (Born and Pfeifer, 2014), or trade policy (Caldara et al., 2020). There, the policies under scrutiny typically have tangible effects in the short term. As a result, agents can form expectations and adapt their behavior based on their own experience.

fare cost of policy reform.

Another key challenge Koşar and O'Dea (2023) mention and which we account for in our model is multidimensionality of the policy environment. 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. We argue that frequent reforms and an ongoing public debate make the headline number of the SRA very salient with an *uncertain* future. That is why subjective probabilistic expectations of the future SRA are our measure of policy uncertainty. In contrast, the ERP, which has never been changed since its introduction in 1992, is arguably much less salient, making *information* key to its effect on behavior. For these reasons, we use the ERP to model misinformation, and abstract from expectations about potential future changes. [4]

The previous example illustrates why the interaction of these beliefs is key to understanding forward-looking policy reform response. Consider again a one-year increase in the SRA. This will update the agent's expectation of the future SRA only to the extent that she did not expect the reform. Say she she did not expect it and revises her expectation of the future SRA upward. If she then revises her expected retirement timing upward by less than one for one, which what is typically observed (De Grip et al., 2013; Coppola and Wilke, 2014) [5], there are two counteracting effects on her lifetime income: an increase from the expected extension of her working life, and a decrease from the size of the expected penalty she will have to pay for early retirement. Her perception of the ERP will therefore determine not just the size but even the direction of her forward-looking response. To our knowledge, our model is the first in the literature that can accommodate the interplay of these channels. [6]

To quantify subjective beliefs, we include a questionnaire in the German *Socio-Economic Panel Innovation Sample* (SOEP-IS, Richter and Schupp, 2015a), 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. As life-cycle reactions to pension age reform are second-order effects that depend on the direct reform effect on expected retirement timing, we model the most important classical retirement incentives that have been studied the literature to avoid misattributing observed behavior to policy beliefs (Blundell et al., 2016b). We allow for stochastic factors such

[4] While researchers do not all agree if the ERP 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).

[5] Likewise, the literature on actual retirement timing responses to SRA increase across countries typically finds semi-elasticies of less than one.Dolls and Krolage (2023) estimates an effect size of around 0.4 years of retirement age reduction after per year of decrease in the SRA for a recent German reform. Manoli and Weber (2016); Mastrobuoni (2009); Lalive et al. (2023) produce similar estimates for reforms in Austria, France, and the United States.

[6] The closest ones are the models of Hentall-MacCuish (2025), who includes biased expectations about the pension eligibility age, and Bairoliya and McKiernan (2025), who feature biased beliefs about the early pension claiming penalty. Both of these models focus on explaining existing puzzles in claiming behavior rather than

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). We further include important institutional features, such as alternative paths to retirement based on disability or long working lives, to allow for program substitution effects which reforms of pension eligibility ages have been shown to cause (Atalay and Barrett, 2015; Duggan et al., 2007; Staubli and Zweimüller, 2013).

In line with previous research, our survey evidence shows that people on average are misinformed about current policy rules and uncertain about their future development (e.g., Bottazzi et al., 2006; Caplin et al., 2022; Luttmer and Samwick, 2018), but that beliefs become more accurate at higher ages Manski (2004); Rohwedder and Kleinjans (2006) Respondents on average expect further increases in the SRA, those closer to retirement expecting smaller increases, which is consistent with a gradual convergence of expectations and policy. Forecast uncertainty is lower for older respondents, meaning policy uncertainty resolves gradually. We model expectations with a simple nonstationary, autoregressive process, which is similar to Hentall-MacCuish (2025), who measures the parameters from past reform frequencies rather than subjective expectation data. This functional form matches the desired features of the data, while remaining computationally tractable. [7] Our survey further shows 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 as people approach retirement, suggesting that people learn about the retirement system as they age. Accounting for these belief dynamics is another key contribution of our model.

We find that a perceived reduction in pension system generosity – whether it is caused by overestimated penalties or by expected SRA increases – leads agents to expect shifting from pension wealth to private wealth to finance retirement consumption. For small changes with small effects on expected working life, this may imply higher anticipatory savings and lower labour supply. Generally, however, forward-looking effects, particularly on labour supply, are ambiguous in size and direction. We discuss this theoretically and illustrate it with simulations of agent expectations.

Simulated expectations further reveal that expected welfare costs of policy reform are significant, particularly to the misinformed. This is because the misinformed expect that SRA increases leave them hardly any other choice but to postpone claiming, even if they are cash-constrained or in bad health by the time of retirement. The informed on the other hand know they can react more flexibly. We find that a 30-year old would trade expecting an SRA increase of one year for 0.8 percent of lifetime consumption if he is misinformed about the ERP, compared with only 0.3 percent if he was correctly informed. Since we find that a large majority of young people are misinformed, that suggests that the welfare cost of SRA reform is generally overestimated.

Our counterfactual simulations show that, from a policymaker perspective, however, both policy uncertainty and misinformation can have positive consequences. In our policy simula-

[7] This matters in the context of a dynamic markov decision process model, which only only allows for limited history-dependence. We discuss consequences and potential alternatives to this approach in Section 3.1.

tions, we estimate that agents with perfect foresight and no policy uncertainty would react to increases in the SRA with higher savings (+1 percent per year of SRA increase) and lower labour supply (-0.1 percent per year of SRA increase). This behaviour is consistent with the aforementioned substitution from public pension to private financial wealth upon a decrease in pension system generosity. However, forward-looking reactions to policy reform in our benchmark model, which features uncertain agents who have probabilistic reform expectations, are attenuated by 20-80 percent.

This happens for two reasons. First, uncertain agents in the no-increase baseline still *expect* increases in the SRA even when they do not happen and act accordingly until that belief fades at higher ages. Second, although policy and expectations gradually converge, particularly younger agents in the increasing-SRA counterfactual retain uncertainty over their lives and optimize for a mix of possible outcomes, which further attenuates their response. On the margin of actual retirement timing, however – which is the target of this policy – response sizes are equal between uncertain agents and those with perfect foresight. As a result, we estimate around 20 percent higher effects of SRA increase on labor supply for agents with policy uncertainty. To the extent that forward-looking reactions are unintended and - in our estimation - even counterproductive, uncertainty therefore supports policy reform objectives.

This finding presents an important contribution to a large literature which evaluates responses to pension reform through the lense of forward-looking life-cycle models (e.g., Daminato and Padula, 2024; French, 2005; 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, pessimistic subjective survival expectations are a main driver, although in case of Bairoliya and McKiernan (2025), uncertainty about the policy environment plays a role. We show that uncertainty about the retirement age is an additional mechanism that produces reform effect attenuation.

We then evaluate the effect that eliminating misinformation would have on agent behavior. For this exercise, we assume that SRA is increased gradually by two years from 67 to 69. We compare the baseline with misinformation and random updating to a counterfactual scenario in which everyone is informed from the start. Especially on the margin of retirement, the effects are sizable. Agents retire around 0.8 years earlier with the same incentives, reducing lifetime labor supply by over two percent. The effect is driven by men, particularly low-educated men, for whom pension wealth is the most important source of old-age household income and who, when misinformed, would not have considered early retirement. The individual welfare effect is positive but much smaller when evaluated ex post than the effect of misinformation is on individual expectations. This is due to updating but also because agents who retire early despite misinformation then find out that the penalty was much lower after all. Due to the positive spillovers of labor, it can be expected that these

Furthermore, 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.[8] We contribute by showing that despite the undoubtedly negative effect on individual welfare, efforts to correct misbeliefs or eliminating policy uncertainty may conflict with potential policy goals of stimulating precautionary behavior. 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.

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[9]. While replacement rates have fallen in recent years, contribution rates have been stable at around 19 percent (cf. figure 10). Both are linked to demographic change, so without further reform, replacement rates are expected to fall, while contribution rates are expected to rise.

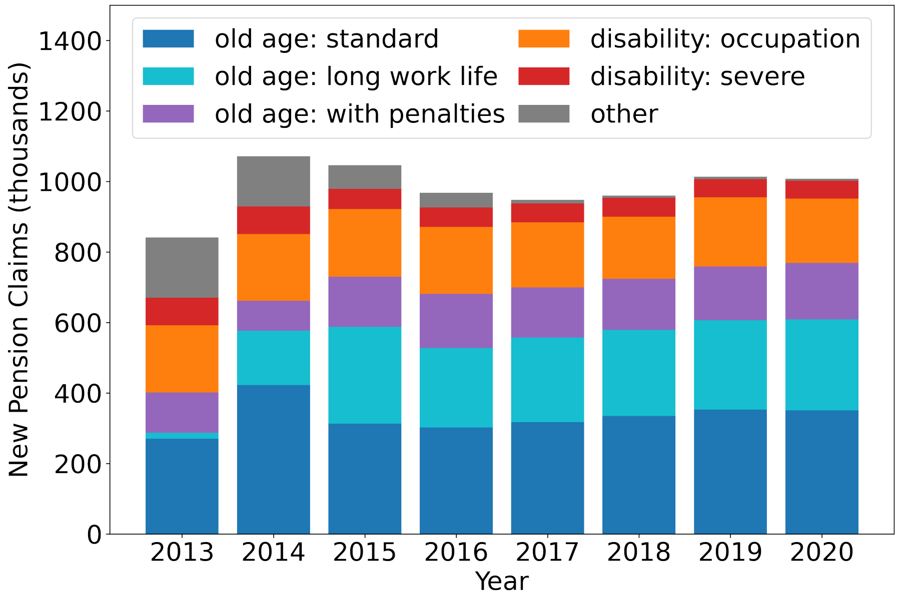
There are two main paths to retirement in Germany: old-age pensions and disability-based pensions. Claiming an old-age pension is possible upon reaching the *Statutory Retirement Age* (SRA). The current SRA is a function of birth year and stands at 67 years for everyone born after 1964. Given certain requirements, claiming a pension is possible up to four years before this age,[10] but no earlier than 63 years. Early retirement generally comes at a penalty (*the*

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

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

[10] 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 1: New Pension Claims 2013-2020 by Type of Pension




Note: "Other Pensions" comprise the phased-out pensions for women and for the unemployed. "Occupation-based Disability" and "Severe Disability" Pension ("Erwerbsminderungsrente" and "Rente für Schwerbehinderte" in German) are based on different eligibility criteria and offer earlier retirement or with reduced penalties compared to the ordinary old age pension. Widower pensions are excluded here since they are transfers or existing entitlements rather than new claims.

Source: German Federal Pension Insurance (Deutsche Rentenversicherung, DRV).

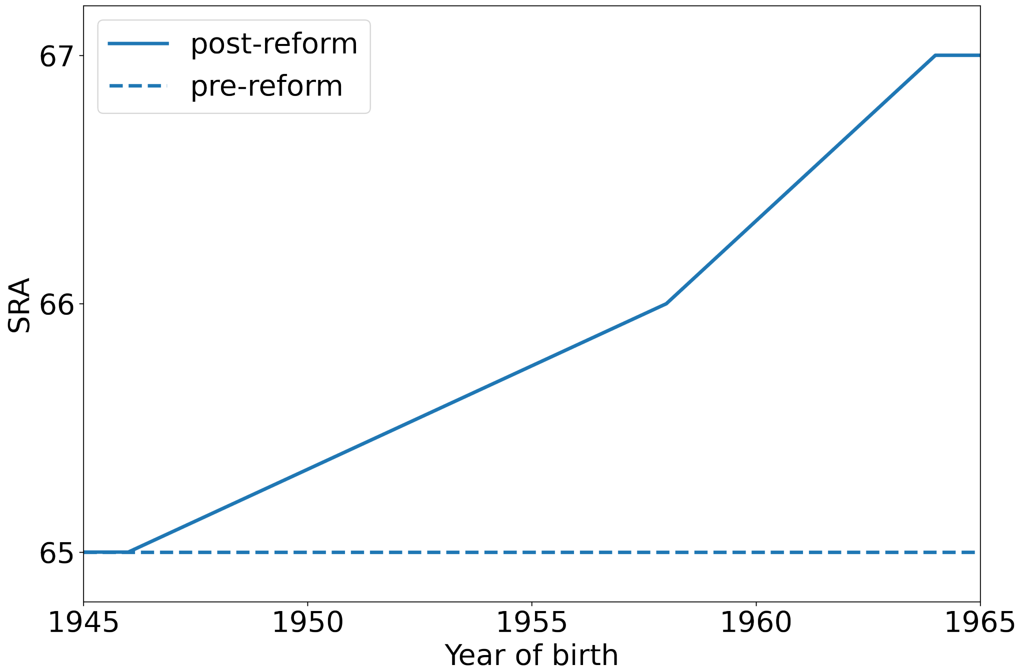
*Early Retirement Penalty*, ERP) of 3.6 percent of the pension value per year of early retirement, or 0.3 percent per month. [11] However, after a 2013 reform, claiming an old-age pension without penalty is possible up to two years before the applicable SRA for people with very long contribution histories of at least 45 years. The most important type of disability-based pension can be claimed at any age if the claimant can prove reduced capacity to work. The size of these occupation-based disability pensions is the same as that of their old-age pensions would have been if they had continued working at the same earnings level until reaching the SRA. Typically, disability pensions are subject to a penalty of three times the ERP, i.e., 10.8 percent.[12]

In 2007 a reform was passed, which gradually increased the SRA from 65 to 67 years for birth cohorts between 1947 and 1964 (cf. figure 2). To offset the erosion of replacement rates and the rise in contribution rates brought about by population ageing, there is a public debate about further increases in the SRA. For example, in 2023 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.

[11] 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 theory, deferring retirement is also possible, which increases the pension size by 6 percent per year of deferral. However, in practice, this option is very rarely used.

[12] More precisely, the penalty the ERP for every year of retirement before the SRA minus two years, capped at 10.8 percent. However, the majority of disability pensioners retire more than three years before the SRA.

Figure 2: 2007 reform of the Statutory Retirement Age




## 2.2. Data

Our analysis relies on two main data sources, the German Socio-Economic Panel (SOEP) and the SOEP Innovation Sample (SOEP-IS). The SOEP-core a rich and representative longitudinal household survey(Goebel et al., 2019). The SOEP-IS is a separate representative sample that is part of the SOEP infrastructure, receives the SOEP-core questionnaire and additionally allows researchers to submit their own questions(Richter and Schupp, 2015b). We elicit subjective policy beliefs from the SOEP-IS sample and use these to predict beliefs in the SOEP-core sample. We then estimate our model on SOEP-core data. In the following, we briefly describe our sample composition and restriction criteria.

*Policy belief sample.* In the 2022 wave of the SOEP-IS, we elicited probabilistic expectations about retirement and pension policy. Specifically, we asked respondents about their own expected pension claiming ages, as well as future development of Statutory Retirement Age and the current Early Retirement Penalty. [13] The sample consists of 798 adult individuals who are not yet retired and are representative of the German working-age population. The panel structure and availability of SOEP-core covariates allow us to account for history-dependence and relevant heterogeneities of beliefs when predicting beliefs in the SOEP-core sample. In section 3 we describe this in more detail.

*Structural estimation sample.* We estimate our structural model on data from the SOEP-core, which we link with administrative pension data to get more precise data on retirement timing(Lüthen et al., 2022). We limit the analysis to the years 2013-2020. Other sample restrictions stem mainly from model restrictions. We focus on individuals above 30 years of age, who are covered by public pension insurance (cf. section 2.1). In the model, there are certain state-choice combinations we do not allow. For instance, men cannot work part-time, and

[13]See appendix A.3 for the exact wording of the questions.

retirement is an absorbing state, meaning that we drop individuals who report having been retired in the past and later report working again.

In addition to the structural estimation sample, we create several auxiliary samples from the SOEP core for the estimation of processes that we estimate outside the model, such as the evolution of health over the life-cycle (cf. section **??**). We do not estimate these on the structural estimation sample because data availability requirements differ. Aside from the linked SOEP data, we rely on very few outside data sources. We use CPI data to deflate nominal variables and population mortality to estimate life expectancy. These data come from the German Federal Statistical Office.

Table 1: Structural Estimation Sample Description

| | Men | | Women | | |
|---|---|---|---|---|---|
| | High Educ. | Low Educ. | High Educ. | Low Educ. | Total |
| Unique Households | 3,209 | 7,656 | 3,343 | 9,335 | 15,387 |
| Unique Individuals | 3,216 | 7,716 | 3,354 | 9,382 | 23,665 |
| Observations | 16,432 | 37,634 | 17,369 | 46,114 | 117,549 |
| Share Full-time | 0.695 | 0.568 | 0.347 | 0.207 | 0.412 |
| Share Part-time | 0.000 | 0.000 | 0.360 | 0.242 | 0.148 |
| Share Unemployed | 0.018 | 0.060 | 0.113 | 0.184 | 0.111 |
| Share Retired | 0.287 | 0.371 | 0.180 | 0.367 | 0.329 |
| Share Good Health | 0.850 | 0.736 | 0.847 | 0.734 | 0.767 |
| Share Single | 0.152 | 0.164 | 0.291 | 0.318 | 0.242 |
| Average Work Experience | 25.4 | 29.8 | 16.5 | 18.9 | 22.9 |
| Average Wealth (1000 EUR) | 411.7 | 196.7 | 317.9 | 192.3 | 242.9 |

*Notes: Data from the German Socio-Economic Panel (SOEP) 2013-2020. Sample restricted to individuals aged 30 and above who are covered by public pension insurance. High education defined as having at least a university entrance qualification (Abitur). Single is defined as not living with a partner in the same household. Work experience is measured in years since labor market entry, where a year of working part-time counts as half a year. Wealth includes all reported financial and real assets minus debts, inflated to 2020 levels, censored at 0 and measured in 1000 euros.*

# 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[14], 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. [15] On the other hand, people could be misinformed about the current size of the pension to which they are entitled.[16] 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 more 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 study.

## 3.1. Policy Uncertainty and the Statutory Retirement Age

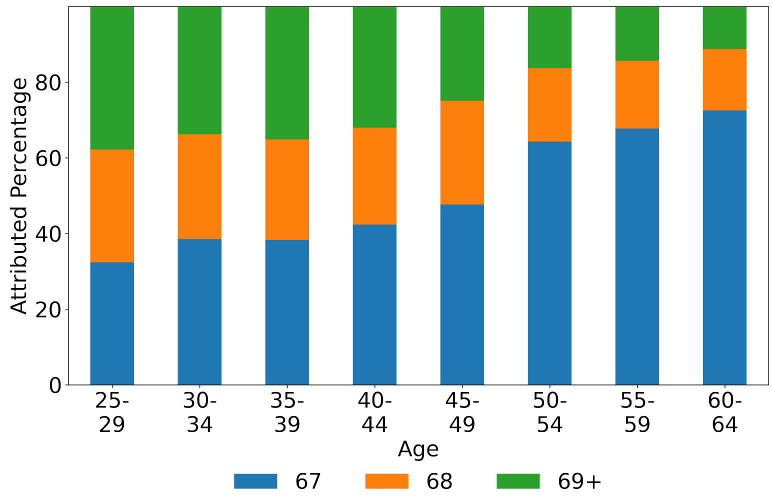
We elicit probabilistic expectations of the SRA at the time respondents expect to retire (see A.3 for question wording). The results are twofold. First, respondents expect further increases in the SRA. The younger respondents are, the higher the SRA they expect. Second, the further away respondents are from expected retirement, the larger the uncertainty. Figure 4 illustrates these findings. In other words, uncertainty increases with age; policy and expectation converge over time. In the model, we implement uncertainty about the future SRA in a sparse and computationally tractable way while retaining these key features.

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

[15]The key policy parameter in the public debate about pension size is the replacement rate of a person who worked 45 years full-time at the average wage. It carries limited information for the individual because it only describes a stylized worker.

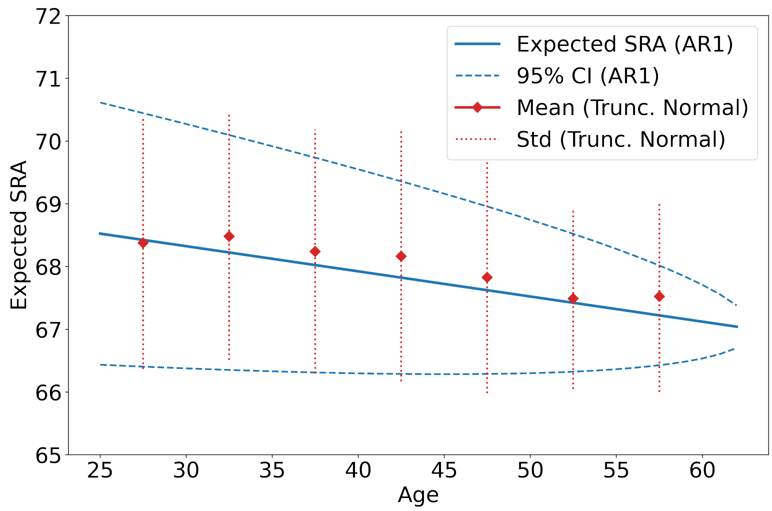
[16]For the US Social Security system, it has been a long established fact that people are, in fact, misinformed about their claims(Bernheim, 1987; Gustman and Steinmeier, 2005).

Figure 3: Subjective Distributions over Future SRAs




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

Figure 4: Expectation process fit




*Fit of individual truncated normal distributions by AR1 process*

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 $\upsilon_t$ is i.i.d. normally distributed with mean zero and constant variance $\sigma^2_{SRA}$.[17] 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

[17] 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 $\upsilon_t$ result in a Markov process that depends only on the current SRA as its state.

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

Although this model captures the key features of our survey data, it is simple and abstracts 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.[18]

Table 2: Expectation process parameter estimates

| Parameter Name | Parameter | Estimate |
|---|---|---|
| Drift | $\alpha$ | 0.040 |
| | | (0.0014) |
| Variance of belief process | $\sigma^2_{SRA}$ | 0.030 |
| | | (0.0010) |

*Notes:* Standard errors in parentheses.

Table 3: Early Retirement Penalty parameter estimates

| Parameter | Low Education | High Education |
|---|---|---|
| Initial informed share | 0.074 | 0.288 |
| | (0.048) | (0.062) |
| Hazard rate | 0.011 | 0.007 |
| | (0.003) | (0.004) |
| ERP uninformed belief | 18.919 | 16.246 |
| | (0.954) | (0.779) |

*Notes:* Standard errors in parentheses.

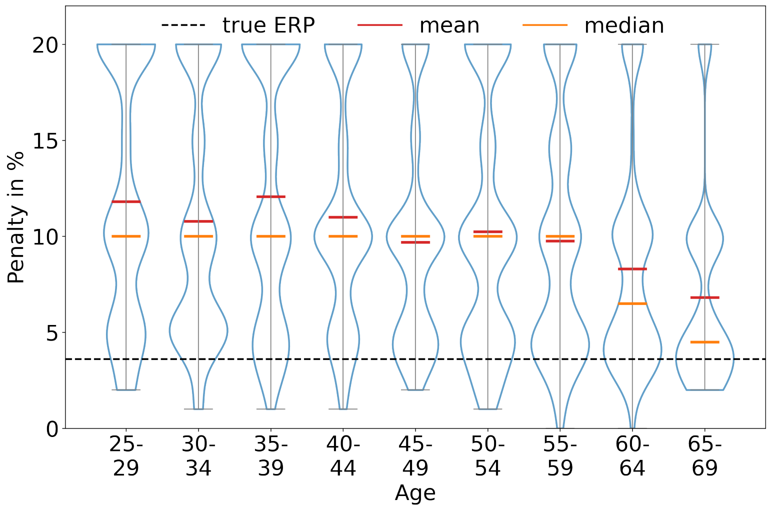
Table (2) reports our estimate for the random walk of our policy belief process. As a benchmark, the implied expected SRA increase of 0.41 years every ten years is close to the German Council of Economic Advisors recommendation, which is 0.5 years every ten years (Grimm et al., 2023). We observe considerable 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.

[18]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.

## 3.2. Misinformation and the Early Retirement Penalty

We further elicit probabilistic beliefs of the current ERP(see A.3 for question wording). Figure 9 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[19]. By contrast, at the average reported ERP size of around 12 percent, early retirement would be prohibitively expensive for most people.

Figure 5: Belief about Current ERP



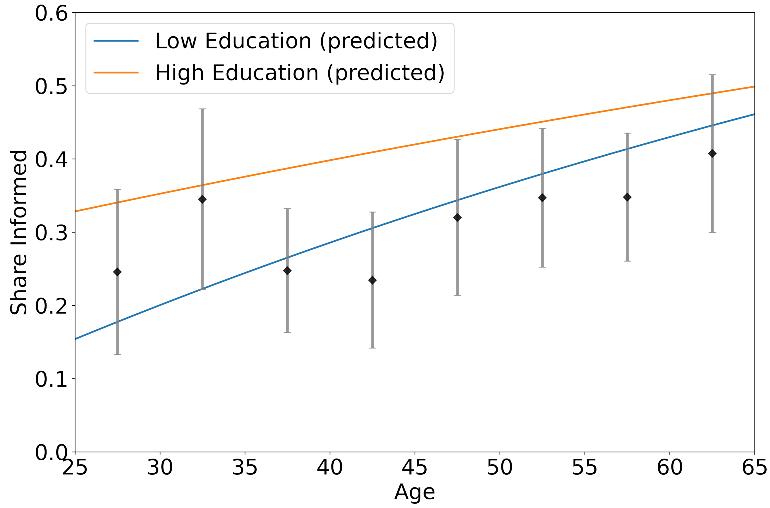

*Notes:* Respondents' beliefs about the current ERP. distributions censored above at 20 percent. See appendix A.3 for question wording.

For these reasons, we classify people into informed and uninformed in the model, as Bairoliya and McKiernan (2025) do[20] 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 tend to become informed about the ERP. This can be interpreted as evidence in favor of rational attention models (Brown and Jeon, 2024; 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.

[19]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).

[20]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.

Figure 6: Belief about Current ERP




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

# 4. Model

The model is a dynamic life-cycle consumption-saving and labor supply model in the tradition of French (2005). We model men and women who completed either high or low education, determining four exogenous types $\tau \in \{men, women\} \times \{high, low\}$.[21] Agents choose labor supply and savings $\{d_t, c_t\}$ to maximize the discounted sum of expected utilities over their whole life, subject to an inter-temporal budget constraint from age 30 until their stochastic death. Upon death, agents bequeath all remaining assets.

Aside from uncertainty about the future policy environment through the stochastic statutory retirement age $SRA_t$, agents face uncertainty from transitory wage shocks, stochastic job offers, and destruction $o_t$, as well as the arrival, departure, and retirement of partners $p_t$, as well as the evolution of health $h_t$ over the life cycle. In addition, agents differ on wealth $a_t$ and work experience $e_t$. Together, these variables constitute the state $x_t$. An overview of the state, decision, and derived variables, including domain and notation, can be found in the appendix A.1.

## 4.1. Work, Health, and Paths to Retirement

At every age during their lives, agents choose discrete labor supply $d_t \in \mathcal{D} = \{0, 1, 2, 3\}$ representing retirement ($d_t = 0$), unemployment ($d_t = 1$), part-time ($d_t = 2$), and full-time work ($d_t = 3$) respectively. During their working life, agents may decide to work part- or full-time[22] if they have a job offer in the current period, i.e., $o_t = 1$. [23] Otherwise, they can always choose

[21] From the model solution perspective, being informed about the early retirement penalty $\imath_t$ constitutes an additional type, as agents do not expect the penalty to change over time or for their belief about it to be updated.

[22] We allow for part-time work only for women, because few men work part-time and the decision usually is not well explained by observable data.

[23] The law of motion of $o_t$ is described in Appendix (A.4.2)

unemployment.

In our model, retirement and pension claiming happen simultaneously, and we do not distinguish between the two decisions. In the standard path to retirement, agents can choose to retire before the statutory retirement age (SRA) but no earlier than the Early Retirement Age of 63, following a simplified version of the current German law. Note that we assume that the Early Retirement Age does not automatically change with reforms of the SRA. Early retirement incurs permanent pension reduction penalties. To simplify further, we restrict decisions so that retirement is absorbing and from age 72 everyone must be retired.

Our model features the two main alternative paths to retirement beyond the standard old-age pension in Germany (cf. section 2.1). First, very long work life: agents can retire two years before the SRA without penalties if they worked 45 years of credited periods, denoted $CP(x_t)$. Credited periods are predicted from the current state $x_t$ and are not a state variable in themselves. Agents can increase their stock in credited periods by working more, generating an additional incentive to work. Any reform of the SRA would also shift the age at which they can retire on this path.

Second, disability pension: agents can retire at any point in their lives if they are eligible for disability pensions. We track eligibility as a separate health state in the Markov health process $h_t$, in addition to good and bad health. If agents claim disability pension, they pay a reduced penalty of the true ERP times the difference in their retirement age to the Early Retirement Age, but only up to a maximum of three years. If they do, the counterfactual foregone work life if disability had not occurred is extrapolated until the currently applicable SRA for the calculation of the pension.

Work experience $e_t$ increases by one year for full-time work and 0.5 years for part-time work.[24] Work experience is the main determinant of three key outcomes: wages, pension benefits, and credited periods for eligibility for the very long work life pension.

## 4.2. Income, Budget and Family Dynamics

Every period, agents choose continuous consumption $c_t \in \mathcal{C}_t = [0, a_t]$ on behalf of the household, where they may consume 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, ensuring agents can always afford a positive level of consumption. Households include a potential partner $p_t$ following a Markov process and a deterministic number of children conditional on the agent's age, sex, education, and partner state.[25]

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:

$$a_{t+1} = (1 + r)(a_t - c_t) + Y_t(d_t, x_t), \tag{3}$$

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

[25] 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.

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 $T(\cdot)$:

$$Y_t(x_t, d_t) = y_t(x_t, d_t) + y_t^p(x_t) + B(x_t, d_t) - T(x_t, d_t). \tag{4}$$

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 $\tau$:

$$y_t(x_t, d_t) = w_t(x_t)\, hrs(x_t, d_t), \text{ for } d_t \in \{2, 3\}. \tag{5}$$

The wage is given by

$$\ln w_t(x_t) = \gamma_{0,\tau} + \gamma_{1,\tau} e_t + \gamma_{2,\tau} e_t^2 + \zeta_t. \tag{6}$$

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:

$$y_t(x_t, 0) = PP(x_t) \times PPV. \tag{7}$$

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

$$y_t(x_t, 0) = PP(x_t) \times PPV \tag{8}$$
$$\times (1 - ERP \times (SRA_{t^R} - t^R) \times \mathbb{1}(SRA_{t^R} > t^R)). \tag{9}$$

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

$$ERP(i_t) = \begin{cases} \tilde{ERP}, & \text{if } i_t = 0 \\ 0.036, & \text{if } i_t = 1. \end{cases} \tag{10}$$

where $\tilde{ERP}$ is the expectation of uninformed agents. If we simulate from this model, the expectations of the agent follow the above equations, while the realized reductions in pension for early retirement follow the true ERP.

Partner income $y_t^p(x_t)$ deterministically depends on the agent's state. For model sparsity, we do not track any state variables, such as work experience, for the partner. In particular, the partner's income depends on the agent's age, education, and sex. Conditional on $x_t$, we do not model any additional uncertainty in the partner's income (Blundell et al., 2016a; Adda et al., 2017). [26] We abstract from widow and survivor pensions by assuming that after age 75 the partner state does not change anymore, implying that the partner pensions continue

[26]Details on the approximation of partner income can be found in appendix A.5.3.

contributing to household income.

Household-level benefits account for the presence of a partner, the agent's own labor supply decision, and the wages of both partners. 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. 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.

## 4.3. Preferences and Model Solution

In each period of their lives, agents derive flow utility that is additively separable between consumption and leisure:

$$u(c_t, d_t, x_t) = \frac{(\frac{c_t}{n_t(x_t)})^{1-\mu} - 1}{1-\mu} - L_t(x_t, d_t) + \epsilon_t(d_t) \tag{11}$$

where $n_t(x_t)$ is the consumption equivalence scale, calculated as the square root of the household size. The term $L_t(x_t, d_t) \geq 0$ captures the disutility of work relative to retirement. This additively separable functional form is a simplifying assumption. However, unlike much of the literature, we estimate both men and women who make consumption choices on behalf of the household but have different utility of work parameters. Marginal utility of consumption conditional on state should therefore not differ between sexes, which it would if utility was multiplicative instead (as in Cobb-Douglas specifications).

The disutility of work has the functional form:

$$L_t(x_t, d_t) = \begin{cases} 0, & \text{if } d_t = 0 \\ Z_L(x_t, d_t)'\kappa_{d_t}, & \text{if } d_t > 0 \end{cases} \tag{12}$$

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, sex, and partner state to capture joint leisure motives. The vector $\kappa_{d_t}$ 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 $\sigma_u$. 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:

$$u_b(a_T) = \vartheta \frac{a_T^{1-\mu}}{1-\mu} \tag{13}$$

where $\vartheta$ 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).

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:

$$V(x_t) = \max_{0 \leq c_t \leq a_t, d_t} u(c_t, d_t, x_t) + \beta \, \mathrm{E}\left[V(x_{t+1}|c_t, d_t, x_t)\right] \tag{14}$$

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).

## 4.4. Discussion

To illustrate how agents react to policy reform in our model, consider an agent of age $t$. Assume that she currently plans to retire exactly at the SRA she expects to be in effect when she retires, that is $E_t[t^R] = E_t[SRA_{t^R}]$. She plans to finance retirement household consumption and her desired level of bequest from three sources at the time of her retirement: the household financial wealth $a_{t^R}$, her pension wealth $\omega_{t^R}$, denoted as the discounted sum of pension payments, formally

$$\omega_{t^R} = (R-1)^{-1}\left(1-(1+R)^{-(T-t^R)}\right) E_t[y_{t^R}(x_{t^R}, 0)] \tag{15}$$

and her partner's pension wealth $\omega^P_{t^R}$, which is defined analogously and in our model is entirely outside of her control.

Investments into financial wealth at time t yield for every Euro $R^{(t^R-t)}$ at the time of retirement. The agent can 'invest' in her pension wealth by increasing her labor supply before retirement, thus collecting more pension points. For instance, if she works full-time instead of being unemployed in period $t^R - 1$, she increases her pension by

$$\Delta y(x_{t^R}, 0) = PPV \times (PP(x_{t^R}, d_{t^R-1} = 3) - PP(x_{t^R}, d_{t^R-1} = 1)). \tag{16}$$

Additionally, if she switches from unemployment to full-time work at her current age $t$, the contribution of all our future work towards her pension rises. This is because the additional year of experience increases her future wage, which in turn increases the pension points she collects in all future working years until retirement. The increase in expected pension size from working at age $t < t^R - 1$ instead of being unemployed is then given by

$$\begin{aligned}\Delta E[y(x_{t^R}, 0)] = PPV \times E_t\big\{&(PP(x_t, d_t = 3) - PP(x_t, d_t = 1)) \\ &+ \sum_{j=t+1}^{t^R-1} (PP(x_j, d_j|d_t = 3) - PP(x_j, d_j|d_t = 1))\big\}.\end{aligned} \tag{17}$$

This implies that financial and pension wealth are substitutes for financing retirement consumption and the desired bequest. Investing in either one is more effective the earlier in life it is done.

Now, if instead she expects to retire earlier than $E_t[SRA]$, that is $E_t[t^R] < E_t[SRA_{t^R}]$, she expects to incur a penalty on her pension. Investments into pension wealth by working an additional year at age $t < t^R$ will then yield a lower increase in pension size, as the penalty applies to the entire pension. Equations 16 and 17 would then be multiplied by $(1 - ERP \times (E_t[SRA_{t^R}] - E_t[t^R]))$. This reduces the incentive to invest in pension wealth, making investments into financial wealth relatively more attractive.

*SRA reform.* Having established the returns to investing in financial wealth versus pension wealth, we now examine how agents respond to an SRA reform that revises upward their expectation $E_t[SRA_{t^R}]$ by one year. Say, they previously expected to retire at the SRA. Re-optimizing the problem in equation 14 means jointly choosing new paths for consumption, savings, and labor supply over the life cycle. However, to gain intuition for the direction of reform effects, it is illustrative to consider the three possible revisions to the agent's expected choice in period $t^R$: she may plan to be retired, unemployed, or working. We examine each case in turn.

First, consider an agent who does not update her expected retirement age, meaning she still expects to claim her pension at age $t^R$ and now expects to pay a penalty for early retirement. There are two effects. As established, the expected penalty makes 'investments' into pension wealth (i.e., working) a less attractive way to finance retirement consumption relative to investments into financial wealth. A substitution effect may therefore entice the agent to work less and save more in periods $\{t, ..., t^R - 1\}$. On the other hand, the increase in penalty size represents a reduction in lifetime income to the agent. Depending on how large it is, the income effect of that reduction may make her more inclined to increase labor supply during those years. In summary, her labor supply reaction is ambiguous, while her savings should increase.

Second, consider an agent who expects to postpone claiming by one year in response to the expected increase in $E_t[SRA_{t^R}]$ by being unemployed in $t^R$ and claiming the pension in $t^R + 1$. Her expected pension size will not change. Yet, her expected pension wealth will decrease due to the forgone year of payments (cf. equation 15). If we include the period $t^R$ in her retirement time, since - presumably - the unemployment benefits are below her permanent level of lifetime consumption, then the direction of the two effects does not change. Just as in the first case, it becomes more profitable to substitute pension wealth with private wealth, and the agent's lifetime income decreases. Again, her savings should increase, while her labor supply reaction is ambiguous.

Third, consider an agent who expects to postpone claiming and to extend her work life into age $t^R$. Assume that the income she earns in $t^R$ is higher than her permanent level of lifetime consumption, meaning her retirement life is shortened. Now the income effect reverses as her total lifetime income increases, meaning she could work less. However, when re-balancing between financing retirement consumption through public pension wealth or financial wealth, note that the return to working more in order to invest in public pension wealth now increases. This is because additional labor supply in the current period $t$ increases the wage and therefore the number of pension points generated in a longer working life (i.e., the second term in equation 17).

In summary, in our model the direction of the substitution effect depends on whether agents extend their expected working life in response to the SRA increase. When agents keep their working life constant (scenarios 1 and 2), the substitution effect incentivizes less labor supply and more private savings, as pension wealth becomes relatively less attractive. When agents extend their working life (scenario 3), the substitution effect reverses because the return to investing in pension wealth increases. In all cases, the income effect opposes the substitution effect, rendering the net labor supply response theoretically ambiguous and consistent with the mixed empirical findings in the literature.

# 5. Estimation

In the parametrization of the model, we distinguish between three sets of parameters. 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 $\beta$, and the inter-temporal elasticity of substitution $\mu$. The interest rate is set to $r = 0.03$, 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 three different groups of deep structural parameters in the model with maximum likelihood. First, we estimate the structural disutility parameters governing the utility reduction of each choice in comparison with retirement (equation 12). We identify these parameters in particular from observations, where we observe the job offer status in the data. These are all observations of people who have been working part-time or full-time last year. Second, we estimate the parameters determining the probabilities of a job offer for unemployed individuals. In the data, we observe whether individuals start a job after being unemployed the previous year, but not whether they reject a job offer. Job offer probabilities. Job offer probabilities are identified by the observed decisions of the unemployed, which directly impact them. Similar to job offers, we do not observe disability pension eligibility and instead only observe take-up. We also estimate these parameters jointly via Maximum Likelihood.

*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 observation their labor supply decision $d_k$ and their observed states. In the following, we denote an agent's state, excluding the taste shock's realization, which we do not observe, by $x_k$. The likelihood of a fully observed state $x_k$ and decision $d_k$ is given by the choice probability of $d_k$ (Rust, 1987). As the choice-specific taste shocks $\epsilon_k(d_k)$ 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 (McFadden, 1973). Therefore, the probability to observe choice $d_k$ in state $x_k$, is given by:

$$P(d_k|x_k) = \frac{\exp\{V(d_k|x_k)\}}{\sum_{d\in\mathcal{D}} \exp\{V(d|x_k)\}}$$

where $V(d_k|x_k)$ is the conditional value function given by

$$V(d_k|x_k) = \max_{c_t}\{u(x_k, d_k) + \mathbb{E}[V(x_{it+1})]\} \tag{18}$$

The agent's policy belief on how the $SRA$ develops in the future enters the value function through the expectation of future states. They can be seen as an additional parameterization of the value function and therefore of the choice probabilities, i.e., the likelihood contributions. Maximum likelihood estimation allows us to directly use the beliefs, without imposing additional assumptions on realized policy regimes. This is a clear distinction from an alternative method of the simulated moment estimator, where simulation from the model would require direct assumptions about the evolution of the policy environment.

Additionally, our agents differ in the knowledge of the $ERP$, captured by the information state $i$. We do not observe $i$ in our dataset $\mathcal{M}$. Recall that the agent does not expect her information state to change, so the value function only depends on the current information state. We use our survey evidence from the SOEP-IS to predict agent-specific information probabilities $G_k(i)$. The choice probability of an observation $k$, where all other states are observed, is formally given by:

$$\sum_i P(d_k|x_k, i) * G_k(i) \tag{19}$$

In the SOEP-Core, we do not observe the job offer and disability eligibility state.[27] Let

$$\pi_o(o_k = 1|x_k) = \Lambda_o\bigg(Z_o(x_k)'\phi_o\bigg) \quad and \quad \pi_h(h_k = 2|x_k) = \Lambda_{dis}\bigg(Z_{dis}(x_k)'\phi_{dis}\bigg) \tag{20}$$

be the probabilities of receiving a job offer conditional on being unemployed last period and of being disability pension eligible, conditional on having experienced a bad health shock in this period. Then the probability of choosing $d_k$ of an observation $k$ in state $x_k$, where we do not observe a job offer and disability pension eligibility, is given by:

$$\sum_o \sum_h \sum_i P(d_k|x_k, i) G_k(i) \pi_o(o|x_k) \pi_{dis}(h|x_k) \tag{21}$$

The likelihood function is then a composition of separate likelihoods, where we observe the state fully or do not observe disability pension eligibility and the job offer.[28] The log likelihood of all states where we fully observe $x_k$, including $h_k$ and $o_k$ is given by:

$$\mathcal{LL}_{fo} = \sum_k \log\bigg(\pi_h(h_k|x_k)\pi_o(o_k|x_k) \sum_i P(d_k|x_k, i) * G_k(i)\bigg) \tag{22}$$

[27] We assume that individuals in good health can never be eligible for disability.

[28] The case where we observe disability pension eligibility or the job offer follows directly.

and the log likelihood of states $x_k$, where we do not observe both $h_k$ and $o_k$ is given by:

$$\mathcal{LL}_{uo} = \sum_k \log\left(\sum_o \sum_h \sum_i P(d_k|x_k, i) * G_k(i)\pi_h(h|x_k)\pi_o(o|x_k)\right). \tag{23}$$

We then estimate the deep structural parameters $\theta$ by

$$\hat{\theta} = \arg\max LL(\mathcal{M}, \theta) \tag{24}$$
$$= \arg\max LL_{fo}(\mathcal{M}, \theta) + LL_{uo}(\mathcal{M}, \theta) \tag{25}$$

and use Gabler (2022) with the limited memory Broyden–Fletcher–Goldfarb–Shanno algorithm from Virtanen et al. (2020) to maximize the log-likelihood. 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 12). Table (4) 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.[29]. Likewise, women in bad health are indifferent between working part-time or working full-time while consuming 15 percent less.[30]

Table 4: 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.

[29] $1 - \exp(-0.3896)$

[30] $1 - \exp\left(-(1.6879 - 1.8497)\right)$

Table 5 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.

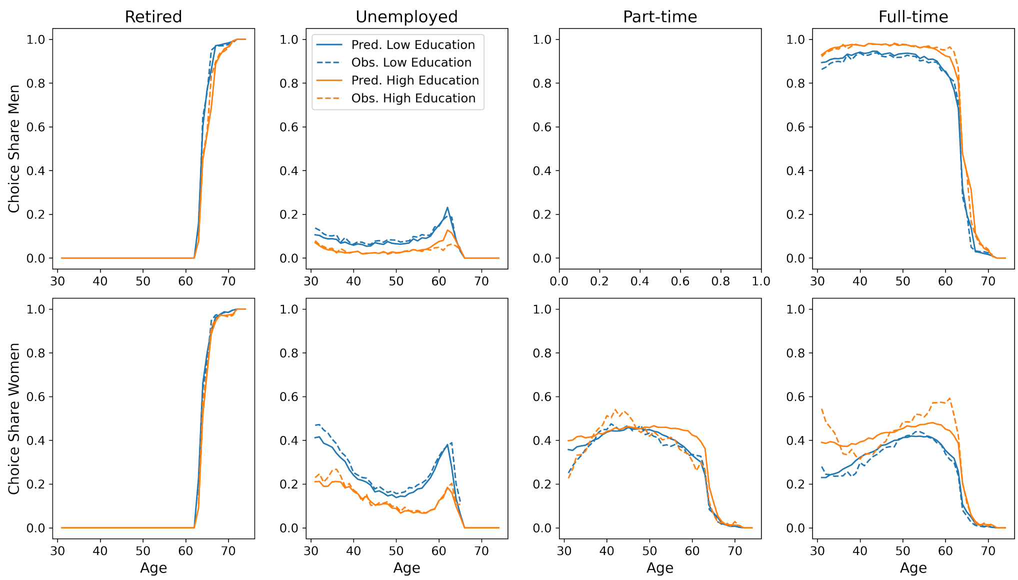
Table 5: Job offer parameters

| 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 (7) 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 7: Model fit




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

# 6. Counterfactual Policy Simulations

In this section, we evaluate the effects of policy beliefs by using the estimated model to simulate life cycles of initially 30-year old agents. In each simulation, we make specific assumptions about the future evolution of the policy regime and the agents' policy beliefs. Policy beliefs in our benchmark model are characterized by uncertainty and misinformation, as specified and parametrized in Section 3. The policy regime always starts at an SRA of 67 years, as the current German law prescribes, and we consider different scenarios for future increases by up to three years.

Outcomes we examine include individual labor supply, annual household savings, financial wealth, pension wealth, and individual welfare. We report annual labor supply in hours as a way of aggregating discrete choices.[31] We report annual labor supply and savings separately for agents' "work lives", i.e., the time before agents turn 63 and can first retire without qualifying for disability pension. Pension wealth is the present value of an agent's expected future pension payments.[32] 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.6.1 for details).

Before we commence, it is useful to understand the initial expectations of the agents in our simulations and how they depend on policy beliefs. Specifically, consider the modal 30-year-old man in our simulation sample. He is low-educated, meaning he does not have a high school degree, which would qualify him to enter university. He has a job, a partner, and is in good health. So far, he has accumulated 8 years of work experience and 8,300 euros in household wealth. Table 6 summarizes his expectations. Recall that having "Policy Uncertainty" means holding probabilistic expectations about the future evolution of the SRA. Expectations at age 30 are centered at an estimated SRA of 68.32 years upon reaching age 63. Recall further that being classified as misinformed means strongly overestimating the size of the ERP.

The first column summarizes what the agent would expect if he were informed about the true ERP, which, according to our estimates, he most likely is not. Conditional on not becoming disabled, he would expect to retire at around 65 years and two months, with around 235,000 euros in household wealth and a present value of 193,000 euros of pension wealth. If he were sure that the SRA would remain at 67 (column 2), he would only expect to retire about two months earlier, with a larger pension wealth (+6,000 euros) and less financial wealth (-5,000 euros).

By contrast, being misinformed (column 3) implies that he expects to retire around age 67 and 3 months. Most notably, he expects to retire with a much lower pension wealth with a present value of over 22,000 euro less than if he was informed about the ERP. That is because in the few future states in which he would retire with penalties,[33] he expects a very large pension deduction. Misinformation intuitively implies that expecting further SRA increases has a

[31] Since we only allow for limited reactions at the intensive margin, these largely reflect probabilities that agents quit jobs or accept job offers. For women, this measure includes switching between part-time and full-time work.

[32] This does not include the expected present value of his partner's pension wealth, because it is exogenous in our model.

[33] They usually involve a combination of bad health, a relatively low pension claim due to a short/irregular employment history, and high taste shock, which represents factors outside of our model.

Table 6: Example Agent Initial Expectations and Policy Beliefs

| Expected Outcome | Informed | | Misinformed | |
|---|---|---|---|---|
| | Unc. (1) | No Unc. (2) | Unc. (3) | No Unc. (4) |
| *Retirement* | | | | |
| SRA at 63 | 68.32 | 67.00 | 68.32 | 67.00 |
| Retirement Age (excl. Disability) | 65.17 | 65.00 | 67.28 | 66.47 |
| Pension Wealth (PV at Retirement) | 192.99 | 199.94 | 160.63 | 172.82 |
| Financial Wealth at Retirement | 235.34 | 231.04 | 230.21 | 228.58 |
| *Work Life (< 63)* | | | | |
| Annual Labor Supply (hrs) | 1739.06 | 1732.08 | 1801.98 | 1811.23 |
| Annual Consumption | 33.88 | 33.93 | 34.40 | 34.53 |
| Annual Savings | 5.60 | 5.45 | 5.35 | 5.21 |
| *Lifecycle (30+)* | | | | |
| Annual Labor Supply (hrs) | 1184.22 | 1176.17 | 1288.13 | 1275.99 |
| Average Financial Wealth | 111.71 | 109.20 | 109.74 | 105.65 |
| *Welfare* | | | | |
| Compensated Variation (%) | 0.00 | 0.41 | -4.48 | -3.49 |

*Notes:* Expected outcomes of a 30-year-old man conditional on policy beliefs. Expectations are averages of model simulated outcomes in which policy evolves exactly

much larger effect on his expected retirement timing; not expecting reform would decrease it by around 0.7 years (over 8 months, cf. column 4).

In the context of the discussion in Section 4.4, we can observe that lower generosity of the pension system – both perceived and expected – leads to substitution from pension wealth to financial wealth. Expecting SRA increases leads the agent to expect that he will save about 150 euros more per year (around 3 percent) over his work life. Effects of policy beliefs on expected life-cycle labor supply are ambiguous.

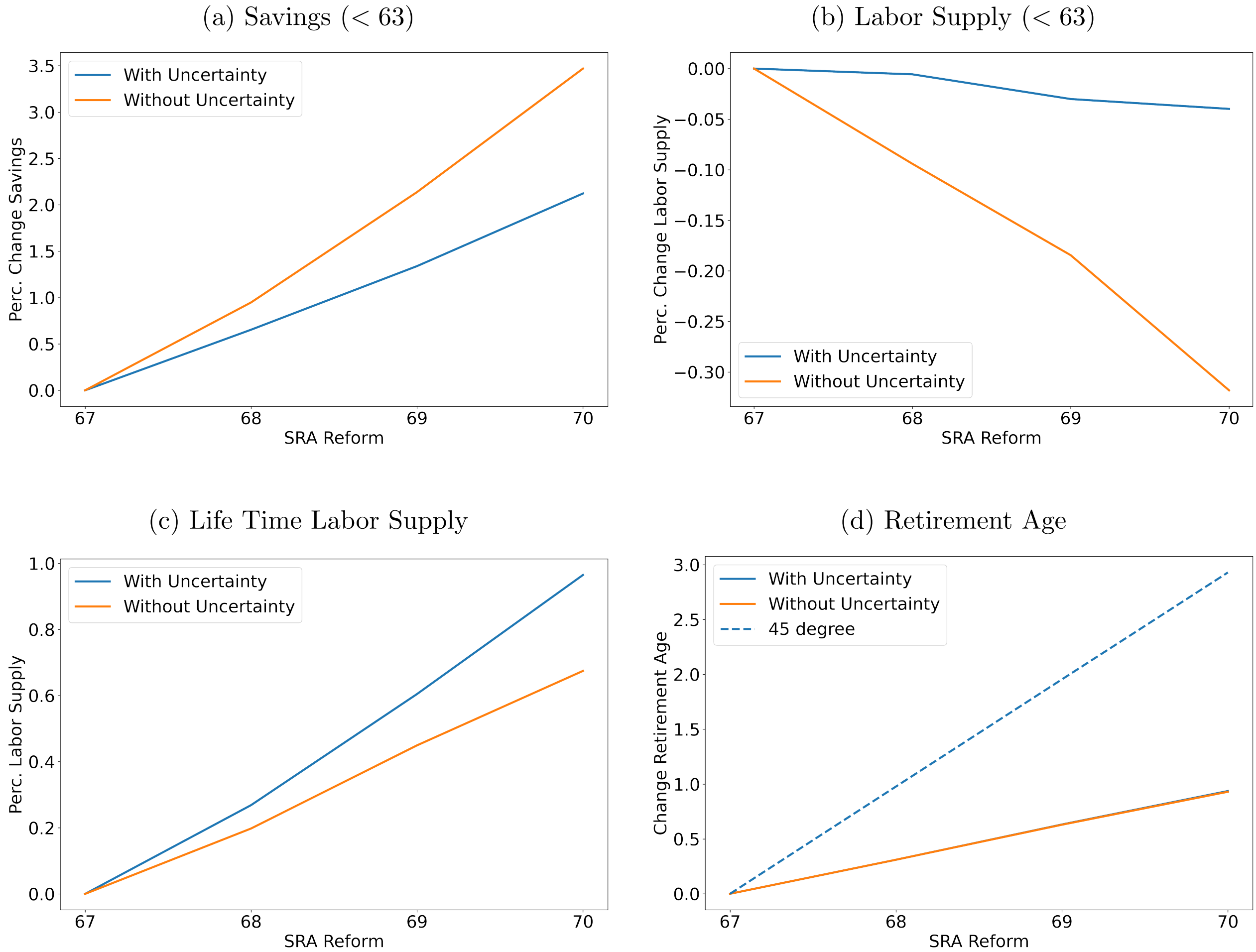
## 6.1. Retirement Age Increases and the Role of Reform Expectations

We begin our counterfactual analysis by examining the impact of SRA increases on behavior and how subjective reform expectations moderate their effects. We simulate the life cycles of 30-year-old agents under different SRA reform scenarios. We compare a baseline scenario in which the SRA stays at 67 throughout agents' lives with a gradual[34] increase of the SRA to 68, 69, and 70. We make this comparison under two sets of assumptions for agents' beliefs: (i) agents know the future policy regime from the start, as traditional models assume, and (ii) our benchmark model with probabilistic reform expectations. Figure 9 illustrates the results for behavior during the working life, i.e., below the age of 63, on the left panel, while the right panel shows the overall change in working hours and retirement age.

[34] In this exercise, we abstract from the timing of reform announcement by having increases occur gradually over the course of agents' lives.

Examining reform effects without policy uncertainty first, we find that SRA increases cause a shift in investment from public pension wealth to private financial wealth. That is, over the life cycle, agents work less and save more. At the end of their working lives, actual retirement is delayed by around 0.4-0.5 years for each year of SRA increase. Referring to the discussion in Section 4.4, this implies two key points. First, the extension of expected working lives due to the SRA increase is not strong enough to outweigh the expected penalty decrease, so agents choose to emphasize financial wealth over public pension wealth. Second, the substitution effect outweighs the income effect, resulting in a negative effect on labor supply during agents' working lives.

Figure 8: Reform Effects and Reform Expectations




*Notes:*

Reform expectations significantly attenuate forward-looking responses. This can be understood in light of the preceding description of agent expectations in the baseline. The fact that agents expect reform even when it does not occur causes them to pre-empt some of the reform effects—in this case, working less and saving more. Therefore, the forward-looking effects of actual reforms are weaker. Contributing to this attenuation is the fact that in the counterfactuals where reforms do occur, probabilistic expectations imply that particularly younger agents remain uncertain. They optimize for a mix of possible scenarios, so their actual choices do not fit the true policy trajectory perfectly.

The final result is that at the intended margin of the policymaker—actual retirement age—agents react more strongly when they hold reform expectations. Compared to agents who know the true policy, those with probabilistic expectations arrive in their 60s with fewer financial assets and a higher pension claim, giving them a stronger incentive to avoid early retirement penalties. In sum, we find that probabilistic reform expectations weaken unintended life-cycle effects while slightly strengthening the main intended reform effect at the margin of retirement timing.

## 6.2. De-Biasing and the Puzzle of Retirement Bunching

A natural question in a model with biased expectations is what would happen if the bias were eliminated. The purpose of this counterfactual exercise is to uncover the effect of misinformation on individual behavior and welfare, both at the margin of retirement timing and over the lifecycle.

We again simulate the life cycles of a representative cohort of 30-year-old agents. The true SRA is gradually increased from 67 to 69, and agents hold probabilistic expectations about it. In the baseline simulation, the majority is initially uninformed (xx to xx percent, depending on education type) and gradually updates their beliefs according to the estimated Markov transition process. In the counterfactual, everyone is correctly informed about the ERP from age 30 onward. Table 7 summarizes the results.

Table 7: Effects of Removing Early Retirement Penalty Bias

| Outcome | Baseline with Misinformed | Only Informed | Difference (%) |
|---|---|---|---|
| *Work Life* ($< 63$) | | | |
| Annual Labor Supply (hrs) | 1315.44 | 1307.99 | -0.57 |
| Annual Consumption | 37.54 | 37.59 | +0.14 |
| Annual Savings | 5.41 | 5.29 | -2.11 |
| *Retirement* | | | |
| Retirement Age | 63.25 | 62.30 | -1.49 |
| Retirement Age (excl. Disability) | 66.35 | 65.38 | -1.45 |
| Pension Wealth (PV at Retirement) | 187.11 | 188.47 | +0.73 |
| Financial Wealth at Retirement | 312.26 | 308.38 | -1.24 |
| *Lifecycle (30+)* | | | |
| Annual Labor Supply (hrs) | 869.29 | 843.46 | -2.97 |
| Average Financial Wealth | 179.24 | 176.04 | -1.78 |
| *Welfare* | | | |
| Compensating Variation (%) | | | +0.99% |

*Notes:* Averages for simulated lifecycles of 10,000 agents. Statutory Retirement Age increases gradually from 67 to 69 years. In *Baseline* scenario, agents are partially misinformed about the ERP and learn over time. In *Only Informed*, everyone is informed from age 30. Monetary quantities in 10,000 Euros.

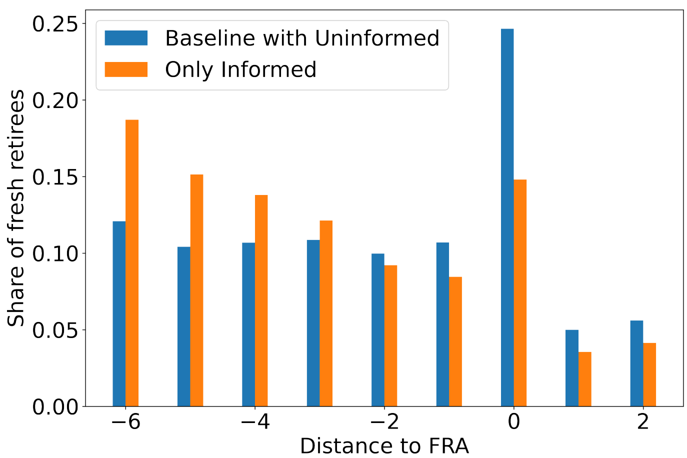
Eliminating the bias has strong behavioral effects. During their working lives, agents on average work slightly more but reduce their savings by around 2.4 percent. Removing the bias in expected penalty size increases the value of investing in pension wealth through work relative to investing in financial wealth through savings (cf. section 4.4). Intuitively, removing the Early Retirement Penalty overestimation significantly shifts retirement timing. Excluding agents who claim a disability pension, the average pension claiming age is reduced by 1.93 years. The stock of financial assets at retirement is around 0.41 percent lower due to the lower savings rate. Both results are driven by men—especially low-educated men—who are most likely to be the main income earners in the household and would under hardly any circumstances consider early retirement when facing high penalties.

From a life-cycle perspective, the strong increase in early claiming more than compensates for the working-life increases in labor supply, so that aggregate labor supply and savings both decrease by over 2 percent. At the same time, removing the bias increases individual welfare according to the Low et al. (2010) measure by xx percent. In sum, while removing the bias increases welfare, both aggregate labor supply and aggregate savings decline. We abstract from general equilibrium effects as well as positive fiscal and other externalities of work. Accounting for these would likely amplify the adverse behavioral effects and thereby dampen or even reverse the positive welfare effects.

*Retirement Bunching Puzzle.* Our model fits historical choice data very well, as shown in Figure 7, and can therefore reproduce the well-known spike in claiming decisions at the SRA, which seems to contradict the smooth evolution of economic incentives around the cutoff. This raises the question of whether this behavior persists when incentives change.

For better comparability with the recent literature, we define the *Full Retirement Age* (FRA), which is the same as the SRA unless the conditions for early retirement based on long working life are met (cf. section 4.1), in which case it is the SRA minus two years. Figure **??** illustrates that despite changing incentives at higher ages, in this counterfactual world, in which the SRA is increased by 2 years, the spike persists in our baseline model. By comparison, in the counterfactual, retirement evolves more smoothly around the cutoff.

Figure 9: Information Effect on Retirement Bunching




*Notes:* Share of retirement/ pension claiming choices relative to the *Full Retirement AGE* (FRA). The FRA is the Statutory Retirement Age (69, in this simulation), except when the number of credited periods is high enough for the agent to qualify for penalty-free early retirement due to long working life. In this case, the FRA is 67. Choice share is relative to all agents in the sample.

The reason is intuitive. People on average would prefer to retire before the FRA, but the uninformed consider early retirement prohibitively expensive except in rare circumstances.[35] Furthermore, even agents who spend most of their lives uninformed but become informed a few years before retirement have saved less than they would have if informed from the start. Therefore, they are less less likely to retire early than their counterfactual counterparts.

This finding is in line with Hentall-MacCuish (2025), who shows that misbeliefs about the policy environment can complement existing explanations of retirement spikes around the SRA. We discuss it in context of the recent literature in the concluding section.

# 7. Conclusion

This paper quantifies how subjective policy beliefs shape behavioral responses to pension reform. We develop and estimate a structural life-cycle model in which forward-looking agents hold probabilistic expectations about the future Statutory Retirement Age and are systematically misinformed about the Early Retirement Penalty. Using survey-elicited beliefs from the German SOEP, we estimate the model and simulate counterfactual policy scenarios.

Our findings have important implications for policymakers. Agents already anticipate future SRA increases, behaving as if reform were imminent. Consequently, lifecycle responses to actual reforms are attenuated compared to models that assume perfect foresight or no reform expectations. This suggests that the adverse behavioral effects policymakers might fear—such as reduced savings or labor supply during working life—emerge more weakly than traditional models predict. The analysis thus raises questions about whether policymakers should prioritize eliminating policy uncertainty. Similarly, while misinformation about the ERP makes agents uncomfortable with early retirement—because they overestimate penalties and thus their own behavioral response—correcting these beliefs generates adverse spillovers. De-biasing increases individual welfare but significantly reduces old-age labor supply, particularly affecting the retirement timing margin.

For the literature, our results demonstrate the importance of modeling expectations explicitly to avoid overestimating policy responses. Moreover, we offer a belief-based mechanism for retirement bunching at the SRA. Like reference-dependent preferences, our mechanism generates testable predictions: bunching should diminish when misinformation is corrected, whereas reference-dependent models predict persistence. These competing mechanisms could be distinguished empirically through targeted information interventions.

[35] Examples include low-income singles whose pension claim is so low that they will rely on social assistance anyway, or people in bad health with very low pension claims—usually women with short employment histories—who expect to live off financial assets and spousal income during retirement.

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# A. The appendix

## A.1. Variable Overview

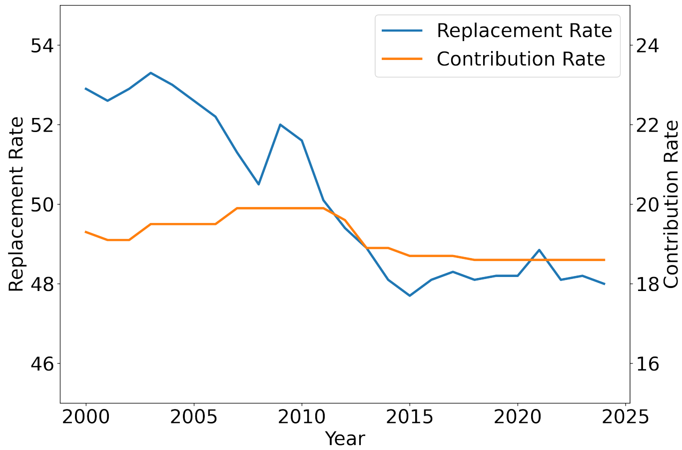
Table 8: Variable Overview

| 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 | $\tau$ | 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 | $h_t$ | $\{0:\text{Good Health}, 1:\text{Bad Health},$ |
| | | $2:\text{Disabled}, 3:\text{Dead}\}$ |
| Statutory Retirement Age | $SRA_t$ | {65, 65.25, 65.50, ... , 72} |
| Information State | $i_t$ | {0 : Uninformed, 1 : Informed} |
| | | |
| **Continuous 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 |

*Note: Key derived variables include pension points $PP(x_t)$, credited periods $CP(x_t)$, consumption equivalence scale $n_t(x_t)$, number of children, hourly wage $w_t(x_t)$, partner income $y_t^p(x_t)$, total household income $Y_t(x_t, d_t)$, benefits $B(x_t, d_t)$, and taxes $T(x_t, d_t)$, all of which are deterministic functions of the state variables listed above.*

## A.2. Data and Institutional Background

Figure 10: 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)

## 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 a person retires one year before their regular retirement age?*

## A.4. Auxiliary Markov Processes

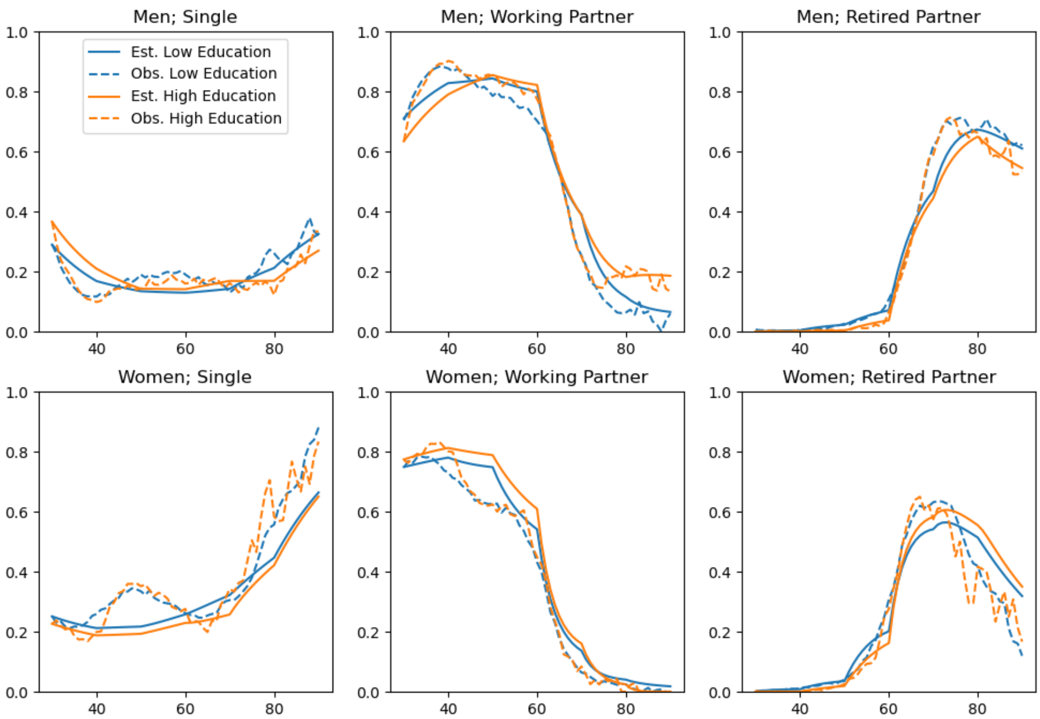
### A.4.1. Partner Transitions

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:

$$\pi(p_{t+1}|x_t) = \Lambda_p\bigg(Z_p(x_t)'\,\phi_p\bigg) \tag{26}$$

where $\Lambda_p$ 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:

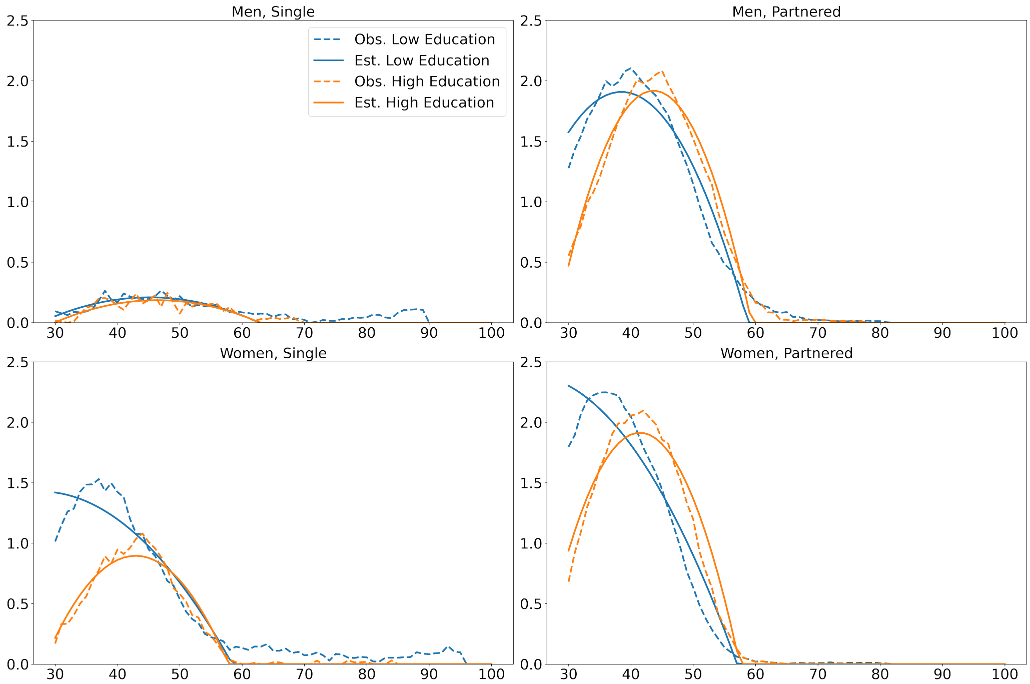
Figure 11: Shares of population in partner states




*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 12: Number of Children




*Notes:* OLS estimation of 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

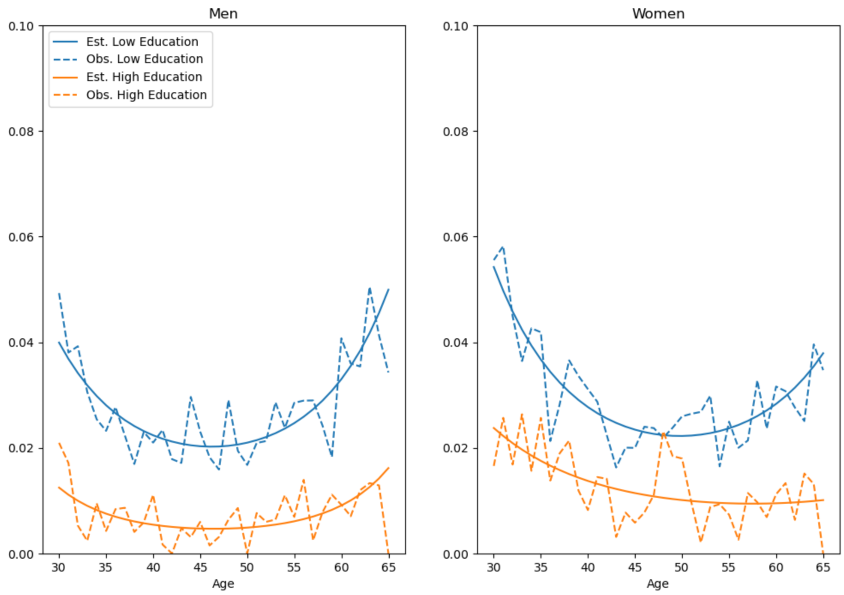
The job offer state governs the agent's ability to choose employment; the agent can choose part- or full-time if the job offer state $o_t$ equals 1. We incorporate two processes with the job-offer state. Namely, job destruction and job offer. If the agent chooses employment in the current period, the job could be destroyed, and she has job offer state $o_{t+1} = 0$ in the next period, forcing her to choose unemployment[36]. In this case, the transition probability for the job offer state is given by:

$$\pi(o_{t+1} = 0 | x_t, d_t \in \{2, 3\}) = \Lambda_{sep}\left(Z'_{sep}\phi_{sep}\right) \tag{27}$$

where $\Lambda_{sep}$ 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 15:

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

Figure 13: 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):

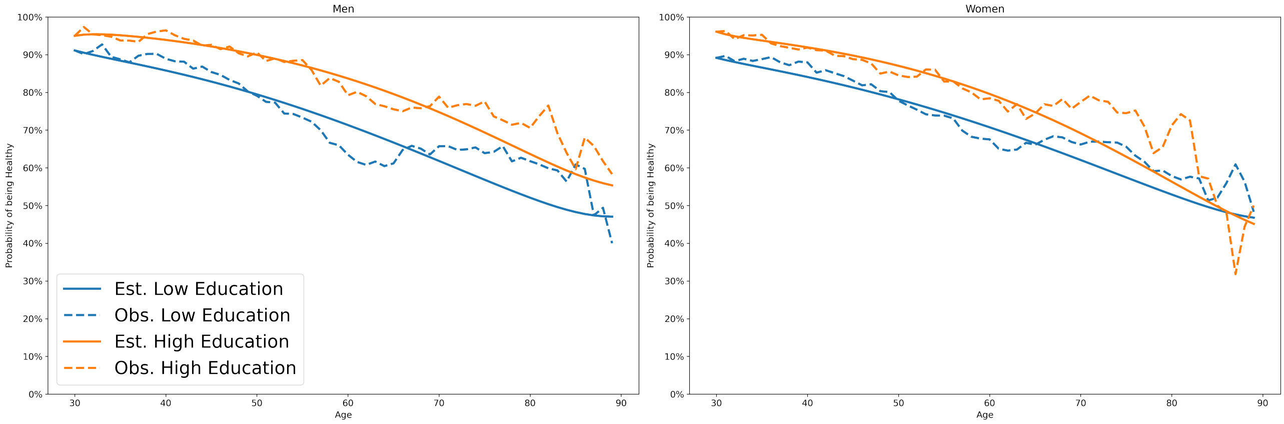
### A.4.3. Health and Death

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:

$$\pi(h_{t+1}|x_t) = \Lambda_h\Big(Z_h'\phi_h\Big) \tag{28}$$

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:

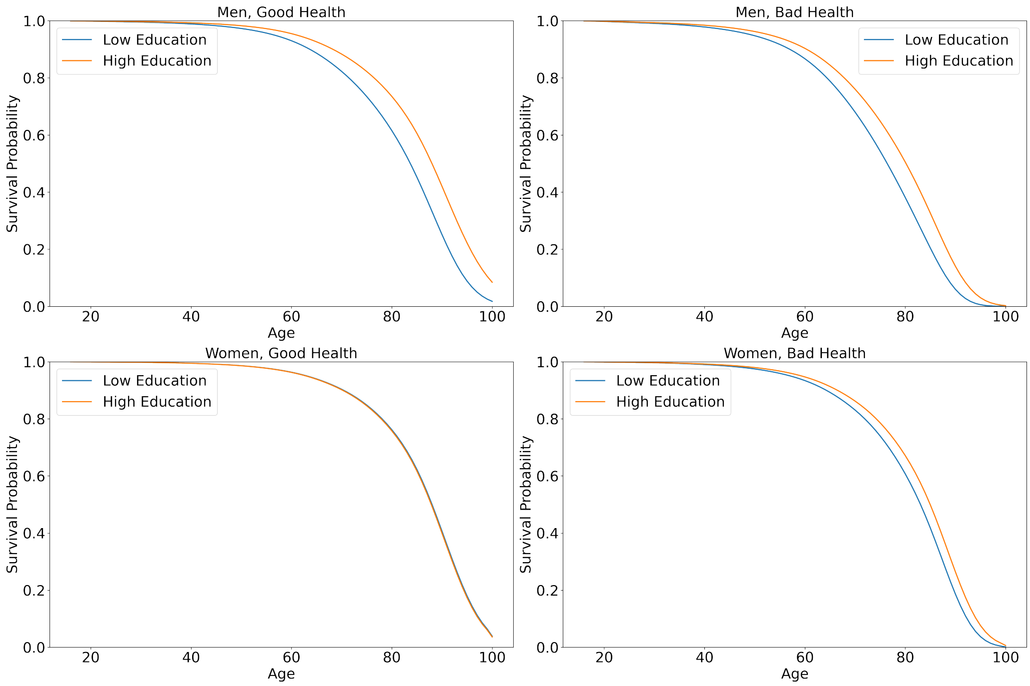
Figure 14: Share of People in Good Health




*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 15: Share of People 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:

$$y_t(x_t, 0) = PP(x_t) * PPV \tag{29}$$

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:

$$y_t(x_t, 0) = PP(x_t) * PPV * (1 - 0.036) \tag{30}$$

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.

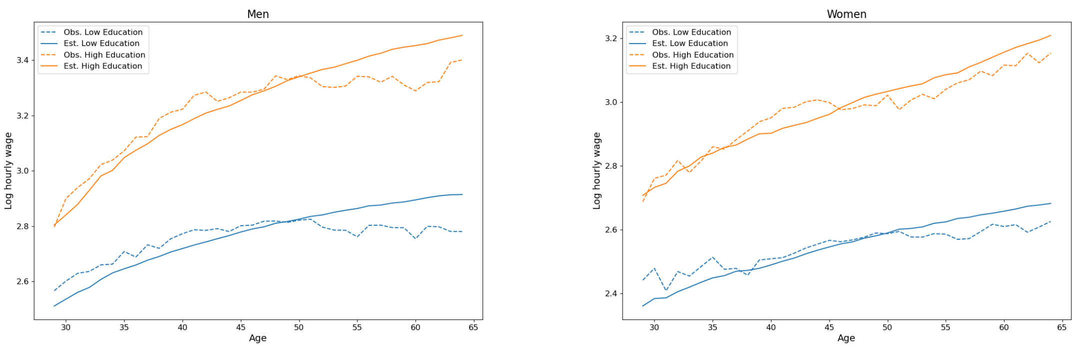
### A.5.2. Wage Process

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 $t$:

$$log(w_{it}) = \gamma_{0,\tau} + \gamma_{1,\tau} * log(exp_{it} + 1) + \xi_i + \mu_t + \zeta_{it}. \tag{31}$$

Our estimates of $\gamma_{0,\tau}, \gamma_{1,\tau}$, directly correspond to the parameters in equation (6). We cluster standard errors across individuals and time and estimate the wage process's variance $\sigma_w^2$. We document the fit of our estimates below:

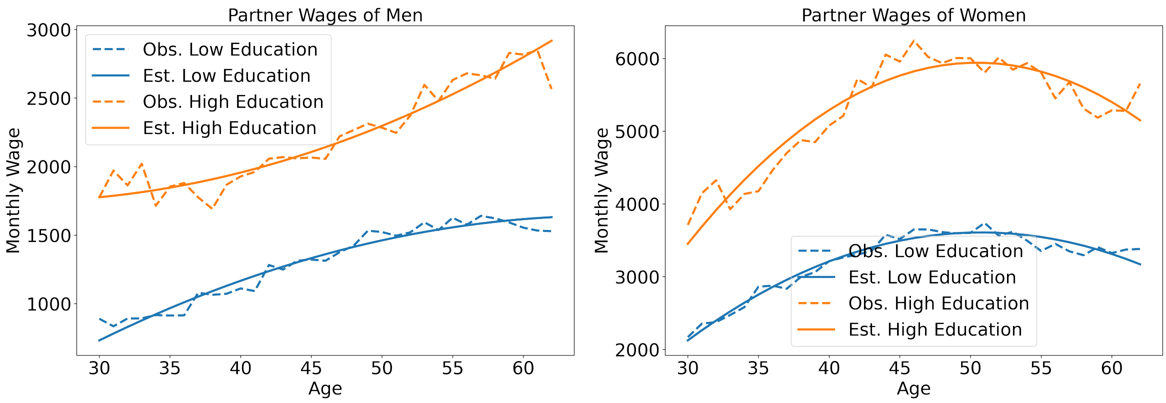
Figure 16: Wage fit




### A.5.3. 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 17: 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.6. Counterfactuals

### A.6.1. 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 $\gamma_A$ and solves $V_B(\gamma_A) = V_A(0)$, where

$$V_e(\gamma) = \mathbb{E}\left[\sum_{t=30}^{T} \beta^t u(c_t(1+\gamma), d_t, \theta, X_t)\right], \text{for } e \in \{A, B\}. \tag{32}$$

Thus, $\gamma_A$ describes the relative increase in per-period consumption to equal the average discounted utility in the counterfactual scenario [37]. Consequently, a positive value is associated with a welfare gain in the counterfactual and a negative vice versa.

[37] In this calculation, the consumption adjustment $\gamma_A$ is implemented ex-post and, therefore, does not affect behavior.