Policy Uncertainty, Misinformation, and Retirement Age Reform

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

JEL Codes D15, D83, I38, J11, J26

Contents

1. Introduction

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 unavoidable unpredictability of the future policy environment. 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.

Consider a one-year increase the the *Statutory Retirement Age* (SRA), which is the policy we focus on in this study. 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 retirement by one entire year, this reduction in pension system generosity actually leads to an increase in her lifetime income. Consumption smoothing behavior would then imply a reduction in her current labor supply. That is not what is typically observed, past increases in pension eligibility ages across countries have led to moderate anticipatory increases in labor supply among middle-aged workers (Carta and De Philippis, 2024), and somewhat larger increases among elderly workers (cf. Pilipiec et al., 2021, for a literature review), albeit with very heterogeneous effect sizes. This example illustrates two things. First, extrapolating observed reform effects into the future is challenging because with higher ages, the multitude of incentives that affect expected retirement timing change (Blundell et al., 2016). Second, to predict reform effects, it is critical to model expectations of agent behavior and policy beliefs jointly. Koşar and O'Dea (2023) name this non-stationarity of the policy environment one of the key challenges for including beliefs about late-in-life policies in structural models. [1]

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

[1] 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.

changes. [2]

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 is the typically observed behavior [3], there are two counteracting effects on her lifetime income, an increase from the expected extension on 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 determine not just the size but even the direction of her forward-looking response. Finally, the more uncertain she is about the future policy environment, the more attenuated her reaction to policy reform will be. To our knowledge, our model is the first in the literature that can accommodate the interplay of these channels. [4]

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., 2016). We allow for stochastic factors such as declining health (Blundell et al., 2023) and longevity risk, declining wages Fan et al. (2024), joint leisure with retired partners (Carta and De Philippis, 2024), age-dependent probabilities losing or finding a job (Rabaté, 2019; Rabaté et al., 2024). 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 show that people on average are misinformed about current policy rules and uncertain about their future development (Caplin et al., 2022; Luttmer and Samwick, 2018, e.g.,), 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, which is consistent with gradual resolution of policy uncertainty. We

[2] 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).

[3] For example, 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. Mastrobuoni (2009); Lalive et al. (2023) produce similar estimates for reforms in France and the United States.

[4] 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 claming penalty.

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. [5] 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.

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

This finding represents an important contribution to a large literature which evaluates responses to pension reform through the lense of forward-looking life-cycle models (e.g., 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, biased subjective survival expectations are a main driver, although in case of Bairoliya and McKiernan (2025), biased beliefs about the ERP also play a role. We show that uncertainty about the retirement age is an additional mechanism which produces reform effect attenuation.

We then simulate the effects of 'policy belief management policies', specifically (i) early SRA announcement with credible commitment and (ii) a de-biasing reform that eliminates misinformation. For the expectation management reforms, we assume that the actual SRA is increased to 69 years. *Announcement timing.* We compare a baseline in which the SRA is announced at 63 years - the earliest possible time at which agents can retire in the model - to scenarios in which the SRA is announced at 55, 45, or 35 years. Note that this means that the timing of announcement presents a negative shock to agents' expected lifetime income who were continuously downward revising their expectations before the announcement. As soon as the SRA is announced, agents start to increase savings, so that they can retire earlier than they would in a late-announcement scenario. *De-biasing.* We compare the baseline with misinformation and random updating to a counterfactual scenario in which everyone is informed from the start. Since agents already in the baseline expect to retire early on average, de-biasing implies

[5] 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.

an increase in lifetime income, which agents spread over the life cycle by saving less, working less, and eventually retiring earlier. Also, compared to the baseline, retirement behavior of the debiased agents in the counterfactual is a much smoother function of their age. In the baseline, retirement behavior exhibits the classical spike at the SRA, which the empirical literature across different countries has documented extensively (cf. Lumsdaine et al., 1996; Rust, 1997, for an early discussion of the phenomenon in the US). This is due to the fact that even close to retirement, close to half of agents are still uninformed, implying they hold early retirement to be almost prohibitively expensive.

A growing literature has emerged that explores the implications of objective policy uncertainty and biased beliefs. Cottle Hunt (2021); Caliendo et al. (2019); Kitao (2018) assume scenarios with probability distributions over future policy parameters to quantify welfare cost of uncertainty about timing and design of inevitable retirement reform.[6] We contribute by showing that despite the undoubtedly negative effect on individual welfare, efforts to correct misbeliefs or eliminating policy uncertainty may conflict with policy goals about the type of behavior that policymakers wish to stimulate. Furthermore, we join Hentall-MacCuish (2025) and Bairoliya and McKiernan (2025) in offering a subjective-belief-based complementary explanation for the bunching of retirement decisions around the SRA, which the literature has recently attributed chiefly to reference-dependent preferences (Gruber et al., 2022; **?**; 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

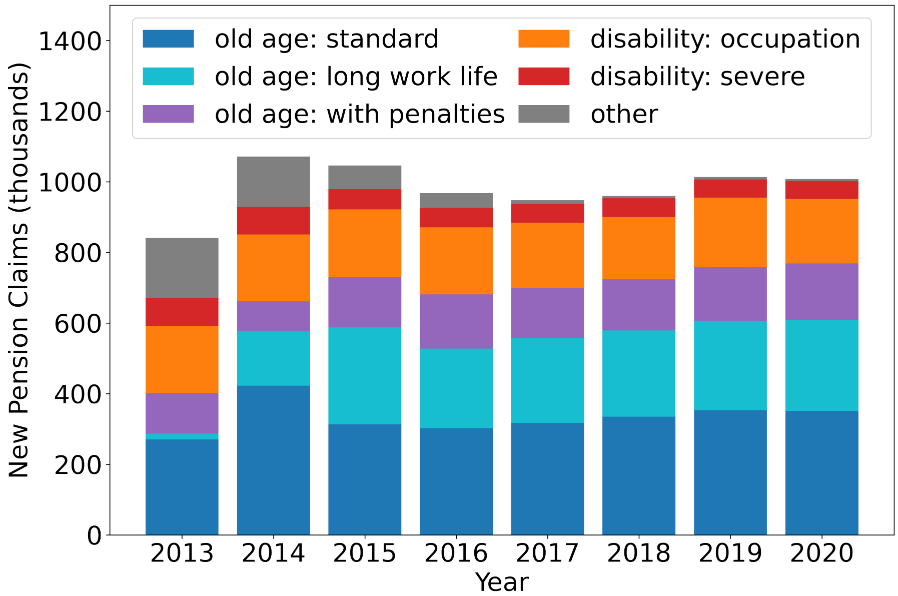
Germany has a pay-as-you-go pension system, which is financed by flat-rate contributions from employees and employers. The pension system is mandatory for nearly all employees and, as of 2023, covers 87 percent of the working population (70 percent of people aged 15-64). The most important exceptions 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[7]. While replacement rates have fallen in recent years, contribution rates have been stable at around 19 percent (cf. figure 9). Both are linked to demographic change, so without further reform, replacement rates are expected to fall, while contribution rates are expected to rise.

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

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

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).

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,[8] but no earlier than 63 years. Early retirement generally comes at a penalty (*the Early Retirement Penalty*, ERP) of 3.6 percent of the pension value per year of early retirement, or 0.3 percent per month. [9] 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.[10]

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

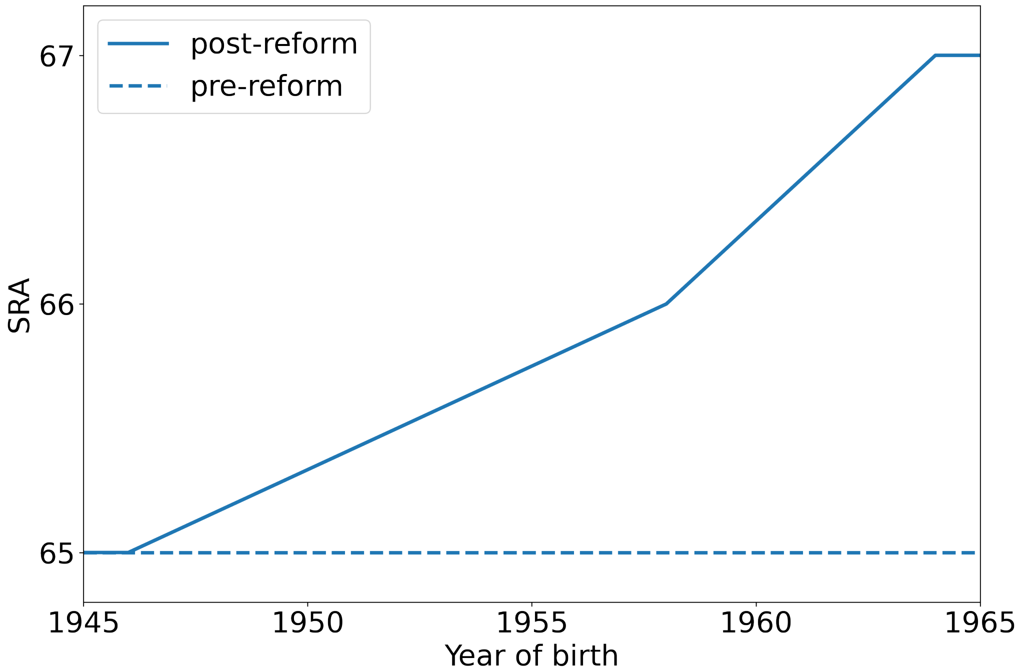
[8]A claimant needs to have 35 years of *credited periods*. In addition to years of work, these include unpaid childcare and elderly care, as well as short-term unemployment and sickness.

[9]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.

[10]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.

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.

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. [11] 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

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

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 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[12], part of the public debate, and it is clear

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

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. [13] On the other hand, people could be misinformed about the current size of the pension to which they are entitled.[14] In annual letters, the German Pension Insurance informs insurees about the pension they can expect if they continue to earn their current wage until retirement. This information has been found to influence behavior (Dolls et al., 2018) and is important for individuals to form expectations over, but it is difficult to connect it to a specific policy environment in a structural model. That is why we abstract from beliefs about these policies in this study.

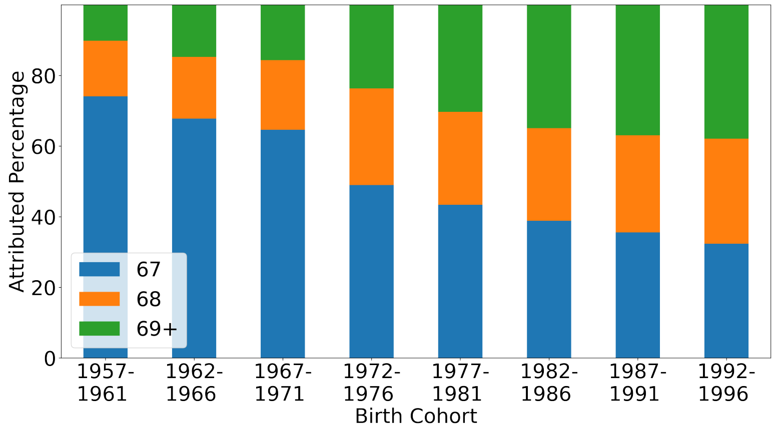
3.1. Policy Uncertainty and the Statutory Retirement Age

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 **??** 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 simple and computationally tractable way while retaining these key features.

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

[14] 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.

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

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

where υ_t is i.i.d. normally distributed with mean zero and constant variance σ^2_{SRA}.[15] This formalization is similar to objective policy uncertainty in Hentall-MacCuish (2025), except that we allow for negative and non-integer shocks, to account for people born before 1964 to whom a non-integer SRA currently applies. As a result, at any time t before retirement, agents' expectations and associated uncertainty about the SRA at time $T > t$ are given by

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

Although this model captures the key features of our survey data, it is rather simple and abstracts entirely from the determinants of expectation formations aside from current policy. One alternative would be to model reform expectations as a function of previous experience (Malmendier and Nagel, 2016; Kuchler and Zafar, 2019), but such reforms are rare and allowing for too much history-dependence in a dynamic programming model quickly becomes computationally untractable.[16]

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

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

Table 2: Expectation process parameter estimates

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

Notes: Standard errors in parentheses.

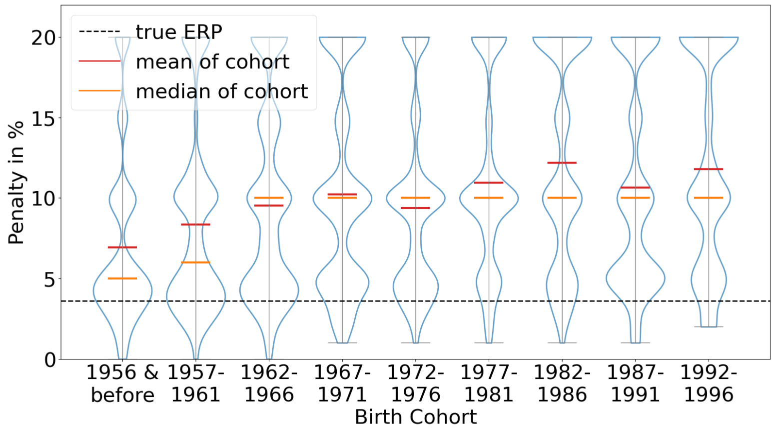
Table (2) reports our estimate for the random walk of our policy belief process. As a benchmark, the implied expected SRA increase of 0.41 years every ten years is close to the German Council of Economic Advisors recommendation, which is 0.5 years every ten years (Grimm et al., 2023). We observe considerable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

3.2. Misinformation and the Early Retirement Penalty

We further elicit probabilistic beliefs of the current ERP(see A.3 for question wording). Figure 4 illustrates respondents' point estimates. Except for respondents in their 60s, the average belief about this number is around 12 percent across ages, while in reality, it is only 3.6 percent. This misinformation may significantly distort people's reasoning about retirement and how they react to reforms. While it may be too much to expect people to know the exact Early Retirement Penalty, knowing its magnitude is crucial for everyone who considers early retirement. At its true size, early retirement is a viable option for many[17]. By contrast, at the average reported ERP size of around 12 percent, early retirement would be prohibitively expensive for most people.

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

Figure 4: Belief about Current ERP



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

For these reasons, we classify people into informed and uninformed in the model, as Bairoliya and McKiernan (2025) do[18] 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.

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 $\tau \in \{men, women\} \times \{high, low\}$.[19] 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 and 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, de-

[18] 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.

[19] 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.

cision, 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[20] if they have a job offer in the current period, i.e., $o_t = 1$. [21] Otherwise, they are unemployed. Health h_t follows a Markov process and influences the disutility of work.

In our model, retirement and pension claiming happen simultaneously, we do not distringuish between the two decisions. Under the standard old-age pension, agents can choose retirement before the statutory retirement age (SRA) but no earlier than age 63, following a simplified version of the current German law. 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.

The 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 $CP(x_t)$. Second, disability pension: agents can retire at any point in their lives if disabled and pay a reduced penalty of only up to 3 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.[22] 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.[23]

At the end of each period, assets saved for future periods generate income at a risk-free

[20] 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.

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

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

[23] 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.

interest rate of r. Assets evolve according to the following intertemporal budget equation:

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

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 τ:

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

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 constructing their expectations. Dependent on the informed state i_t, the agent expects the following ERP:

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

where $\tilde{ERP}$ is the expectation of uninformed agents.

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. Details on the approximation of partner income can be found in appendix A.6. 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 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 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 men and women, 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 κ_{d_t} is the collection of corresponding choice-specific disutility parameters. The transposed vector multiplication leads to a sum of characteristic times parameter entry.

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

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

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

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

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).

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 β, and the inter-temporal elasticity of substitution μ. The interest rate is set to $r = 0.04$, the discount factor $\beta = 0.97$, and the inter-temporal elasticity of substitution $\mu = 1.5$.

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

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

5.1. Structural Estimation

Identification. We estimate 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

$$V(d_k|x_k) = \max_{c_t}\{u(x_k, d_k) + \mathbb{E}[V(x_{it+1})]\} \tag{15}$$

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 agent's 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:

$$\sum_i P(d_k|x_k, i) * G_k(i) \tag{16}$$

and the log likelihood for all of these observations is given by:

$$\mathcal{LL}_f = \sum_k \log\bigg(\sum_i P(d_k|x_k, i) * G_k(i)\bigg) \tag{17}$$

The dataset $\mathcal{M}$ does not contain for each observation the full-state. Job offers and disability eligibility are partially unobserved. The likelihood contribution of an observation depends on which states are observed. The likelihood contribution from an observation where we observe job offer and disability eligibility in the

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

$$\pi(o_{t+1} = 1|x_t, d_t = 1) = \Lambda_o\bigg(Z_o(x_t)'\phi_o\bigg) \tag{18}$$

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

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

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

$$\mathcal{L}(\mathcal{M}, \theta) = \Pi_{i=0}^{N} \Pi_{t=0}^{T} \left(\sum_{o_t=0}^{1} \sum_{i_t=0}^{1} P(d_{it}|x_{it}, o_t, i_t\theta) \pi(o_t|x_{it-1}) G(i_t|x_{it}) \right) \tag{19}$$

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

5.2. Estimation Results and Model Fit

After parametrizing the model with the estimates from the literature and our first step estimation, we use maximum likelihood to estimate the disutility parameters of our model (cf. equation 12). Table (3) 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.[24]. Likewise, women in bad health are indifferent between working part-time or working full-time while consuming 15 percent less.[25]

[24] $1 - \exp(-0.3896)$
[25] $1 - \exp\left(-(1.6879 - 1.8497)\right)$

Table 3: Disutility parameters

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

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

Table 4 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.

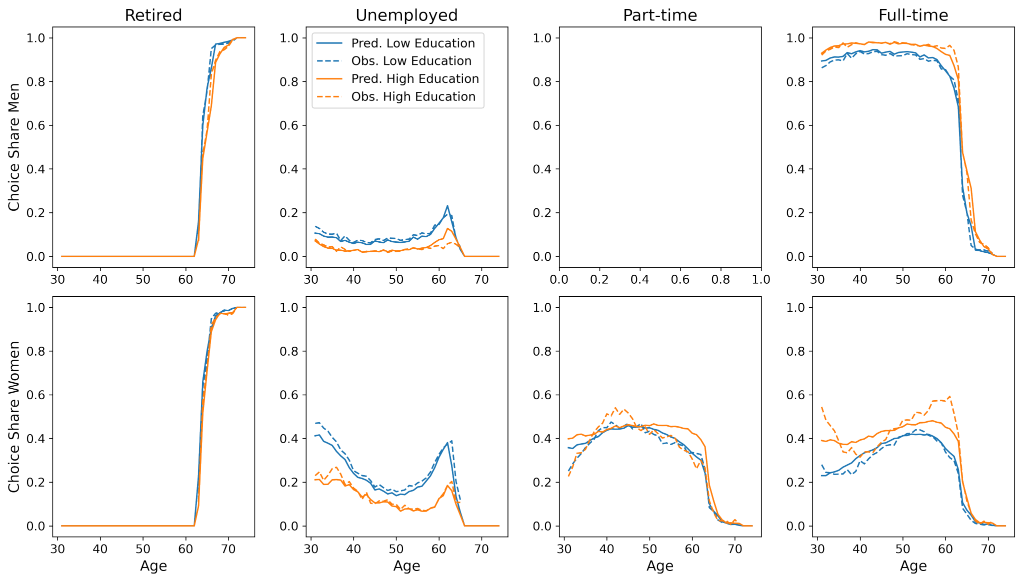
Table 4: Job offer parameters

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

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

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

Figure 5: Model fit



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

6. Counterfactual Policy Simulations

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

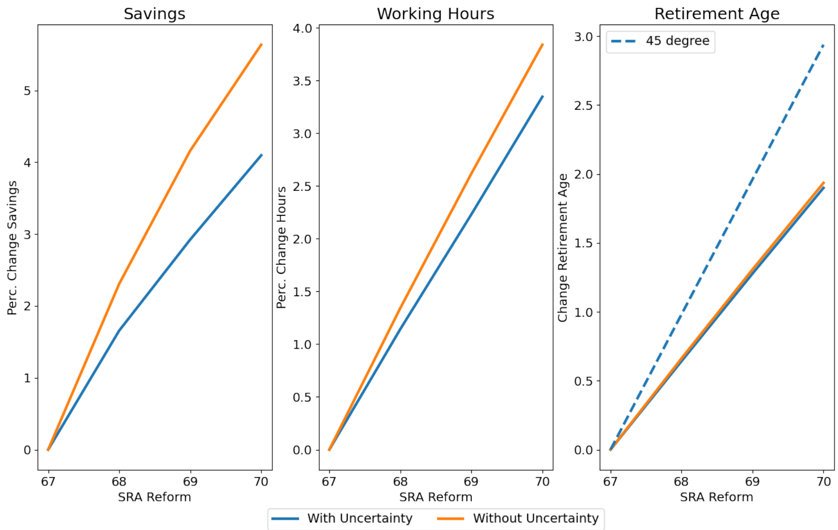
In simulation exercise i. and iii. we consider different true future policy trajectories, which we call *scenarios*. We denote true policy SRA_t^s in scenario s at time t. We quantify the effects of policy reform by considering changes in behavior and welfare. For the welfare analysis, we follow Low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

In all of our policy simulations, agents start at age 30. We assume an initial Statutory Retirement Age $SRA_{30}^s = 67$, which is the case in Germany for everyone born after 1963 as of the 2007 reform. In the scenarios without policy commitment, agents form expectations according to equations **??**, parametrized with the estimates shown in 2. We draw initial experience and wealth from our estimation sample's observed distributions of 30-year-olds. We then draw a series of shock realizations and simulate N=100,000 life cycles for each scenario.

6.1. Policy Uncertainty and Raising the Retirement Age

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

Figure 6: Behvaioral Reactions to SRA increase



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

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

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

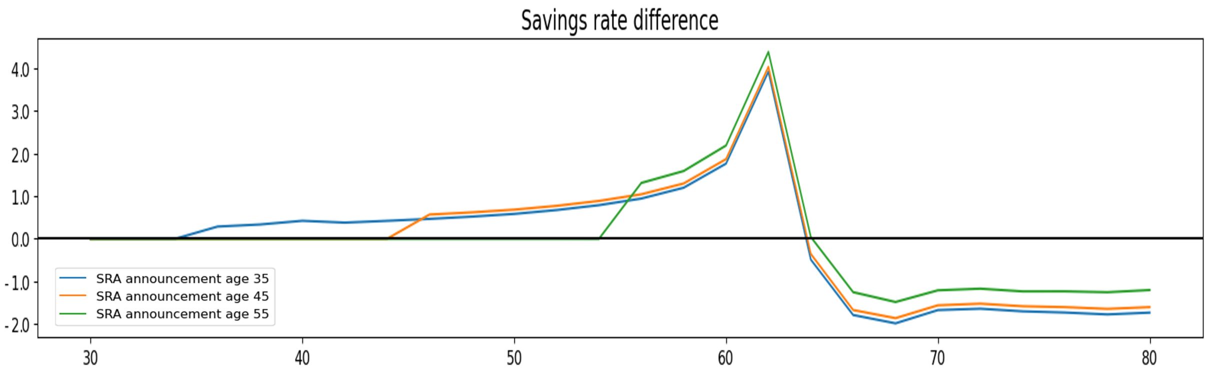
6.2. Announcement Timing

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

For this exercise, we focus on a 2-year increase in the SRA to $SRA_{63} = 69$ for all scenarios. In the baseline, this increase is announced at the latest possible point but before anyone could retire, at 63 years. In the counterfactuals, we look at different variations of *early announcement* at 55, 45 or 35 years. People have subjective expectations before and after the announcement as described in Section 3.1.[26]

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

Figure 7: Effects of Announcement Timing



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

6.3. Removing Early Retirement Penalty Bias

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

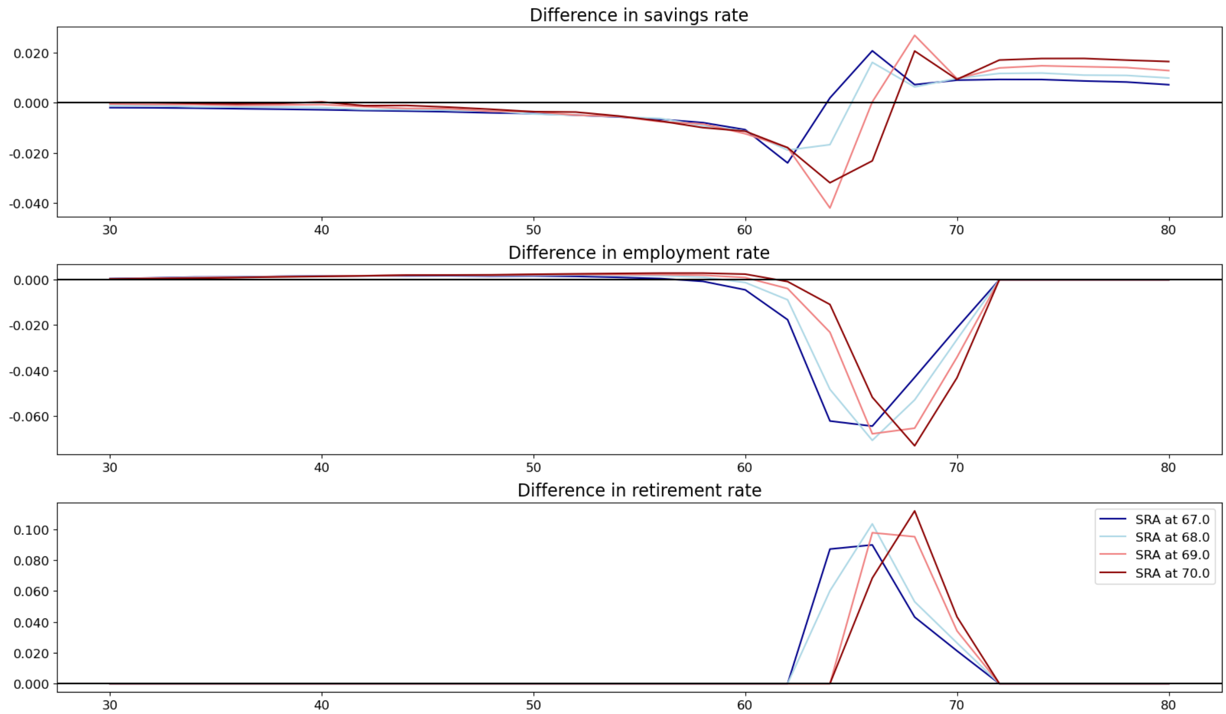
[26]Since we only have a cross-section of policy expectation data, we do not know how expectations react to policy reform. Therefore, we assume that the parameters of Equation 1 remain the same.

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

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

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

Figure 8: Effects of De-Biasing



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

7. Conclusion

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

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

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A. The appendix

A.1. Variable Overview

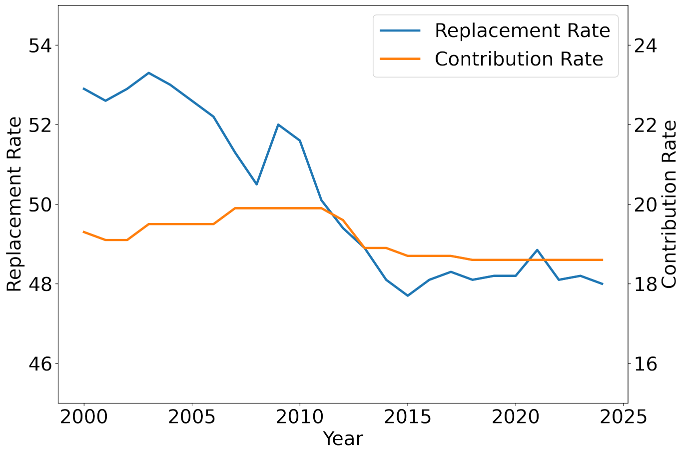
Table 5: Variable Overview

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	$30, \dots, 100$
Type	τ	4 Types as combination of
		Low/High Education and Men/Women
Job Offer	o_t	$\{0$: No Offer, 1 : Job offer$\}$
Partner State	p_t	$\{0 : \text{Single}, 1 : \text{Partner working age}$
		$2 : \text{Partner retired}\}$
Health State	h_t	$\{0 : \text{Good Health}, 1 : \text{Bad Health},$
		$2 : \text{Disabled}, 3 : \text{Dead}\}$
Statutory Retirement Age	SRA_t	$\{65, 65.25, 65.50, \dots, 72\}$
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 9: 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

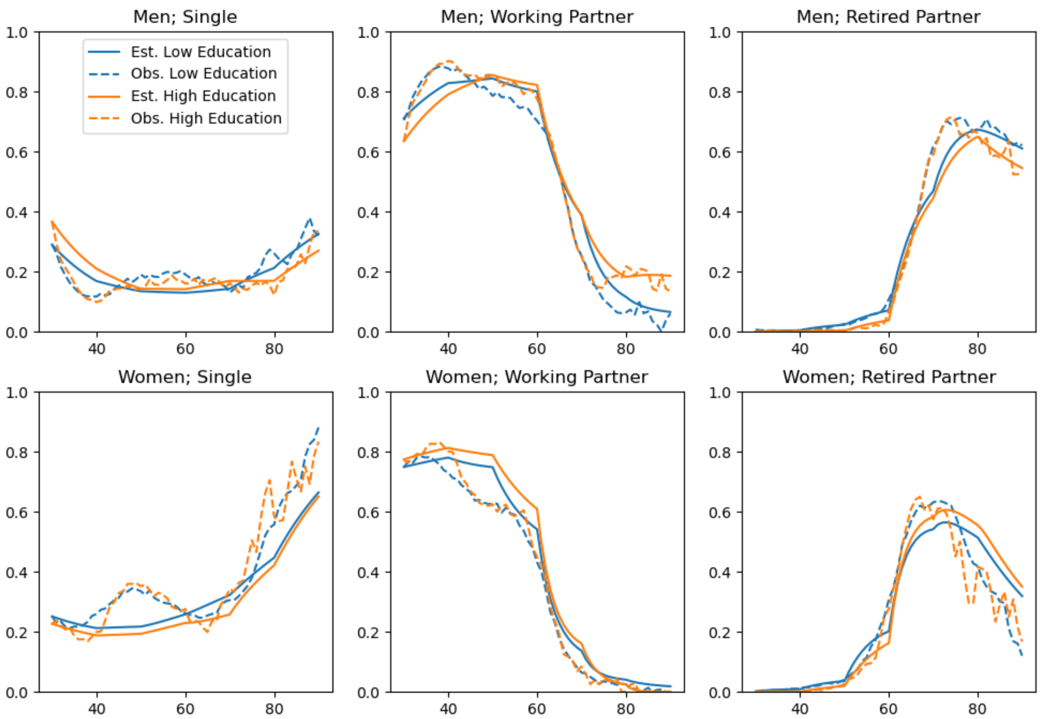
A.4.1. Partner Transitions

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:

$$\pi(p_{t+1}|x_t) = \Lambda_p\bigg(Z_p(x_t)'\,\phi_p\bigg) \tag{20}$$

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

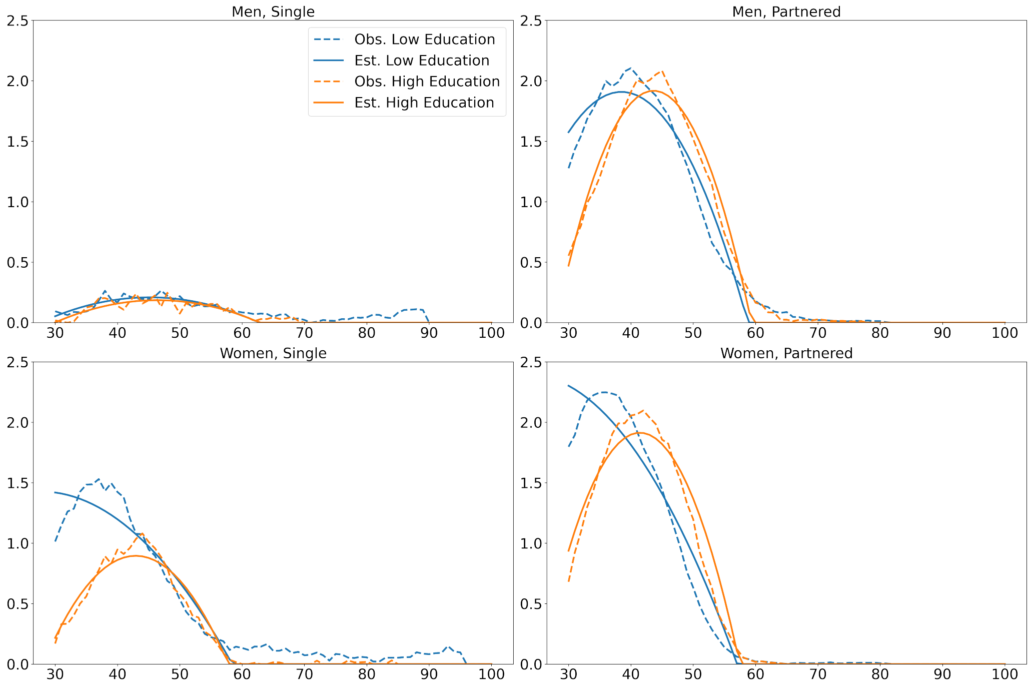
Figure 10: Shares of population in partner states



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 11: 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

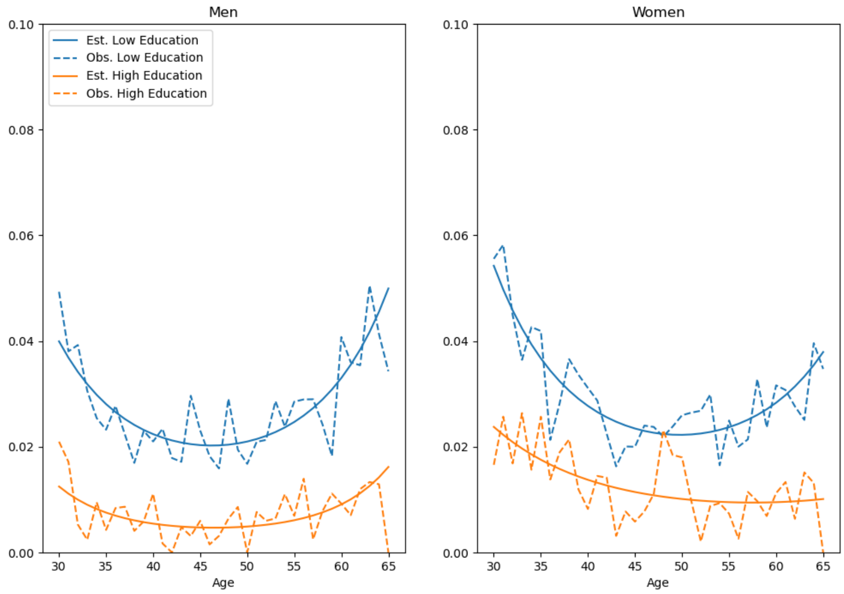
The job offer state governs the agent's ability to choose employment; the agent can choose part- or full-time if the job offer state o_t equals 1. We incorporate two processes with the job-offer state. Namely, job destruction and job offer. If the agent chooses employment in the current period, the job could be destroyed, and she has job offer state $o_{t+1} = 0$ in the next period, forcing her to choose unemployment[27]. In this case, the transition probability for the job offer state is given by:

$$\pi(o_{t+1} = 0 | x_t, d_t \in \{2, 3\}) = \Lambda_{sep}\left(Z'_{sep}\phi_{sep}\right) \tag{21}$$

where Λ_{sep} is the logistic distribution function, which predicts a job separation, conditional on education, age, and a constant. We separately estimate the probability of job separation for men and women. We estimate the probability from SOEP-Core data, where individuals are asked why they left their jobs. We only consider involuntary job loss as job separation. We restrict our sample to the start age of our model and 65 to have enough observational power. We assume that job separation rates remain constant after 65 to the age of forced retirement (72). The fit of our estimated probability can be seen in Figure 14:

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

Figure 12: Share of Job separations



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

Data: SOEP-Core

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

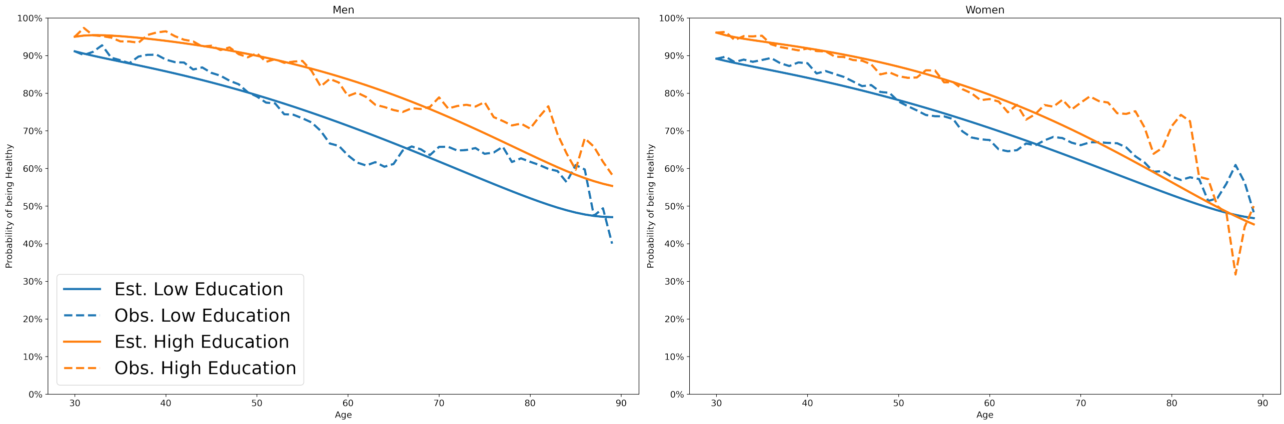
A.4.3. Health and Death

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

$$\pi(h_{t+1}|x_t) = \Lambda_h\bigg(Z_h'\phi_h\bigg) \tag{22}$$

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:

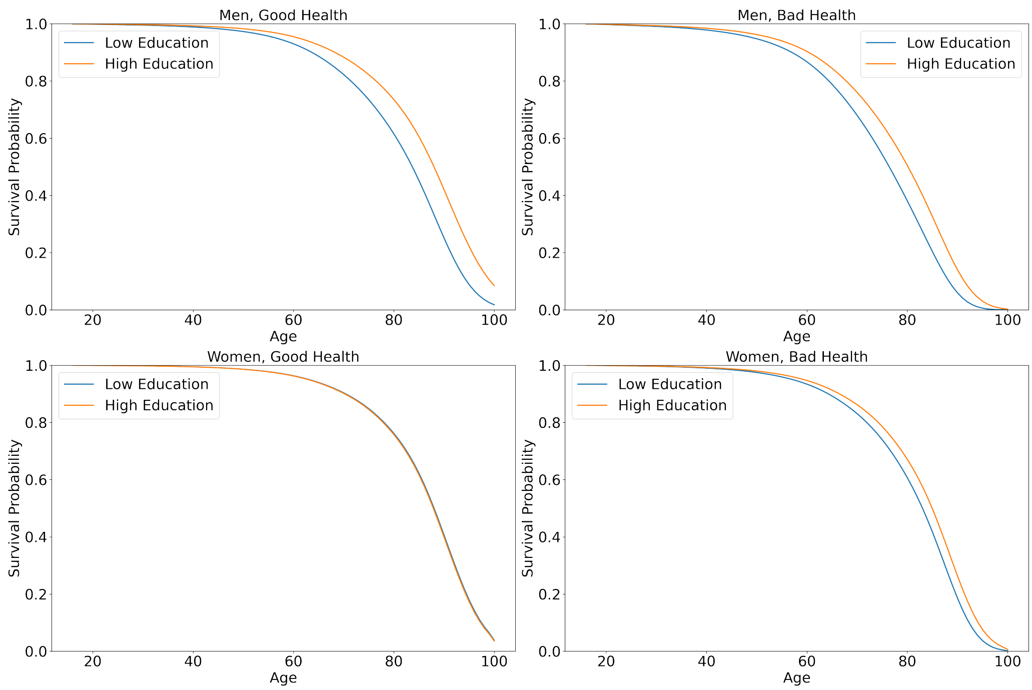
Figure 13: Share of People in Good Health



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 14: 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:

$$y_t(x_t, 0) = PP(x_t) * PPV \tag{23}$$

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:

$$y_t(x_t, 0) = PP(x_t) * PPV * (1 - 0.036) \tag{24}$$

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.

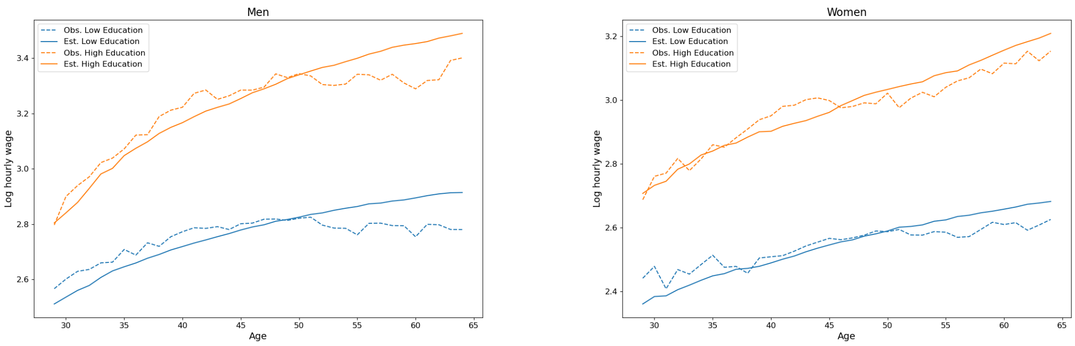
A.5.2. Wage Process

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:

$$log(w_{it}) = \gamma_{0,\tau} + \gamma_{1,\tau} * log(exp_{it} + 1) + \xi_i + \mu_t + \zeta_{it}. \tag{25}$$

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 σ_w^2. We document the fit of our estimates below:

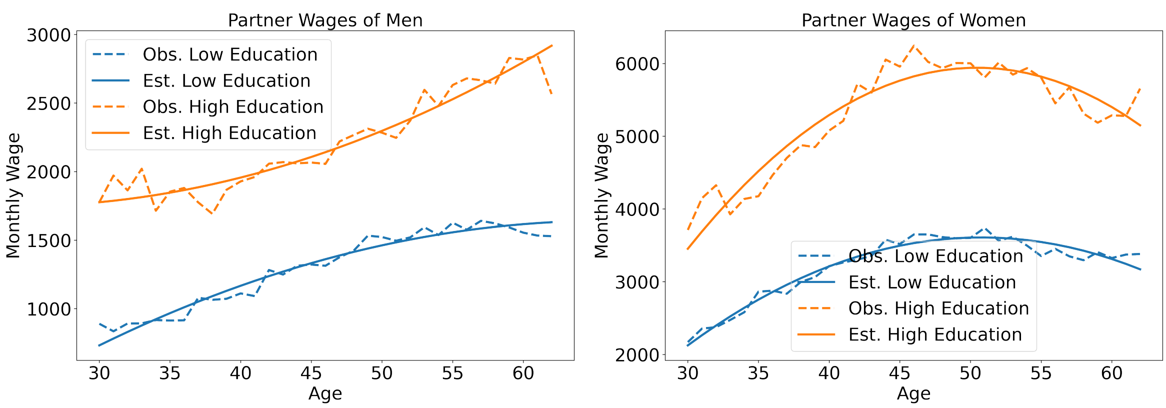
Figure 15: Wage fit



A.6. Partner Income Process

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

Figure 16: Wages of working age partners



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

A.7. Counterfactuals

A.7.1. Welfare Measure

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

$$V_e(\gamma) = \mathbb{E}\left[\sum_{t=30}^{T} \beta^t u(c_t(1+\gamma), d_t, \theta, X_t)\right], \text{ for } e \in \{A, B\}. \tag{26}$$

Thus, γ_A describes the relative increase in per-period consumption to equal the average discounted utility in the counterfactual scenario [28]. Consequently, a positive value is associated with a welfare gain in the counterfactual and a negative vice versa.

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