Policy Uncertainty, Misinformation, and Statutory 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 estimate a structural life-cycle model using the German Socio-Economic Panel (SOEP) data. We incorporate subjective policy uncertainty over the future evolution of the SRA and beliefs on its importance (SOEP-IS). The model accounts for key determinants of life-cycle savings and old-age labor supply, such as human capital accumulation, involuntary job loss, health status, and family dynamics. Individuals can adjust to policy reforms through savings, labor supply, and retirement timing decisions. Our counterfactual simulations yield valuable insights for the design of SRA reform.

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1. Introduction

The age at which full retirement benefits can be claimed, called the full retirement age or statutory retirement age (SRA), is a key parameter of social security systems worldwide. SRA reforms have been one of the main tools that policymakers employ in response to demographic change and increasing life expectancy. This has made behavioral responses to SRA reforms the subject of a growing literature.[1] Given the significance of pension income in overall life-cycle earnings, structural life-cycle models are particularly well-suited to studying the effects of SRA reforms. Comprehensive frameworks are needed to capture the intricate interactions between labor supply, savings, and retirement decisions (Haan and Prowse, 2014; Daminato and Padula, 2024). Since retirement decisions are inherently forward-looking, these models need to make assumptions about individual beliefs about retirement systems and their future evolution. Typically, existing models assume that individuals have full knowledge of the current system and expect it to remain unchanged in the future, or they assume some form of rational expectations.

We incorporate *subjective* retirement policy beliefs into a structural life-cycle model of saving, labor supply, and retirement decisions. We include two behavioral insights from Blesch et al. (2024). The first relates to policy uncertainty. After a 2007 reform that increased the SRA from 65 to 67 in Germany, people on average expect further increases in the SRA. The resulting policy uncertainty is found to decrease over the life-cycle. Previous research shows that people are willing to forego significant portions of their expected retirement income to eliminate retirement policy uncertainty (Luttmer and Samwick, 2018), which suggests that it matters for both individual welfare and behavior. The second insight relates to policy misinformation. In a survey of German respondents, Blesch et al. (2024) find widespread strong overestimation of the early retirement penalty (ERP) that is associated with claiming benefits before the SRA. This overestimation of the ERP implies that people overestimate the importance of the SRA, which adds to the distortionary effects of policy uncertainty. Misinformation rates decline over the life-cycle, suggesting that people learn about the retirement system as they age. We incorporate these two behavioral insights into our model and use it to study the effects of SRA reforms on behavior and welfare.

We estimate the life-cycle behavioral effects and welfare costs of SRA reforms with counterfactual policy simulations. Specifically, we assess four sets of potential reforms.

i. *Further SRA increases.* We evaluate behavioral reactions to an increase in the SRA to $\{68, 69, 70\}$ years. In the baseline, the SRA remains at 67 years. Behavioral reactions are theoretically ambiguous (Etgeton et al., 2023) since, depending on reform effect on *actual* retirement timing, lifetime income may increase or decrease. Our findings suggest that SRA increases lead to a combination of complementary behavioral responses. In line with existing reduced-form evidence, actual retirement is postponed but less than one-for-one. Specifically, a one-year SRA increase leads to an average increase in the actual retirement age of 0.5 years. Moreover, individuals increase their savings by approximately four percent and life-cycle labor supply by around one percent.

ii. *Policy Commitment.* For the same SRA scenarios as in (i.), we estimate the impact of credible policy commitment in the counterfactuals, i.e. we estimate the effect of eliminating policy uncertainty entirely. In the baseline, SRA is gradually increased to the same level as in the counterfactual but people are uncertain about it until they retire. We find

[1] cf. Carta and De Philippis (2024); Deshpande et al. (2024); Rabaté et al. (2024) for recently policy evaluation studies.

that commitment to increasing (decreasing) the SRA by one year relative to expectations increases (decreases) savings rates by 0.1 percentage points.

iii. *Announcement Timing.* In simulation (ii.) we abstract from the timing of the announcement of the reforms by introducing the new policies gradually over the life cycle. By contrast, in (iii.) we look at the effects of announcing it at different times in the life-cycle, namely when agents are $\{35, 45, 55\}$ years old. In the baseline, agents are informed about the new SRA at the latest possible time, i.e. just before they can claim their pension. We find that early announcement increases working life savings without unintended effects on early retirement.

iv. *De-biasing.* We simulate the effects of eliminating misinformation about the early retirement penalty. In the counterfactual, individuals are always informed about its true size. As can be expected, this leads to earlier retirement relative to the SRA. Furthermore, savings during the working life decline, which leads to a decrease in consumption during retirement.

There is a growing body of empirical literature on the behavioral effects of retirement policy uncertainty, using observational data (Aaberge et al., 2017; Ciani et al., 2023; Delavande and Rohwedder, 2011) or survey experiments (Blesch et al., 2024; Delavande and Rohwedder, 2017). While they find significant effects of uncertainty on consumption and labor supply behavior, they are reduced-form studies that do not allow for counterfactual policy simulations or incentive decomposition of behavior. At the same time, welfare effects of retirement policy uncertainty have been studied in the macroeconomic literature (Caliendo et al., 2019; Cottle Hunt, 2021; Nelson, 2020). However, these studies typically do not explicitly model the retirement decision and investigate the welfare effects of policy uncertainty on an abstract level with aggregate data, employing rational expectations assumptions. This paper adds to this literature by explicitly identifying the structural parameters of decision-making and estimating the subjective belief process on individual policy uncertainty.

We contribute to a rich literature of structural economic life-cycle models, studying retirement decisions and policies (French, 2005; Haan and Prowse, 2014; Iskhakov and Keane, 2021; van der Klaauw and Wolpin, 2008; Daminato and Padula, 2024). Large strands focus on effects on savings (Alessie et al., 2013; Attanasio and Rohwedder, 2003) as well as retirement timing and forward-looking labor supply (Gustman and Steinmeier, 2005,0). We add to this literature by exploring the effects of long-term policy uncertainty in a framework that combines savings, labor supply, retirement timing, and subjective beliefs. Thereby, we contribute to a fast-growing literature on the importance of subjective expectations in retirement analysis (Bairoliya and McKiernan, 2021; de Bresser, 2020) and to the expanding use of subjective expectations in structural models(see Koşar and O'Dea (2023) for a recent summary).

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 we focus on, how they are treated in our model, and how we estimate them. In Section 4, we explain the rest of the structural 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.

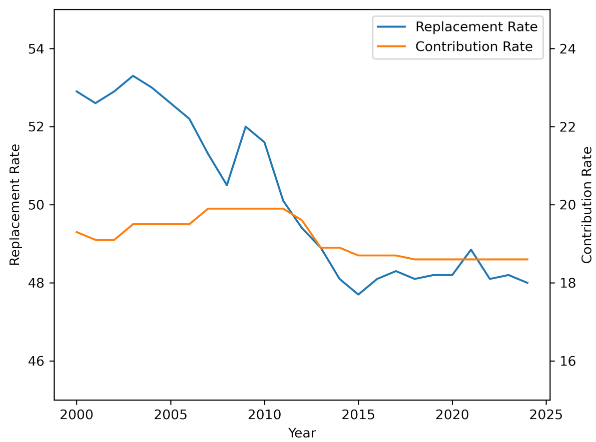
2. Institutional Background and Data

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[2]. While replacement rates have fallen in recent years, contribution rates have been stable at around 19 percent (cf. figure 1). Both are linked to demographic change, so without further reform, replacement rates are expected to fall, while contribution rates are expected to rise. Details can be found in appendix A.1.1.

Figure 1: Replacement Rate and Contribution Rate



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

Source: German Pension Insurance (DRV)

The *statutory retirement age* (SRA), similar to the *full retirement age* of the American social security system, is another key policy parameter. The current SRA is a function of birth year and stands at 67 years for everyone born after 1964 (cf. Figure 2). Given certain requirements, claiming a pension is possible up to four years before this age,[3] but no earlier than at 63 years.[4] Early retirement comes at a penalty of 3.6 percent of the pension value per year of early retirement, or 0.3 percent per month. In 2023, one in three pensions was claimed before

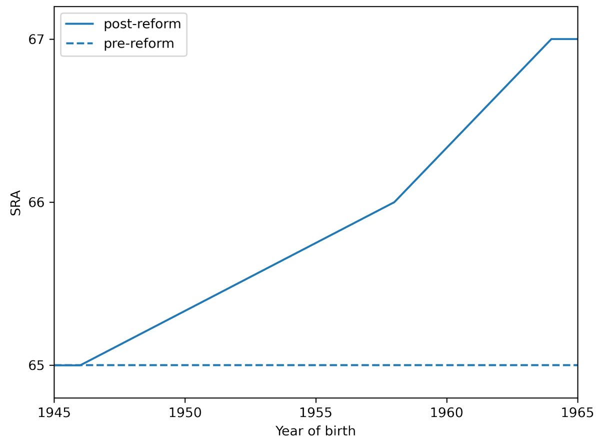
[2]This holds until a cap of roughly twice the average wage, beyond which no contributions have to be made and no claims are accumulated

[3]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.

[4]As an exception, people who have contributed for 45 years can retire at 63 without a penalty.

the applicable SRA. On average, pensions that were claimed early were claimed 30 months in advance, implying an average penalty size of 9 percent.

Figure 2: 2007 reform of the Statutory Retirement Age



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

2.2. Data

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

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

We generate the model estimation sample from the SOEP-Core, the main household panel dataset. We limit the analysis to the years 2010-2017, after the Great Recession, and until the last available household wealth elicitation in 2017. Other sample restrictions stem from model restrictions, such as not being allowed to work after a certain age, and from data availability (see table 1 for some descriptives). In addition, we create several auxiliary samples from the SOEP core for the estimation of some processes that we estimate outside the model, such as the evolution of health over the life-cycle. We do not estimate these on the structural estimation sample because data availability requirements differ (see appendix table 5).

We use subjective expectations data from a survey we included in the SOEP Innovation Sample (SOEP-IS), which allows researchers to submit their own questions. In the 2022 wave, we included various questions on social insurance uncertainty.[5] From this survey, we use the data on respondent SRA uncertainty and planned retirement age. See appendix A.2 for the exact wording of the questions. Sample composition between the expectation data and our structural estimation sample differ, as table 1 illustrates. That is why we use SOEP population weights for our analysis to make results comparable.

Table 1: Main datasets

	Structural Estimation Data	Policy Belief Data
Years	2010-2017	2022
Nb. of Observations	95511	775
Age Range	30-104	18-84
Median Age	52.0	46.0
Female Share	0.528567	0.508387

Notes: Structural Estimation Data from the Soep-Core, Policy Belief Data from the SOEP-IS.

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

3. Policy Beliefs

Unlike classical models, in our framework agents do not expect the policy environment to stay the same, nor are they perfectly informed about it. We also do not have a model of rational expectations or rational inattention, in which we would need to make assumptions about true evolution of policy or about the agent learning process. Instead, we focus on subjective expectations, which we elicit directly from people rather than deriving them from behavior.

The policy belief we focus on in this study is the Statutory Retirement Age. While actual pension size is just as relevant for household retirement planning, it is less suited for our purposes. First, it is less clear what potential reforms would look like. Recent reforms have added or amended factors in the pension value growth formula, but eliciting beliefs about these kinds of reforms would be challenging. Second, the key policy parameter in the public debate about pension size, the replacement rate, carries limited information for the individual because it only describes a stylized worker.[6]

[5] Blesch et al. (2024) analyze the whole survey. The data will be available in the next release of the SOEP-IS.

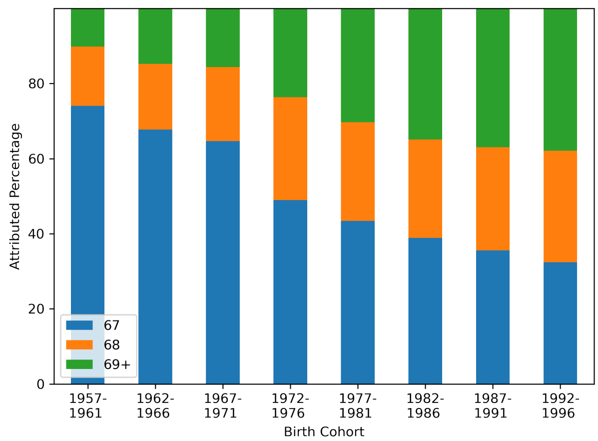
[6] In annual letters, the German Pension Insurance informs insurees about the pension they can expect if they continue to earn their current wage until retirement. This may be the more relevant number for individuals to form expectations over, but it is difficult to connect it to a specific policy environment in a model.

By contrast, the Statutory Retirement Age is simpler. It is one number, which holds for most of the working-age population. It is salient, 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 less clear if people understand to what extent the SRA is a binding prescription and to what extent it is mere guidance.

3.1. Descriptive Statistics

(Blesch et al., 2024) elicit probabilistic expectations of the SRA at the time respondents expect to retire. 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 3 illustrates these findings.

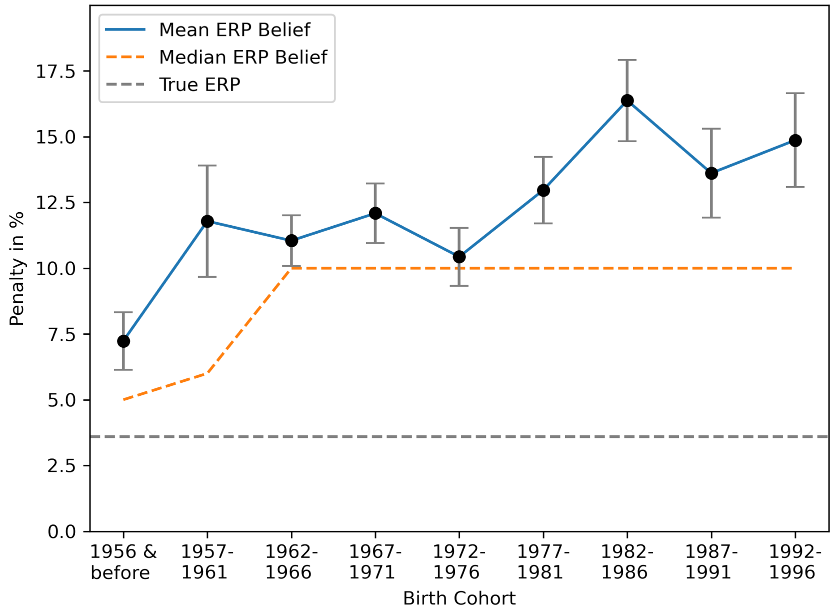
Figure 3: Subjective Distributions over Future SRAs



Notes: Figure from (Blesch et al., 2024). See appendix A.2 for question wording.

Furthermore, (Blesch et al., 2024) document that people are, on average, very poorly informed about the Early Retirement Penalty. Figure 4 illustrates this. With the exception of 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. Since many people would like to retire early - and currently around a third of people do retire before their respective SRAs - this is very relevant. It suggests that before respondents become informed about the ERP, they believe that early retirement is close to being prohibitively expensive. This misinformation may significantly distort people's reasoning about retirement and how they react to reforms.

Figure 4: Belief about Current ERP



Notes: Mean and median of subjective belief about Early Retirement Penalty (ERP), as well as true penalty size. Standard error bars around subjective means. Figure from (Blesch et al., 2024). See appendix A.2 for question wording.

3.2. Policy Uncertainty

In the model, we implement uncertainty about the future SRA in a simple and computationally tractable way while retaining two key features. First, agents update their expectations as current policy changes and are not surprised by it at the end of their working lives. Second, uncertainty about the SRA at retirement decreases over time, reflecting the findings from (Blesch et al., 2024). 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}.[7] Agents expect the SRA used to calculate their pensions not to change anymore once they retire.

As a result, at any time t before retirement, agents' expectations and associated uncertainty about the SRA at time $T > t$ are given by

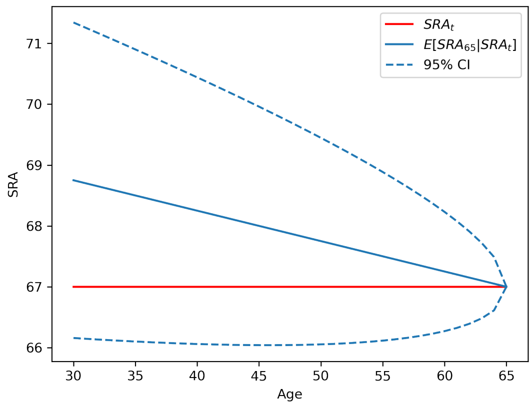
$$E[SRA_T|SRA_t] = SRA_t + (T-t)\alpha \tag{2}$$
$$Var[SRA_T|SRA_t] = (T-t) * Var(\epsilon) = (T-t) * \sigma^2_{SRA} \tag{3}$$

In our counterfactual policy simulations, policy changes. For example, consider an individual aged 30 who expects her applicable SRA to increase at an annual rate of $\alpha = 0.05$, or one year every 20 years, with an associated uncertainty of $\sigma^2_{SRA} = 0.05$. Assume that true policy evolves exactly as expected at a true $\alpha^* = 0.05$. As a result, the expected SRA for any given point in

[7]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.

the future never changes, but her forecast error becomes smaller over time. Figure 5 illustrates the evolution of her belief over her life.

Figure 5: Example: SRA Belief Evolution without Policy Change



Notes: Belief evolution over the life-cycle of a 30 year old according to equation 2, where $(\alpha, \sigma_{SRA}) = (0.05, 0.05)$. True SRA remains at its initial level of 67. Confidence intervals are given by $E[SRA_T|SRA_t] \pm 1.964 * \sqrt{(65-t)\sigma^2_{SRA}}$.

Parametrization of the SRA expectation process relies on the (Blesch et al., 2024) survey data. In it, respondents were asked to i. state the age at which they expect to start claiming public pensions (which we denote $t^{E,R}$) and ii. allocate probability mass to certain possible SRAs that may be applicable to them at that age.[8]. We estimate the parameters α, σ^2_{SRA} from the survey data in two steps. First, we fit truncated normal distributions through the subjective probability distributions that people stated. For each individual i, this yields expectation $E_i[SRA_{t_i^{E,R}}]$ and variance $Var_i[SRA_{t_i^{E,R}}]$.

Because there is cross-sectional variation in time until expected retirement, this identifies α and σ^2_{SRA}, conditional on the model assumption of 1. Both parameters can then be estimated simply via OLS be re-writing equations 2. Table (2) reports our estimate for the random walk of our policy belief process. Note that the implied expected SRA increase of 0.41 years every ten years is close to the German Council of Economic Advisors recommendation, which is is 0.5 years every ten years (Grimm et al., 2023).

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: OLS estimate of equation 2. Standard errors in parentheses.

[8]The exact wording of the questions can be found in appendix A.2

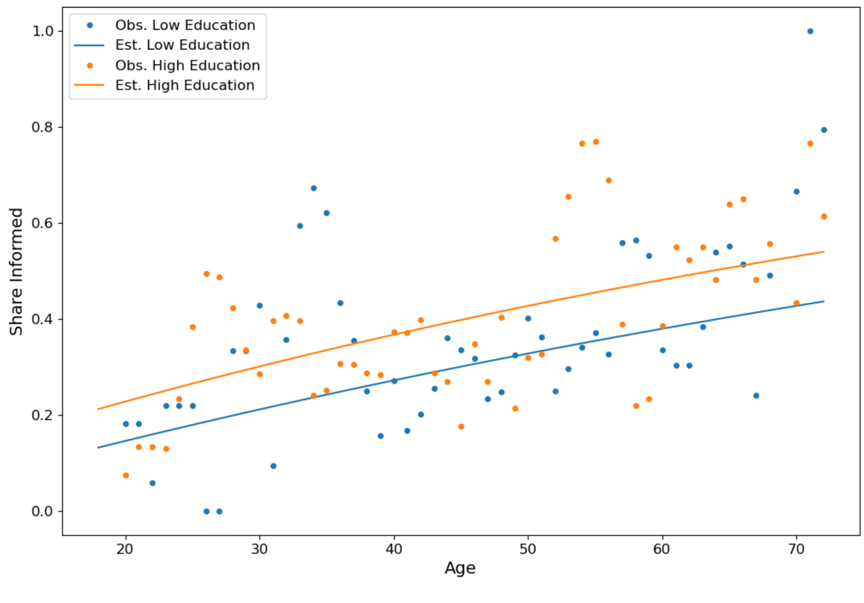
3.3. Policy Misinformation

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[9]. By contrast, at the average reported ERP size of around 12 percent, early retirement would likely be too expensive for most people to consider.

For these reasons, we decided to classify people into informed and uninformed in the model. An individual who is in either category in our model does not expect to switch from one to being informed. However, in the counterfactual model simulations, a simple Markov process governs transitions from being uninformed to being informed. Being informed is an absorbing state.

Again, parametrization relies on the same survey data. In the data, we classified as informed a respondent who answered "5" or less to the question eliciting beliefs about the current ERP.[10] We then computed transition rates between the informed and the uninformed via the method of moments, using the share of informed people at a certain age as moments. We estimated the transition rates separately for high and low-education individuals[11] Figure 6 visualizes the fit.

Figure 6: Informed shares over time



Notes: 'Observed' refers to the share of individuals we classify as informed in each age group in the (Blesch et al., 2024) survey data. 'Estimated' refers to the predicted share of informed individuals over the life-cycle.

We split the sample into informed and uninformed individuals and determined their expected ERPs for each group. We assume informed agents expect an accurate deduction of 3.6 percent for ERP. We do not find any heterogeneity among uninformed individuals but keep the

[9] 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).

[10] We chose the threshold so respondents whose answers were below it were as close as possible to the true ERP.

[11] 'High education' refers to individuals who have completed at least the *Fachabitur* or *Abitur*, which are secondary school qualifications that grant eligibility for higher education in Germany."

educational split in line with the differences in informed shares. High-educated, uninformed individuals expect, on average, 18.0 percent, while low educated expect 18.4 percent. Both expectations are too high for individuals to assess early retirement as feasible.

4. Model

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

We model men and women who completed their education, determining four exogenous types $\tau \in \{men, women\} \times \{high, low\}$ in the model. Wealth inequality arises through heterogeneity in initial endowments and due to type-specific income and endogenous investments in work experience e_t. Income uncertainty arises from transitory wage shocks, stochastic job offers, and destruction o_t. A modeled approximation of the German tax and transfer system partially offsets these risks. Additionally, the model includes Markov processes capturing the arrival, departure, and retirement of partners p_t and the evolution of an individual's health over the life cycle[12]. An individual's state at each age, $x_t \in \mathcal{X}$, is further defined by two policy states, SRA_t and i_t, described in Section (3).

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, 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:

$$V(x_t) = \max_{0 \leq c_t \leq a_t, d_t} u(c_t, d_t, x_t) + \beta \, \mathrm{E} \left[V(x_{t+1} | c_t, d_t, x_t) \right] \tag{4}$$

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 proceduresCarroll (2006). The remainder of this section describes the modeling of decisions and utility, the agent's income, the tax and transfer system, and the additional Markov processes.

4.1. Decisions and Utility

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

Labor supply $d_t \in \mathcal{D} = \{0, 1, 2, 3\}$ can take values of retirement ($d_t = 0$), unemployment ($d_t = 1$), part-time ($d_t = 2$), and full-time work ($d_t = 3$). Full-time work increases an agent's experience stock by one year, while part-time work increases it by half.[13]. During their working life, agents can decide to work part- or full-time if they have a job offer o_t in the current period.

[12] The empirical parametrization of the Markov processes for job-offers and destruction, partners, health and death can be found in the Appendix.

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

Otherwise, they must choose unemployment. The law of motion of o_t is described in Appendix (A.3.2). Retirement can be chosen up to four years before the statutory retirement age (SRA) but no earlier than age 63, following a simplified version of the current German law. To simplify further, we restrict decisions so that retirement is absorbing and from age 72 everyone must be retired.

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

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

$$u(c_t, d_t, x_t) = \frac{(\frac{c_t}{n_t(x_t)} L_t(x_t, d_t))^{1-\mu} - 1}{1 - \mu} + \epsilon_t(d_t) \tag{5}$$

where $n_t(x_t)$ is the consumption equivalence scale, calculated as the square root of the household size.[14] The term $L_t(x_t, d_t) \in [0, 1]$ captures the reduction in consumption utility relative to the retirement baseline. Its functional form is given by:

$$L_t(x_t, d_t) = \begin{cases} 1, & \text{if } d_t = 0 \\ exp\Big\{ - Z_L(x_t, d_t)' \kappa_{d_t} \Big\}, & \text{if } d_t > 0 \end{cases} \tag{6}$$

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

The model features choice-specific utility shocks $\epsilon_t(d_t)$, which follow an 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:

$$u_b(a_T) = \vartheta \frac{a_T^{1-\mu}}{1 - \mu} \tag{7}$$

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).

[14] 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.

4.2. Income and Budget

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

$$a_{t+1} = (1+r)(a_t - c_t) + Y_t(d_t, x_t), \tag{8}$$

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 $T(\cdot)$ to be paid:

$$Y_t(x_t, d_t) = y_t(x_t, d_t) + y_t^p(x_t) + B(x_t, d_t) - T(x_t, d_t). \tag{9}$$

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.

$$y_t(x_t, d_t) = w_t(x_t)\, hrs(x_t, d_t), \text{ for } d_t \in \{2, 3\}. \tag{10}$$

The wage given by

$$\ln w_t(x_t) = \gamma_{0,\tau} + \gamma_{1,\tau} \ln(e_t + 1) + \zeta_t. \tag{11}$$

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.4.1) details how we construct this function. The pension income of an agent who retires at the SRA is then given by: for

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

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

$$y_t(x_t, 0) = PP(x_t) * PPV \tag{13}$$
$$* (1 - ERP)(SRA_{t^R} - t^R)\mathbb{1}(SRA_{t^R} > t^R)). \tag{14}$$

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

$$ERP = \begin{cases} \tilde{ERP}, & \text{if } i_t = 0 \\ 0.036, & \text{if } i_t = 1. \end{cases} \tag{15}$$

where $\tilde{ERP}$ is the expectation of uninformed agents. Appendix (A.4.1) also documents how we can track the deduction of pensions due to early retirement with the experience stock. Therefore, we do not need to track t^R.

Partner income $y_t^p(x_t)$ deterministically depends on the agent's state. For model sparsity, we do not track any state variables, e.g., experience for the partner. In particular, the partner's income depends on the agent's age, education, and sex. We do not model any uncertainty in the partner's income; all income uncertainty arises from the agent's income. Details on the approximation of partner income can be found in appendix A.5.

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

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

5. Estimation

There are three sets of parameters that need to be determined for our counterfactual policy simulations. The first set is calibrated using external data sources and established literature estimates. This set includes policy parameters that are assumed to remain constant within the model (e.g., tax brackets), as well as standard utility 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.3.1), health and mortality (A.3.3), and job destruction (A.3.2). Additionally, it comprises wage parameters, such as the return to experience and the variance of income shocks (A.4.2). As described in Section 3, we also estimate the policy belief and misinformation parameters separately and use them to parameterize the model.

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

5.1. Structural Estimation

Identification. We estimate two kinds of parameters in the model with maximum likelihood. First, we estimate the structural disutility parameters governing the consumption utility reduction of each choice in comparison with retirement (equation 6). A higher disutility parameter implies a greater reduction in consumption utility for a given choice. Identification relies on the direct effect of these parameters on the choice probabilities through the utility function, independent of the financial incentives of these choices that generate utility via consumption.

Second, we estimate the parameters determining the job offer probabilities for unemployed individuals. Since job offers are not fully observed, job offer probabilities must be estimated jointly with utility parameters and inside the model.[15] Conditional on the utility parameters, job offer probabilities are identified by the observed decisions of the unemployed, which they directly impact.

Likelihood. Formally, we can derive the likelihood function as follows: We denote the dataset by $\mathcal{M}$. It contains for each individual i at time t their labor supply decision d_{it}, and their observed states. Assume that all state variables of the state x_{it} are observed. As the choice-specific taste shocks $\epsilon_{it}(d_{it})$ are assumed to be i.i.d. extreme value distributed and enter the utility function additive separable, the choice probabilities have a closed form solution. Therefore, the probability to observe choice d_{it} under a fully observed x_{it}, is given by:

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

[15] Unlike job separations, job offers are not directly observed; we only observe job uptake in the data. However, individuals transitioning from unemployment to employment must have received a job offer. Therefore, the only observations for which we do not observe job offers are individuals who stay unemployed or retire directly from unemployment.

However, we do not observe two states or only partially observe them. In particular, we only observe the job offer state o_t if the individual chooses employment. If we observe the job-offer state, we multiply the choice probability by the probability that this job-offer state occurs. If we do not observe the job offer state, we weigh the choice probabilities of the two possible job offer states by the probabilities of a job offer. We construct the probability of receiving a job offer in $t+1$, dependent on the current state and decision of unemployment by

$$\pi(o_{t+1} = 1|x_t, d_t = 1) = \Lambda_o\Big(Z_o(x_t)'\phi_o\Big) \tag{16}$$

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 definition of the probability $\pi(o_{t+1}|xt-1)$ is complemented by the definition of job destructions in appendix A.3.2.

Moreover, we do not observe if agents are informed. However, with the age and education-specific shares $G(i_t|x_{it})$ of informed agents that we estimate from the Blesch et al. (2024) belief data (cf. section 3.3), we can integrate this unobserved variable.

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

$$\mathcal{L}(\mathcal{M}, \theta) = \pi_{i=0}^{N}\pi_{t=0}^{T} \log\Bigg(\sum_{o_t=0}^{1}\sum_{i_t=0}^{1} P(d_{it}|x_{it}, o_t, i_t\theta)dF(o_t|x_{it-1}dG(i_t|x_{it})\Bigg) \tag{17}$$

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 6). 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.[16]. Likewise, women in bad health are indifferent between working part-time or working full-time while consuming 15 percent less.[17]

[16] $1 - \exp(-0.3896)$

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

Table 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.3.2). We document a negative age trend for job offers, in line with estimates from similar contexts in the literature.

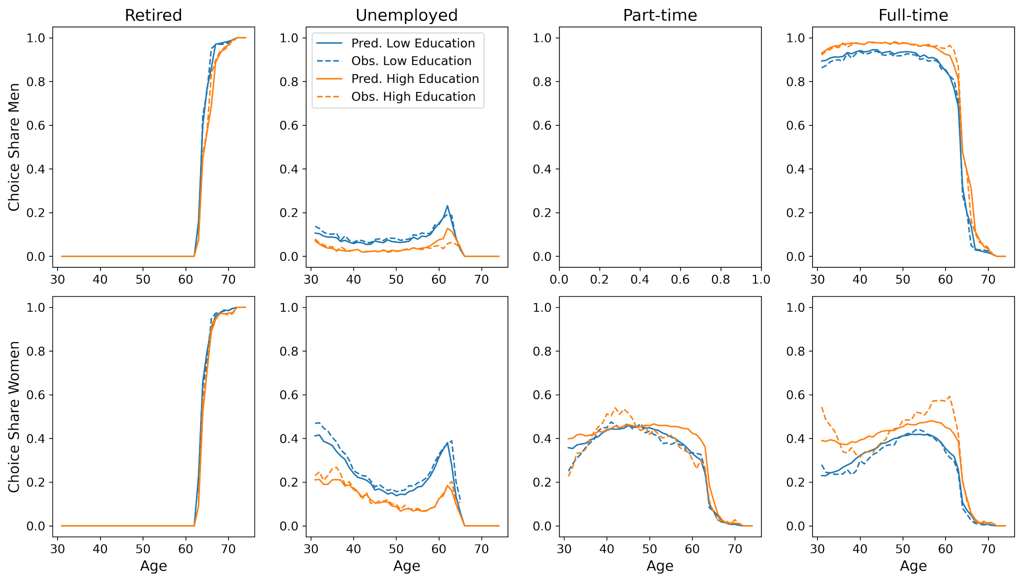
Table 4: Job offer parameters

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 (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 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. policy commitment, iii. timing of reform announcement, and iv. eliminating the ERP bias.

In simulation exercises i. ii. and iv., 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.6.1 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 2, 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. Further Raising the Statutory Retirement Age

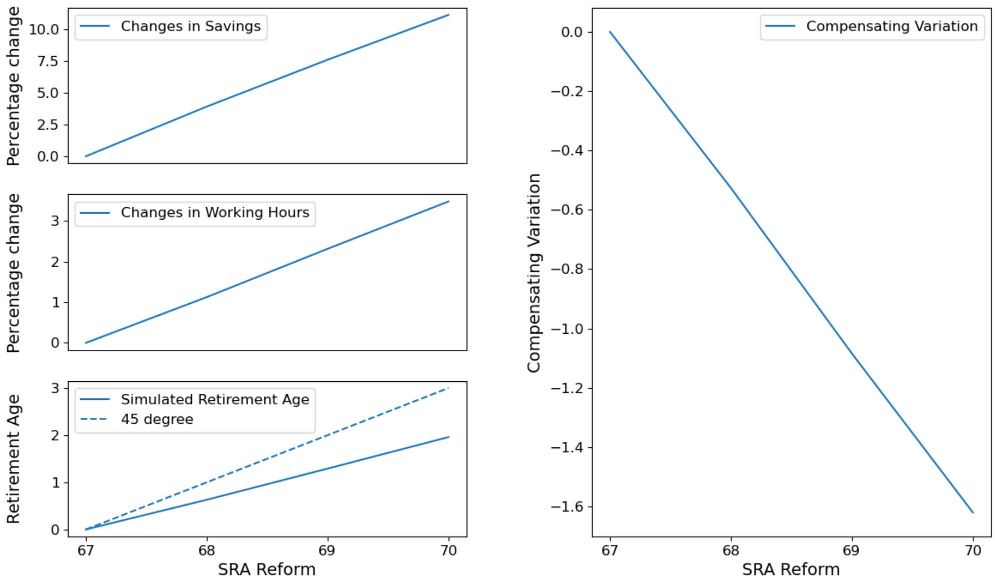
In the first simulation exercise, we compare a baseline of no policy change to different alternative policy trajectories. To facilitate the comparison, we introduce a *resolution age*, after which there is no more policy uncertainty in either the baseline or the counterfactual. We set this age to 63 years.[18] Agents in both baseline and counterfactual know and believe this. In both baseline and counterfactual, subjective beliefs are modeled and parametrized as described in Section 3.2. In the baseline, $SRA_{63}^s = 67$ for all scenarios, while in the counterfactuals $SRA_{63}^s = s$ 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 left panel of figure 8. We can observe that agents react to increased SRAs with a mix of behavioral responses. Roughly, a one-year increase in the SRA induces a 3.5-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 (right panel figure 8). There is no visible break in behavioral adjustment at the SRA_63 that individuals expect, i.e. 68.25. This smoothness can be attributed to the gradual updating of expectations due to the continuous policy adjustment over the life cycle.

Most interestingly, the retirement timing does not follow at the same pace as the SRA increase (bottom left, figure 8). For every additional year of SRA, the retirement age only increases roughly by half a year. This finding has significant consequences for assessing the mitigation of demographic change through increases in the SRA.

[18] We chose this age because it is the lowest one in the model at which someone could retire at the maximum penalty size.

Figure 8: Behavior and Welfare for SRA increases



Notes: Comparison of behavior margins on the left and welfare on the right for different counterfactual SRAs at resolution. The baseline is 67 as SRA at resolution (no increase).

6.2. Policy Commitment

In this counterfactual analysis, we evaluate the effects of full policy commitment. To do so, we compare a baseline in which the applicable SRA is raised gradually and with uncertainty to a counterfactual in which it is raised to the same number but with prior announcement. Again, we introduce a resolution age of 63 years into the model, of which agents are aware and after which the SRA cannot change anymore.

In the baseline, agents have subjective expectations, as described above. We consider different scenarios for true policy development in which the SRA at 63 rises gradually to $SRA^s_{63} = s$ with $s \in \{67, 67.25, ..., 69.75, 70\}$. We contrast each of these baseline scenarios with a counterfactual, in which the eventual SRA^s_{63} is announced immediately and with full policy commitment. This means that immediately from age 30, there is no more policy uncertainty, since agents understand and believe the policy commitment.

Two things are important to note. First, in the baselines SRA^s_t rises linearly, at a constant rate of $\alpha^s = \frac{s-67}{63-33}$. Thereby, we abstract from the specific point in time at which the policy is announced, which in our model implies gradual updating of expectations (cf. figure 5). Second, agents in the baseline model at age 30 expect an SRA when reaching resolution age of approximately 68.25[19]. Therefore, every baseline scenario with $s < 68.25$ is a series of good news for the agents as they receive continuous positive updates about their lifetime income, and vice versa.

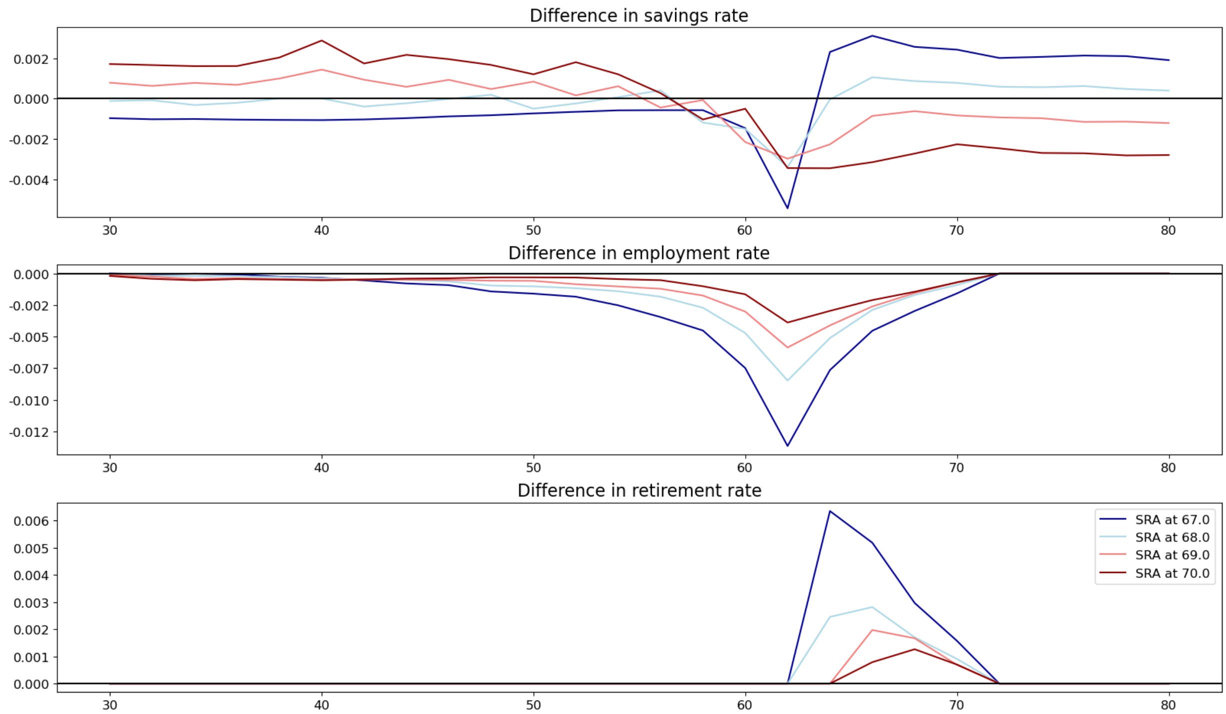
Our results are illustrated in Figure 9. We plot the difference in savings end employment

[19] $E[SRA_{63}|SRA_{30} = 67] = 67 + 0.041 * (63 - 30)$

rates between and counterfactual and baseline for different policy scenarios. We define savings rate as the ratio of the aggregate annual household savings and aggregate annual household income. The employment rate is the average share of people working full-time or part-time. The retirement rate is defined analogously. In the figure, policy trajectories with $SRA_6 3^s$ below subjective expectation are marked in blue, while the ones in which the SRA increases faster than expected are marked in red.

If SRA increases slower than expected, agents react to policy commitment with a reduction in savings and vice versa. Savings rate increases (or decreases) by about 0.1 percentage points over the life-cycle per year of commited SRA increase relative to expectations. Relative to a base savings rate of 2-10 percent, the effect size is small but not trivial. The ability of households to adjust sooner the the eventual policy environment through higher savings is accompanied by a slight increase in early retirement rates of 0.1-0.6 percentage points.

Figure 9: Effects of Commitment to Different Policies



Notes: Comparison of effects of policy commitment on annual savings for different policy scenarios. Scenarios are defined by SRA at resolution. In the baseline, agents are uncertain about future SRA; in the counterfactual, it is announced immediately with full commitment. 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.

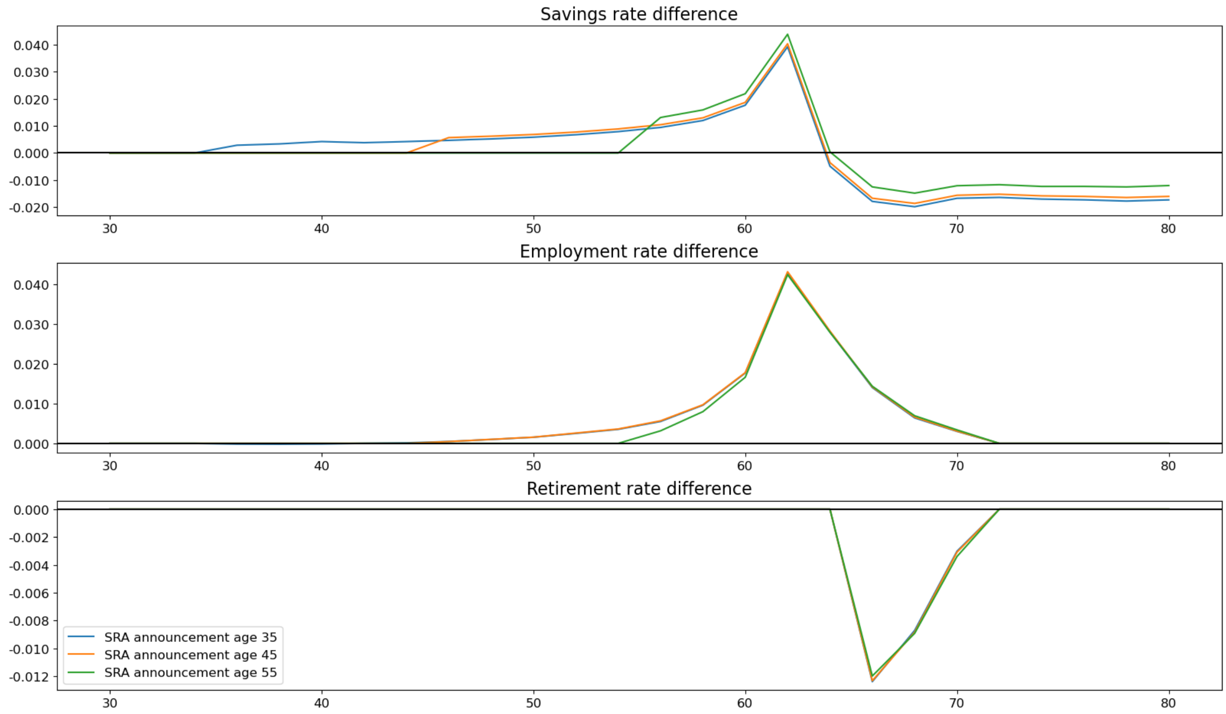
6.3. Announcement Timing

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 typically is 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 other time to explore other margins for adjustment corresponds to the intention of the policymaker. It is therefore interesting to study what difference the timing of the announcement of a reform 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. Before and after the announcement, people have subjective expectations as described in Section 3.2.[20]

We find that people react to the timing of the announcement with a marked increase in savings throughout the working life and a concomitant increase in spending during retirement (cf. Figure 10). 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 10: Effects of Commitment to Different Policies



Notes: Effects 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.

[20]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.

6.4. Removing Early Retirement Penalty Bias

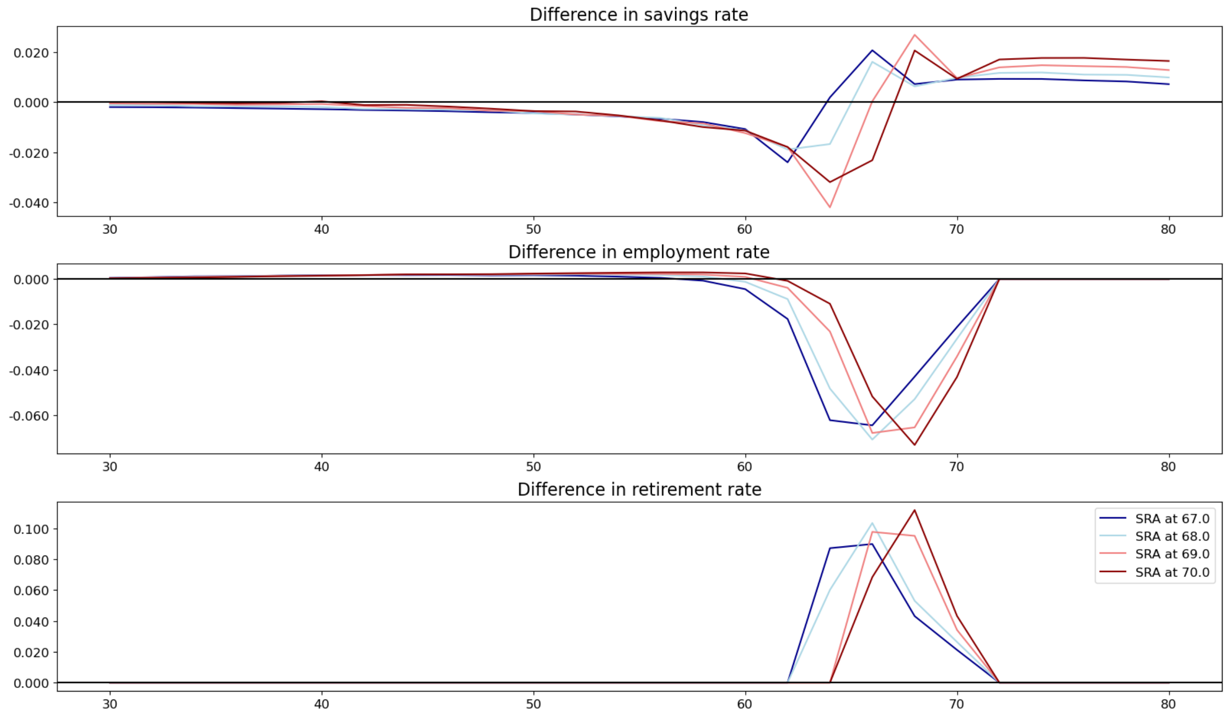
Our final simulation exercise answers the question of how differently people would behave if they were correctly informed about the size of the ERP from the start of their working lives. As in the previous exercises, the resolution age is set to 63 years and we conduct the evaluation for different values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

In the baseline, the process of learning about the true size of the ERP follows the Markov transition rates as described in Section 3.3. 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 11). 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 11: Effects of De-Biasing



Notes: Effects of removing bias about Early Retirement Penalty (ERP) for different policy scenarios. 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 suggest that policymakers need not account for expectations when determining *whether* further SRA increases are necessary. In the context of no policy commitment, our counterfactual simulations show that both behavior and welfare losses evolve smoothly across the policy trajectory that individuals expect. They also reveal that behavioral responses to SRA reform are complementary and go in the expected direction, although, as we discuss, this is theoretically ambiguous. However, expectations do matter when deciding *how* to design policy reform. Our policy simulations suggest that, to the extent that higher private retirement provisions are a policy goal, it may be advisable to present bad news (i.e., higher-than-expected SRA trajectories) and announce SRA increases as soon as possible. Working to remove misinformation about the retirement system may have unintended consequences, however. While it would certainly be beneficial for individual welfare, our simulations show that it would lead to a reduction in savings and an increase in early retirement.

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A. The appendix

A.1. Data and Institutional Background

A.1.1. German Public Pension Formula

Pension amounts are based on the number of *pension points* which the employee has accumulated at the time of claiming the pension. The number of pensions points awarded to an employee at the end of a year is equal to her wage in relation to the average wage, which means that she earns one point in a year in which she makes exactly the average wage. This proportionality, together with the flat contribution rates, implies that the pension system is not redistributive in nature.

The *pension value*, the monetary value of one pension point, is determined annually. In principle, it is set to follow the development of gross wages; however, since the turn of the century, several reforms have added factors that have damped pension growth. Most importantly, the so-called *sustainability factor* reduces pension growth in tandem with the growth of the old-age dependency ratio. These factors have contributed to a slow decline in replacement rates over time. (cf. figure 1) [21] Notably however, the sustainability factor is calibrated so that only 25 percent of the financial burden of demographic change for the Pension Insurance is born by retirees, while the remaining 75 percent are financed through higher contributions.

Contribution rates in 2023 stood at 18.6 percent of gross wages. They are shared equally between employers and employees, so each side pays 9.3 percent. These rates are set to balance the budget of the Pension Insurance.[22] Due to pension reforms, favorable macroeconomic circumstances, and better-than-expected demographic developments, contribution rates have remained relatively stable. This is projected to change with current demographic projections. By 2050, the German Council of Economic Advisors (Grimm et al., 2023) expects an increase of contribution rates to 22 percent and a decrease of the replacement rate to 46 percent in their no-reform baseline scenario.

A.1.2. Auxiliary Dataset Description

Table 5: Auxiliary datasets

	Mortalitiy Data	Job Separation Data	Partner Transition Data	Wage Estimation Data	Partner Wage Data
Years	2010-2017	2010-2017	2010-2017	2010-2017	2010-2017
Nb. of Observations	811014	72638	117905	87534	121690
Age Range	16-107	30-72	30-105	29-81	29-81
Median Age	46.000000	46.000000	51.000000	45.000000	45.000000
Female Share	0.524040	0.487362	0.542479	0.496836	0.485134

Notes: All Data from the Soep-Core Wave 38.

[21] Other amendments to the pension growth formula include: i. a series of growth cuts following the intended increase in the role of private old-age provision (*the Riester factor*, ii. a clause preventing potential decreases in the pension value with subsequent catch up-to the previous trend.

[22] It should be noted that nearly a quarter of Pension Insurance revenues are comprised of direct government subsidies. These subsidies are currently not paid to plug holes in the Pension Insurance budget but to pay for pension claims resulting from certain government programs without being offset by higher contributions. An example is increased pension claims for periods of unemployment due to childcare.

A.2. 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 will deduct from your monthly pension if you retire one year before your regular retirement age?

A.3. Auxiliary Markov Processes

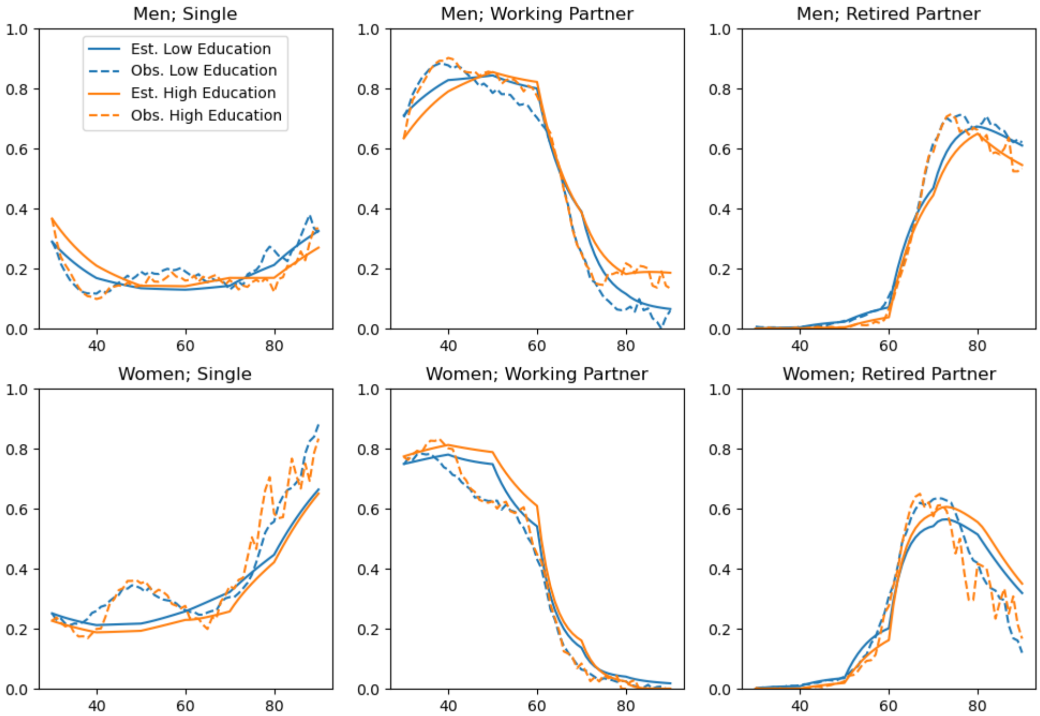
A.3.1. Partner Transitions

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:

$$\pi(p_{t+1}|x_t) = \Lambda_p\Bigg(Z_p(x_t)'\,\phi_p)\Bigg) \tag{18}$$

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:

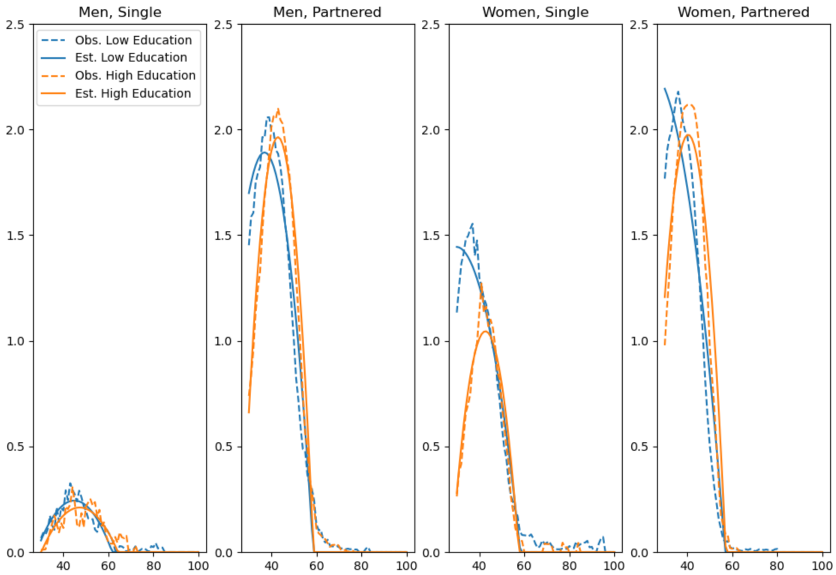
Figure 12: Shares of population in partner states



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 13: Number of children



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

A.3.2. Job-offers and Destructions

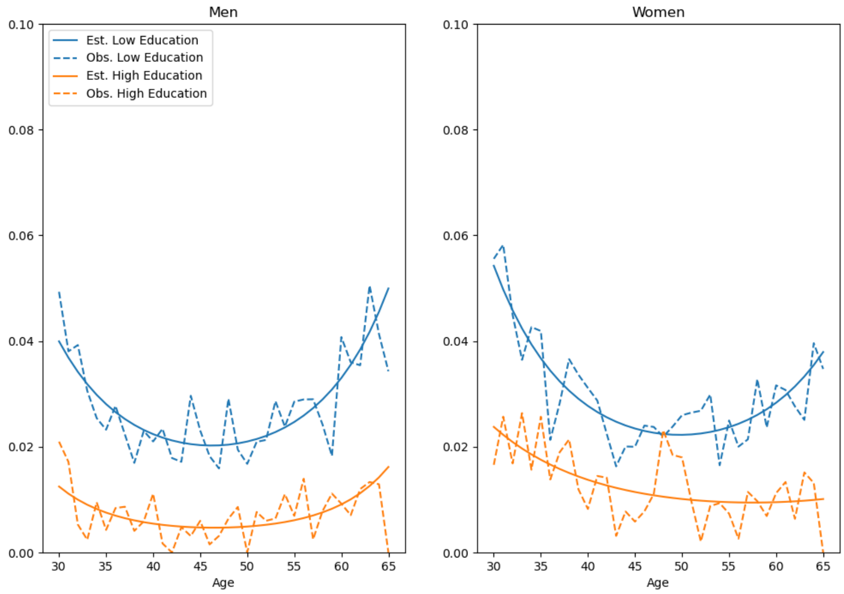
The job offer state governs the agent's ability to choose employment; the agent can choose part- or full-time if the job offer state o_t equals 1. We incorporate two processes with the job-offer state. Namely, job destruction and job offer. If the agent chooses employment in the current period, the job could be destroyed, and she has job offer state $o_{t+1} = 0$ in the next period, forcing her to choose unemployment[23]. In this case, the transition probability for the job offer state is given by:

$$\pi(o_{t+1} = 0 | x_t, d_t \in \{2, 3\}) = \Lambda_{sep}\left(Z'_{sep}\phi_{sep}\right) \tag{19}$$

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 16:

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

Figure 14: 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):

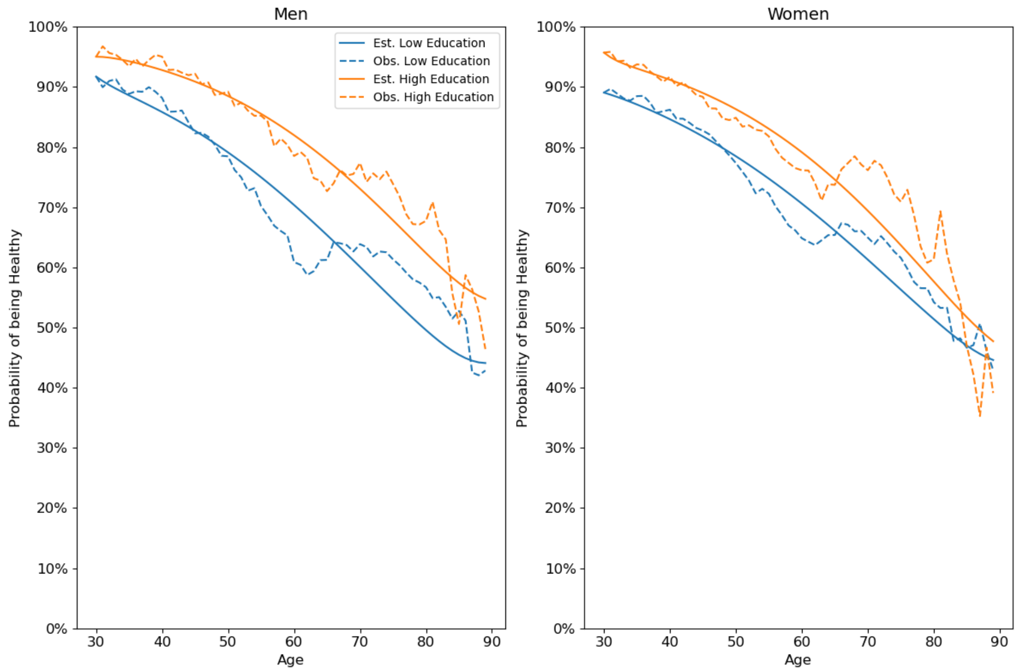
A.3.3. Health and Death

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:

$$\pi(h_{t+1}|x_t) = \Lambda_h\Big(Z_h'\phi_h\Big) \tag{20}$$

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:

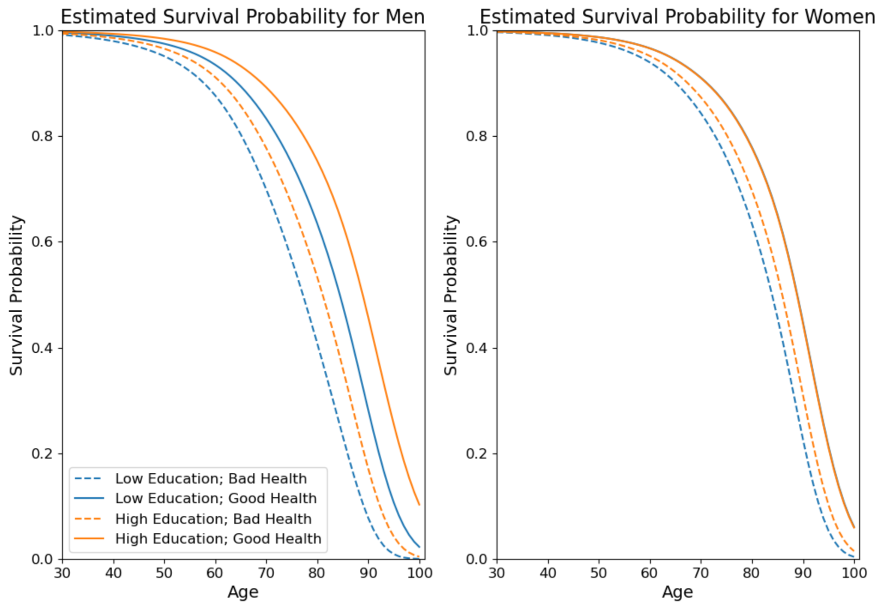
Figure 15: Share of healthy people



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

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

Figure 16: Share of individuals alive



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

A.4. Modelling and Estimation of Income

A.4.1. 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:

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

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

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

The factor PPV is the pension point value, for which we use the 2010 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:

$$y_t(x_t, 0) = PP(x_t) * PPV * (1 - 0.036) \tag{22}$$

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.

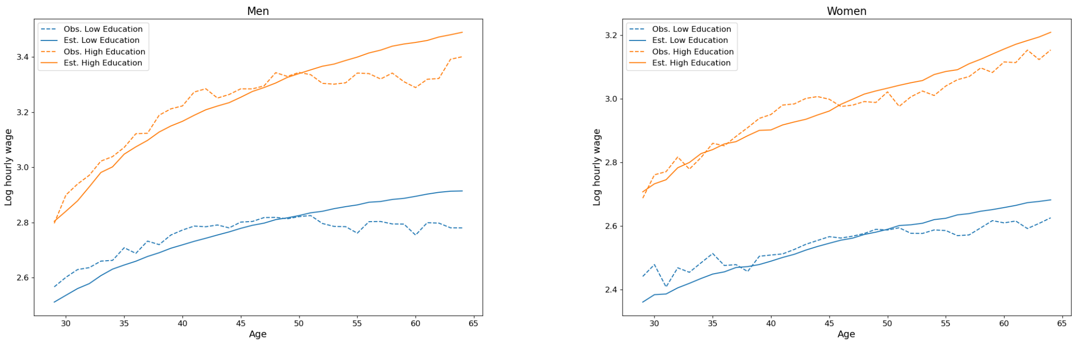
A.4.2. Wage Process

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:

$$log(w_{it}) = \gamma_{0,\tau} + \gamma_{1,\tau} * log(exp_{it} + 1) + \xi_i + \mu_t + \zeta_{it}. \tag{23}$$

Our estimates of $\gamma_{0,\tau}, \gamma_{1,\tau}$, directly correspond to the parameters in equation (11). 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:

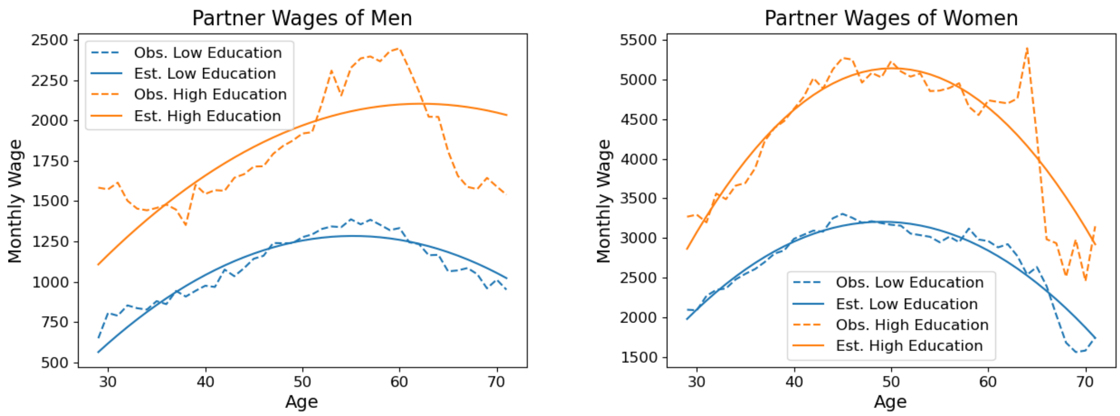
Figure 17: Wage fit



A.5. 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 18: 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 γ_A and solves $V_B(\gamma_A) = V_A(0)$, where

$$V_e(\gamma) = E\left[\sum_{t=30}^{T} \beta^t u(c_t(1+\gamma), d_t, \theta, X_t)\right], \text{ for } e \in \{A, B\}. \tag{24}$$

Thus, γ_A describes the relative increase in per-period consumption to equal the average discounted utility in the counterfactual scenario [24]. Consequently, a positive value is associated with a welfare gain in the counterfactual and a negative vice versa.

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