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# Expectation, Anticipation, and Identification

## Essays on Subjective Expectations and Economic Decision-Making

Lkhagvaa Erdenesuren

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# Expectation, Anticipation, and Identification: Essays on Subjective Expectations and Economic Decision-Making

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# Contents

# Chapter 1.

# Introduction

Over the past three decades, economists have progressively undertaken to elicit probabilistic expectations related to significant personal events from survey respondents (Manski, 2004). This practice of measuring individual-specific subjective expectations has offered researchers various opportunities because data on subjective expectations can be used to relax and validate certain assumptions that are critical to economic analysis.

This thesis consists of three chapters, in which we explore the use of subjective expectations in understanding economic decisions of the elderly population. The theme of these chapters revolves around proposing various modeling and estimation strategies that leverage self-elicited probabilities to enhance existing empirical methods.

In the first paper, presented in Chapter 2, we construct an econometric model to analyze both actual and perceived survival probabilities among married couples. The second paper, presented in Chapter 3, introduces the possibility of controlling for people's anticipatory behavior using self-elicited probabilities. We illustrate this approach in the context of estimating the impact of pension reforms that raise the statutory retirement age on individuals' employment when individuals could have anticipated the reform before its implementation. Finally, our last paper, in Chapter 4, employs elicited probabilities related to bequeathing to estimate specific preference parameters within a life-cycle model. These parameters are traditionally challenging to estimate precisely, but we demonstrate that by incorporating additional information from self-reported probabilities of bequeathing, we can estimate crucial model parameters with reasonable precision.

*Chapter 2: Modeling objective and subjective survival probabilities of couples: heterogeneity and bereavement effects.* In the first paper, we focus on the intricate relationship between actual and perceived survival probabilities within two-person households, particularly married couples. Vital decisions concerning savings, consumption, retirement timing, bequests, and insurance choices are significantly influenced by couples' expectations regarding their own lifespans (Hurd, 1989; Browning, 2000; Van der Klaauw & Wolpin, 2008). It is common for researchers to use actuarial life tables as a proxy for subjective survival probabilities, assuming that couples' assessments align with those. However, growing empirical evidence reveals that, on average, this is not the case: couples' perceptions of their own survival do not align with actuarial survival probabilities, even after controlling for observables (Bissonnette, Hurd, & Michaud, 2017; Heimer, Myrseth, & Schoenle, 2019; O'Dea & Sturrock, 2023).

To further investigate this, we introduce an econometric model, taking into account both actual and perceived survival probabilities of married couples, utilizing data from the U.S. Health and Retirement Study (HRS). The HRS dataset, spanning from 1992 to 2016, offers information on both respondents' subjective survival probabilities and actual mortality. We contribute to the existing literature by estimating the joint perceived survival probabilities among married couples through survey respondents' subjective expectations, combining this with their joint actual survival probabilities. We take into account two key sources of interdependence in the lifetimes of married couples: the common-lifestyle effect, where spouses share similar lifestyles and characteristics, and the bereavement effect, which accounts for the negative impact of one spouse's death on the survival prospects of the surviving spouse. Estimating the dependence between the perceived lifetimes of spouses is valuable because, relying on our estimates, researchers can link the predicted perceived survival probabilities to various aspects of the life-cycle decisions made by married couples, especially those that occur both before and after one of the spouses experiences widowhood.

Another interesting feature of our model is its explicit consideration of people's inclination to round their perceived probabilities to the nearest multiple of five when reporting. We implemented the techniques outlined by De Bresser and Van Soest (2013); Kleinjans and Van Soest (2014), and De Bresser (2019) to address this aspect.

We find that both the actual and perceived remaining lifetimes of spouses exhibit a positive correlation within a couple. Perceived remaining lifetimes show a stronger dependence than actual remaining lifetimes, although this trend reverses as couples age. In our analysis, the bereavement effect emerges as the dominant factor in explaining the interdependence of actual remaining lifetimes, particularly among older couples, but with impact on the perceived lifetime dependence diminishing with age.

Furthermore, after controlling for age, gender, and partner's vital status, we find a significant dispersion in both actual and perceived survival curves across individuals. Most of the dispersion in actual survival curves can be attributed to variations in observed characteristics, including ethnicity, education level, birth cohort, income, and health. Conversely, both observed and unobserved factors contribute significantly to the dispersion in perceived survival curves.

Lastly, our estimation results from the reporting model reveal that Hispanics, college-educated individuals, and those with high cognitive abilities tend to provide more precise answers than their counterparts. In contrast, African-American males and individuals born before 1945 are more inclined to offer rounded responses. Additionally, spouses' rounding patterns are positively correlated, even after controlling for various observed characteristics. Potential explanations for this correlated rounding behavior include assortative matching and mutual influence on each other's response style during joint interviews.

*Chapter 3. Heterogeneous response in labor supply to anticipated pension reforms.* In our second paper, we explore the impact of pension reforms that increase the statutory retirement ages (SRA) on the labor supply of people close to retirement. This is relevant in the context of increasing financial insolvency of pension systems in Europe due to aging populations. In the past two decades, several European governments have introduced reforms, increasing the retirement age to maintain the financial stability of pension systems (OECD, 2017).

A common feature observed in the execution of pension reforms is that, prior to their implementation, there tend to be intense political debates, public opposition, and heightened media coverage (Immergut, Anderson, & Schulze, 2007). These circumstances are likely to heighten public awareness of the imminent reforms, effectively allowing people to anticipate their arrival. From the perspective of an econometrician, this anticipatory behavior poses a significant challenge in the analysis aimed at identifying the causal effects of these reforms. This is because, in response to their anticipation, people may then change their behavior if there is a benefit to doing so before the reform is adopted, and not accounting for such anticipatory behavior can substantially affect the estimated impact of the reforms (Malani & Reif, 2015).

In this paper, we explore two main questions. First, how does anticipation of pension reforms affect individuals' behavior, particularly their employment status? Second, if the reform is implemented, does it impact people's labor supply differently based on their level of anticipation? Compared to the previous literature on the importance of financial incentives for the retirement decisions and the effectiveness of pension reforms (see, e.g., Gruber and Wise (2002); Bernal and Vermeulen (2014); Carone, Eckefeldt, Giamboni, Laine, and Pamies (2016); Scharn et al. (2018)), to our knowledge we are the first to consider anticipatory behavior explicitly.

We start our analysis by developing a life-cycle model of a currently employed agent who is close to retirement, and who may face a SRA change, à la Caliendo, Gorry, and Slavov (2019). The main focus of this economic model is how the agent plans when to stop working depending on his or her reform anticipation. In the next step, we test the predictions of our economic model using data from multiple sources. We combine data from from the Survey of Health, Ageing and Retirement in Europe (SHARE) with detailed records on pension reforms across nine European countries. The unique contribution of this research lies in its use of elicited expectations data from SHARE, allowing for the consideration of heterogeneity in anticipation that may not be captured by other observable factors.

To address potential endogeneity and measurement issues in anticipation data, we employ an instrumental variable approach, using the Google Trends index related to "pension reform" as a key instrument. This index measures online information searches about pension reforms in each country and is used to identify the effect of online search intensity on individuals' employment decisions through changes in their anticipation of future retirement ages. The study benefits from observing variations in the timing of pension reforms across countries and periods, enabling the identification of reform impacts while controlling for age and year effects, a critical advantage given that governments often base treatment assignment on individuals' birth years.

We find that individuals who strongly anticipate being affected by future pension reforms are more likely to remain employed. For instance, among 58-year-old employees, the average probability of remaining employed for the next two years is approximately 77% for those who did not expect any reform impact (0% anticipation) and rises to 92% for those certain of reform effects (100% anticipation). Secondly, the magnitude of the impact of the reform once implemented varies significantly depending on anticipation levels. When the statutory retirement age (SRA) increases by one year, 58-year-old employees who did not anticipate this change experience an approximately eight-percentage-point increase in the probability of remaining employed for the next two years. Conversely, the same reform has no statistically significant impact on 58-year-old employees who were certain about the SRA increase. These results indicate that reforms have a weaker impact on employment decisions when individuals anticipate them strongly because those individuals have already adjusted their employment before the reform is implemented.

The study also explores the possibility of individuals using disability or unemployment insurance schemes as alternative pathways to early retirement in response to SRA increases. However, no statistically significant evidence supports this hypothesis. Additionally, there is no indication that people strategically transition to states other than employment or retirement based on their anticipation of reforms. These results show that individuals primarily respond to their anticipation by prolonging employment and delaying retirement rather than pursuing strategies like registering as disabled or becoming unemployed.

Our results suggest that people's response to pension reforms vary depend on to what degree they anticipated those reforms; thus, it is important take into account the anticipatory behavior when estimating the impact of reforms. We recommend that one effective approach to address this issue is through the utilization of self-reported probabilities when such information is available to researchers.

*Chapter 4. On the identification of bequest and precautionary saving motives using self-reported intended bequest probabilities of retirees.* Our third paper delves into the use of self-reported probabilities to precisely estimate certain preference parameters of a life-cycle model that drive retirees' bequest and precautionary savings motives. The bequest motive refers to retirees saving to leave inheritances to their heirs, while the precautionary motive relates to saving to protect themselves from risks in old age, such as unexpected medical expenses or outliving their resources. Understanding the quantitative contributions and relative importance of these motives is essential for comprehending retiree behavior, intergenerational wealth transfers, and optimal design of public policies (Kopczuk & Lupton, 2007).

Despite numerous empirical studies over the years, there is no consensus on the quantitative importance of these motives on retiree savings. Researchers have grappled with the challenge of distinguishing between them since both have similar implications, especially in later life (Hurd, 1987; Gan, Gong, Hurd, & McFadden, 2015). Earlier studies attempted to identify the bequest motive by examining savings differences between people with and without children or those with higher mortality rates, often concluding that the bequest motive had a minimal impact on savings, suggesting that most bequests were incidental. Recent studies have explored the role of high out-of-pocket medical expenses in retiree savings decisions, with varying conclusions. Some found that the bequest motive significantly influenced savings, while others reported smaller contributions, especially among the wealthy (De Nardi, French, & Jones, 2010; Lockwood, 2018; Ameriks, Caplin, Laufer, & Van Nieuwerburgh, 2011).

In this paper, we introduce a novel approach by incorporating self-reported probabilities of leaving a bequest from the HRS into a structural life-cycle model. These self-reported probabilities reflect individuals' perceptions of their longevity, future survival, and savings objectives, providing insights into the strength and existence of the bequest motive. By considering complex relationships between medical expense risk, longevity risk, and savings, the study aims to shed light on the relative importance of these motives and their implications for retirees' savings behavior. Our approach allows for a more nuanced understanding of retirees' savings motivations without significantly complicating the standard model or adding computational complexity.

Using this novel approach, we come to several interesting conclusions. Firstly, the utilization of self-reported probabilities for bequeathing, alongside conventional data features such as wealth, medical expenses, and annuity income, allows for precise estimation of the parameters related to the bequest motive. The inclusion of this information suggests that the bequest motive exerts a stronger and more prevalent influence on the savings decisions of both wealthy and middle-income retired individuals, compared to models that do not include the self-reported bequest probabilities. This result is relevant in ongoing debates concerning the existence and extent of the bequest motive.

Secondly, the incorporation of self-reported bequest probabilities is crucial for the model's ability to accurately predict the actual bequeathed wealth of respondents from the HRS who passed away between 2002 and 2014. Models lacking self-reported bequest probabilities tend to overestimate median bequests, particularly among wealthy individuals. In contrast, the model that incorporates self-reported bequest probabilities consistently outperforms the alternative model in terms of predicting realized bequests for both wealthier and less affluent individuals.

Thirdly, we find that both the precautionary motive to save for uncertain medical expenses and the bequest motive substantially contribute to savings over the life cycle. A counterfactual analysis demonstrates that shutting down either motive has sizeable effects on the median wealth of individuals at different ages. For instance, if the motive to save in response to medical expenses is eliminated, the median wealth of individuals aged 60-65 in 1998 would be significantly lower at ages 75 and 85. Conversely, eliminating the bequest motive results in lower median wealth at these ages as well. Our results indicate that the majority of savings for wealthy and middle-income individuals is driven by precautionary motives rather than the bequest motive.

Finally, we conduct counterfactual analyses to evaluate the impact of two hypothetical policy changes. In the first counterfactual, the study explores the consequences of the U.S. government fully covering medical expenses for retirees starting in 1998. The results indicate substantial decreases in savings for wealthy individuals due to the absence of a precautionary motive to save for medical expenses. In the second counterfactual, the study examines the effects of increasing the estate tax on savings and bequests. The findings suggest that changing the estate tax does not significantly affect savings but has differential impacts on the median bequests of different income groups due to the increased tax on bequests.

With this study, we contribute to several strands of literature, including research on the retirement savings puzzle, the utilization of self-reported probabilities in structural models, and the validation of model predictions through comparisons with observed data (Van der Klaauw

& Wolpin, 2008; Van der Klaauw, 2012; Ameriks et al., 2011). In addition, we demonstrate the possibility of integrating self-elicited probability data into structural life-cycle models, leading to precise parameter estimates and validating model predictions through observed bequest outcomes without adding substantial computation cost.

# Chapter 2.

# Modeling objective and subjective survival probabilities of couples: heterogeneity and bereavement effects

## 2.1 Introduction

In a life-cycle model with two-person households, decisions of couples – such as how much to save and consume, when to retire and leave a bequest, and what type of insurance product to purchase – hinge upon their survival expectations (Hurd, 1989; Browning, 2000; Van der Klaauw & Wolpin, 2008). Studying these life-cycle models empirically requires modeling the couples' perceptions of their joint survival probabilities. Traditionally, researchers used life tables as a proxy for these subjective survival probabilities, assuming that couples' assessments of their mortality risks are in line with actuarial forecasts (Michaud, Van Soest, & Bissonnette, 2020). This assumption is controversial because couples' perceptions show substantial variation that is not captured by actuarial figures or known risk factors and may deviate from life tables on average. Indeed, acknowledging this controversy and with the increasing availability of data on subjective probabilities, an increasing number of studies using subjective survival expectations have appeared in the past two decades (see, e.g., Smith, Taylor, and Sloan (2001); Van der Klaauw

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and Wolpin (2008); Iannario and Piccolo (2010); Ludwig and Zimper (2013); Bissonnette et al. (2017); Heimer et al. (2019)). The focus of these studies has been on models for individuals' subjective survival probabilities and not on the relation between lifetimes of spouses in a couple.

In this paper, we develop an econometric model for actual, in-sample, as well as subjective survival probabilities of married couples. We estimate the model using 13 waves (from 1992 to 2016) of the U.S. Health and Retirement Study (HRS).[1] The HRS is ideal for our purpose as it has accurate information on the respondents' actual mortality and their subjective survival probabilities. The longitudinal nature of the data allows us to observe respondents' subjective survival probabilities before and after widowhood. Comparison of in-sample survival with subjective expectations rules out sample selection as a driver of discrepancies between objective and subjective survival, for instance due to the exclusion of the institutionalized population from the HRS. It also allows one to condition both survival processes on the same set of observable risk factors. To our knowledge, our paper is the first to analyze the perceived survival probabilities of married couples jointly using subjective expectations held by survey respondents.

Our model of actual and perceived survival accounts for two sources of dependencies between the lifetimes of married couples. The first is the *common-lifestyle effect*: spouses tend to have similar lifestyles and share similar (observed or unobserved) characteristics that affect their actual and subjective survival probabilities, such as their habits, ethnicity, and educational background (Hollingshead, 1950; Burgess & Wallin, 1943). For example, smokers may attract each other, and smoker-couples tend to have lower actual survival rates than non-smoker-couples. The perceived survival rates of spouses in a smoker-couple can also be correlated if both spouses anticipate the effect of smoking on survival to a similar extent (Khwaja et al., 2007; Wang, 2014). The second source is the *bereavement effect*, also known as the broken-heart syndrome: the (negative) impact of one spouse's death on the surviving spouse's survival rate. Surviving spouses tend to encounter elevated stress, loneliness, depression, and anxiety after their spouse passes away (Williams Jr, 2005; Sanders & Melenberg, 2016). These mental and physical health problems reduce the actual survival rate of the surviving spouse (Van den Berg, Lindeboom, & Portrait, 2011; Spreeuw & Owadally, 2013), and their perceived survival rates (Bissonnette et al., 2017).

To model the common-lifestyle and bereavement effects, we follow the Markov-type models proposed by Freund (1961) and Gourieroux and Lu (2015). Freund's model captures the bereavement effect by allowing jumps in mortality hazards at the time of death of the spouse. Gourieroux

[1] Numerous studies used the reported survival expectation data of the HRS, e.g., Bissonnette et al. (2017); Khwaja, Sloan, and Chung (2007); Salm (2010); Gan et al. (2015).

and Lu (2015) extend Freund's model by allowing asymmetric reactions of the mortality hazard rates for male and female surviving spouses at the moment the first spouse passes away. They also mix the model with common unobservable factors to capture common lifestyle effects. We extend the model of Gourieroux and Lu (2015) in three ways. First, we allow that spouses share correlated but not necessarily perfectly correlated (or common) frailty terms. Second, we model that spouses' mortality hazards depend on certain observed characteristics that are known to be good predictors of people's actual and perceived survival probabilities. Third, we impose the same structure on the actual and the perceived mortality hazard rates. Thus, analogously to Bissonnette et al. (2017) our approach enables us to directly test whether people with the same characteristics, on average, correctly perceive their mortality risks.

We do not take the reported survival probabilities at face value, because observed bunching at multiples of five and ten percent suggests that respondents tend to round their subjective responses (Manski, 2004; Manski & Molinari, 2010). Such rounding may be a conscious communication strategy, or may reflect difficulty in thinking in terms of probabilities (epistemic uncertainty) (Bruine de Bruin, Fischbeck, Stiber, & Fischhoff, 2002). Furthermore, rounding may be correlated between spouses. For example, if spouses in a couple are interviewed together, they might want to please their partners by mimicking each other's subjective responses (Aquilino, 1993; Aquilino, Wright, & Supple, 2000), thus influencing each other's answers. Spouses' reporting behavior may also be correlated due to other reasons, such as assortative matching on numerical skill. To overcome these impediments of using subjective reports, we explicitly model couples' reporting behavior. Rounding is accounted for following the models proposed by De Bresser and Van Soest (2013); Kleinjans and Van Soest (2014), and De Bresser (2019). To control for spouses' influence on each others' responses, we allow for correlated observed and unobserved factors that affect the reporting behavior of both spouses.

The main results of the paper are the following. First, we find that both actual and perceived remaining lifetimes of spouses are positively related within a couple. Perceived remaining lifetimes are more strongly dependent than actual remaining lifetimes, but this pattern reverses as couples age. The bereavement effect becomes the dominant factor in explaining the dependence of remaining objective lifetimes, particularly for older couples. However, the impact of the bereavement effect on perceived lifetime dependence decreases with age.

Second, the actual and perceived survival curves are predicted to have substantial dispersion around their corresponding medians for given age, gender, and partner's vital status. Most of the dispersion in actual survival curves is explained by variation in observed characteristics, such as ethnicity, education level, birth cohort, income, and health. Unobserved frailties explain only a small part of the dispersion in actual survival curves. In contrast, both observed and unobserved factors explain substantial dispersion in perceived survival curves. Thus, at given observed characteristics, there is much more heterogeneity in people's subjective survival probabilities than in their actual survival rates.

Third, the estimation results of the reporting model suggest that Hispanics, college educated, and those with high cognitive ability give more precise answers than their counterparts. In contrast, African-American males and people born before 1945 are more likely to give rounded responses. Moreover, we find evidence that spouses' reporting behaviors are positively correlated after controlling for observed characteristics, implying that spouses have similar rounding behaviors. Possible explanations for correlated rounding include assortative matching and influence on each other's response style during joint interviews.

The paper is structured as follows. Section 2.2 describes the data and discusses the survival expectation question in the HRS. Section 2.3 presents the model for actual and perceived survival probabilities of married couples. Section 2.4 presents the estimation results. The final section concludes.

# 2.2 Data

## 2.2.1 Sample selection and descriptive statistics

We use biennial data of the Health and Retirement Study (HRS) from 1992 to 2016. The HRS is a national panel survey of individuals over age 50 and their spouses, representative of the elderly population of the U.S. The HRS contains comprehensive information on each respondent's marital history, vital status, survival expectations, socioeconomic characteristics, and health.[2] Throughout our analysis, we define a respondent as *married* at a given survey wave if the partner is alive and as *widowed* if the partner is dead.[3]

Table 2.1 shows our sample selection procedure. We restrict our sample to couples in which both spouses were alive when they entered the survey. This excludes respondents who entered as widow(er), separated, divorced, or never married. To simplify, we drop respondents who were in a same-sex relationship and only keep respondents who neither divorced nor separated during

2 The HRS samples the non-institutionalized population for each entering cohort entering the study but continues to track existing respondents even if they became institutionalized. Their wealth, medical expenses, marital status, and vital status were observed through proxy interviews if they could not participate in the survey. Subjective survival expectations were only observed if the respondent could participate in the survey.

3 If only one of the spouses in a couple participated in a given survey wave, the non-participating spouse's marital status is coded as missing for that wave. For such cases, we assume those spouses were married as long as both were alive in that wave.

the period of interest. Some respondents lost their first spouse and then married again during the sample period. We assume these respondents' survival dates are right-censored at the time they re-married and discard their second spouse's observations.[4] We also exclude the observations of 36 couples in which both spouses died on the same day.[5] Finally, we only keep couples in which both spouses participated for at least two waves, since if they only responded once, they do not contribute to estimating objective survival probabilities.

Table 2.1: Sample selection

| | number of households | number of individuals |
|---|---|---|
| Initial sample | 26,598 | 42,053 |
| Dropping respondents who were in the same-sex relationship | 26,468 | 41,797 |
| Dropping if divorced or separated | 19,966 | 33,221 |
| Keeping if entered the survey as married | 13,540 | 26,578 |
| Dropping observations of second, third, and fourth spouses | 13,540 | 26,195 |
| Keeping if participated in the survey for at least two waves | 11,838 | 22,994 |
| Dropping if a couple consists of only one active respondent | 11,156 | 22,312 |
| Keeping if provided a valid response to the survival expectation questions at least once | 11,079 | 22,158 |
| Dropping if spouses died on the same day | 11,043 | 22,086 |

### 2.2.2 Observed mortality experience of couples

In our final sample, during the period of interest (1992-2016):

- 48% of couples did not encounter a spousal bereavement
- In 15% of couples, the male spouse died first, and the female spouse died second
- In 21% of couples, the male spouse died first, and the female spouse did not die
- In 8% of couples, the female spouse died first, and the male spouse died second
- In 8% of couples, the female spouse died first, and the male spouse did not die

Around 52% of couples have experienced a spousal bereavement between 1992 and 2016. In these couples, male spouses died first in around 69% of all cases, partly due to the higher average entry age for males than for females (61 versus 58, on average).

4 In our sample, people re-married at most four times. For those who re-married more than twice, we dropped the observations of their second, third, and fourth spouses. For example, if respondent $i$ was married to $j$ from 1992 to 1998 and $j$ passed away, then respondent $i$ remarried respondent $k$ from 2006 until the end of our period of interest. We only consider the period when respondent $i$ was married to his/her first spouse $j$ and the period when $i$ was a widower (from 1998 until the end of 2005). We discard their observations after 2006. Our study does not take into account the (potentially positive) impact of remarrying on remaining lifetimes, as we observe very few cases of remarriage during the period of observation.

5 Spreeuw and Owadally (2013) argued that this occurs primarily because the spouses experience unnatural events together, such as an accident, and special attention is needed to model such events.

### 2.2.3 Survival questions in the HRS

In each wave, the HRS asked the following question:

...Pick an integer between 0 and 100 where "0" means no chance and "100" means absolutely sure. "What is the percent chance that you will live to be $ta$ or more?"

Here $ta$ is the target age, linked to the respondent's age. The target age always exceeds the respondent's age and is a multiple of 5. In each wave, respondents answered at most two survival expectation questions with different target ages.[6] In 1992, the questions were asked with a scale of 0 to 10; in the other waves, responses are scaled from 0 to 100. We multiply the responses in wave one by 10 to make them comparable to the responses in other waves.[7]

The number of observations (respondent $\times$ wave $\times$ number of survival expectation questions at given wave) for these questions is 73,487 for males and 87,961 for females. Respondents can also choose to answer "Don't know" or "Refuse" (DK/R). Since few responses are DK/R (roughly 5% of males and 6% of females of our sample), we do not consider the potential sample selection issue and assume DK/R answers are random conditional on the covariates.

For respondents who gave two responses at a given wave, we checked whether reported probabilities are internally consistent. For example, if the respondents were asked to report their probabilities of surviving to age 75 and then to age 85, the reported probability for the target age of 85 should not be larger than that for 75. It turns out, in around 97% of the cases, the respondents who answered two survival probability questions reported their survival probabilities in a probabilistically sound way. For the 3% of the cases in which respondents gave probabilistically inconsistent answers, we include those cases in our empirical analysis. Because our model interprets such cases as reporting errors.[8]

6 In wave 1, the respondents were asked survival questions with the target ages of 75 and 85 as long as they were younger than the target ages. Since wave 2, only the respondents who are 65 or younger are asked about their probabilities of surviving to both 75 and 85. If the respondent is 66 or older, only the question with a target age of 80+ is asked, in which the target age is set such that it always exceeds the respondent's age by at least ten years and is a multiple of 5.

7 De Bresser (2019) finds that using scales from 0 to 10 or from 0 to 100 gives similar measurements of the subjective survival expectations.

8 We conducted an additional validation exercise to analyze whether people decrease their reported survival probability more if they experience more detrimental chronic conditions or functional limitations. We ran a linear fixed effects model where the dependent variable is the log of reported subjective survival probabilities. The main independent variables are dummies for eight chronic conditions and five functional limitations, whose descriptions are shown in the footnote $C$ of Table 2.3. We also included year effects and dummies for age and income as additional regressors. Our results are in line with what we expected because we find that people who experienced more detrimental chronic conditions or functional limitations on average decrease their survival probabilities more when all else is constant.

Table 2.2 shows the heterogeneity in respondents' reported survival probabilities for each target age by age group. The average reported survival probabilities are shown separately for married and widowed males and females. For each age group, the mean for married respondents is higher than for widow(er)s. The large standard deviations imply substantial heterogeneity in subjective survival expectations and/or in reporting behavior.

Column 2 of Table 2.2 shows average life-table probabilities as a measure of objective survival probabilities, retrieved from the National Center for Health Statistics and the Berkeley Mortality Database.[9] Average reported subjective probabilities to reach target ages 75 and 80 are much lower than the corresponding life-table probabilities for males and females and for married and widowed respondents, revealing considerable differences between subjective survival expectations and actuarial forecasts. Differences between life tables and expectations could reflect discrepancies between the HRS sample and the general population analyzed by actuaries. The model compares in-sample survival with subjective expectations, which negates such selection issues.

The reported probabilities are subject to rounding and focal answers (e.g., 50%). Figure 2.1 shows the sample distribution of the reported subjective survival probabilities, separately for males and females.[10] We present histograms for target ages 80 and 85 as illustrative examples. The figure shows that most responses are multiples of 10%, and the highest frequencies are at 0%, 50%, and 100%. A substantial number of respondents chose 0% or 100%, although these responses are normally not realistic. People may report 50% as a focal answer to express their inability to reason in terms of probabilities rather than their uncertainty regarding the underlying process (Bruine de Bruin et al., 2002). However, De Bresser (2019) did not find excess bunching at 50% once rounding behavior is controlled for. Therefore, in our model, we allow for rounding and assume that the reported probability of 50% expresses respondents' survival expectations, though possibly rounded coarsely, but not epistemic uncertainty.[11]

### 2.2.4 Covariates

Definitions of the covariates are given in Panel A of Table 2.3. Table 2.4 shows some summary statistics. Since survival probabilities vary with health and income, we use the following covariates: functional limitations in daily living, ever recorded chronic conditions, and household-size

[9] The annual life-table is available in the RAND version of HRS.

[10] The figure does not include the observations from wave 1 when a scale of 0 to 10 was used.

[11] In their study, Giustinelli, Manski, and Molinari (2022) introduced a novel elicitation method to explore how individuals express probabilities amid uncertain events. The method involves a two-step process where respondents provide point probability estimates, similar to the survival expectation questions in the HRS. Subsequently, participants indicate whether they expressed their probabilities precisely or rounded their responses, with further prompts to specify the corresponding intervals. However, the current paper cannot adopt this approach due to the constraint of only having access to point estimates of survival probabilities.

Table 2.2: Descriptive statistics of reported survival probabilities and life-table probabilities

| | Current age | Mean Life-table | Married | | | Widowed | | |
|---|---|---|---|---|---|---|---|---|
| | | | N | Mean | S.D. | N | Mean | S.D. |
| *Column* | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| **Males** | | | | | | | | |
| Target age 75 | 64-66 | 73.45 | 2,995 | 65.12 | 27.90 | 132 | 64.05 | 29.76 |
| Target age 80 | 68-70 | 63.53 | 2,598 | 58.53 | 28.33 | 234 | 55.41 | 29.98 |
| Target age 85 | 73-75 | 47.22 | 2,933 | 53.43 | 29.59 | 301 | 47.79 | 32.21 |
| **Females** | | | | | | | | |
| Target age 75 | 64-66 | 82.32 | 2,697 | 67.66 | 27.53 | 456 | 64.41 | 27.70 |
| Target age 80 | 68-70 | 73.11 | 2,970 | 61.63 | 28.30 | 791 | 58.22 | 29.84 |
| Target age 85 | 73-75 | 59.73 | 2,524 | 54.27 | 29.00 | 917 | 52.79 | 30.17 |

*Note:* Column (2) shows the sample average of the life-table probability of reaching a certain target age conditional on having survived until the current age. The life-table probabilities are only available conditional on age, sex, and year of birth. Columns (4) and (7) show the sample average of the reported survival probabilities of reaching a certain target age conditional on survival until the current age for married and widowed respondents, respectively. The number of observations (19,548 observations) is lower than that used for estimation because the table does not show the descriptive statistics of responses to target ages 90, 95, and 100 (since very few people responded to the survival expectation question with these target ages).

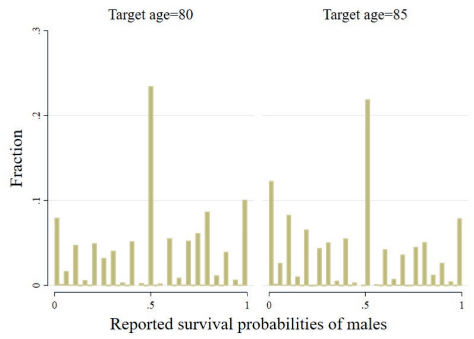
adjusted log income at the time the respondent entered the survey. These variables are measured at the time of entry into the panel and are thus time-invariant, which simplifies modeling (Bissonnette et al., 2017).[12] We control for basic demographics and socio-economic status, including dummies for whether a respondent is Black or Hispanic, and whether a respondent's highest obtained degree is high-school or college. We also control for three birth-cohort dummies (i.e., dummies for respondents born before 1930, those born between 1931 and 1945, and those born after 1946) because people from different cohorts experience different longevity risks.

As already shown in Figure 2.1, the reported probabilities bunch at multiples of ten percent. In the equation explaining rounding (see Section 2.3.3.2), we use the covariates in Panel A of Table 2.3. In addition, as suggested by Manski and Molinari (2010), we use the reported probabilities of other subjective expectation questions than the survival expectation questions asked in the HRS in a given wave. These variables are described in Panel B of Table 2.3. We expect that if respondents choose mostly 0%, 50%, or 100% in other subjective probability questions, they are more likely to report coarse answers to the survival probability questions also.

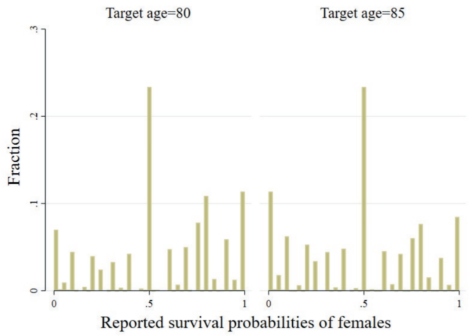
Moreover, Hurd, McFadden, and Gan (1998) and Lillard and Willis (2001) find that whether respondents report rounded or more precise probabilities is correlated with their education and

[12] A common problem in studies of human survival is that most of the observed time-varying variables are meaningful only if respondents are alive. If we model these variables as time-varying, we need an additional (unrealistic) assumption to determine the values of these regressors after respondents have passed away; see Chapter 3 of Lancaster (1990).

Figure 2.1: Self-reported probabilities




(a) Males




(b) Females

*Note:* The figure shows the empirical distribution of the reported probabilities to the subjective survival expectation questions with targets ages 80 and 85, separately for males and females. The observations from wave one are not included.

cognitive abilities. We therefore also use respondents' education degree and their score on the immediate word recall test (a proxy for cognitive capacity). Finally, we include a dummy for the first wave, to capture the different response scale used in that wave.

Table 2.3: Variable descriptions

| **Variable** | **Description** |
|---|---|
| *Panel A: time-constant variables (at entry into panel)* | |
| Log of income | Log of real total household income in 2016 U.S. dollars divided by square root of household size[a] |
| Ever smoked | =1 if ever smoked or current smoker |
| Never smoked | =1 if never smoked (reference) |
| Functional limitations | Number of functional limitations in daily living[b] |
| Chronic conditions | Number of chronic conditions ever recorded[c] |
| College | =1 if having at least college or graduate degrees |
| High school | =1 if highest obtained degree is high school or GED |
| At most middle school | =1 if highest obtained degree is middle school or less (reference) |
| Hispanic | =1 if Hispanic |
| Non-Hispanic | =1 if not Hispanic (reference) |
| African American | =1 if African American |
| Non-African American | =1 if not African American (reference) |
| Born before 1930 | =1 if born before 1930 |
| Born between 1931 and 1945 | =1 if born between 1931 and 1945 |
| Born after 1946 | =1 if born after 1946 (reference) |
| *Panel B: time-varying variables* | |
| Prop. multiples 50 | proportion of choosing responses of 0, 50 and 100 in other subjective expectation questions[d] |
| Immediate word recall | proportion of correctly recalled words in immediate word-recall test[e] |
| First wave dummy | =1 if the first survey wave (in 1992) |

[a] : We use the imputed version of the household income available in the RAND version of the HRS. Household size counts the number of spouses plus the number of children living in the same household.

[b] : Respondents were asked whether they have difficulty with the following five activities: (1) walking across a room, (2) getting in and out of bed, (3) dressing, (4) bathing, and (5) eating. Depending on the number of activities respondents have difficulties with, the variable takes values from 0 to 5.

[c] : The number of chronic conditions respondents ever had, considering (1) diabetes, (2) cancer, (3) lung disease, (4) heart disease, (5) stroke, (6) arthritis, (7) high blood pressure and (8) psychiatric problems. The variable takes values from 0 to 8.

[d] : The number of subjective probability questions varies from wave to wave. In addition to survival probabilities, the most common questions in the survey are the probabilities of (1) receiving any inheritance, (2) leaving any bequest, (3) leaving a bequest of more than 10,000 \$, (4) leaving a bequest of more than 100,000 \$, (5) working full-time after age 62, (6) working full-time after age 65, (7) moving to a nursing home in the next 5 years, and (8) having a work limiting health problem in the next 10 years. Some probability questions were not asked due to the respondent's work, marital or health status, or age. We construct the proportions of choosing $\{0\%, 50\%, 100\%\}$ to make this variable comparable across individuals and waves.

[e] : The HRS asks respondents to memorize a particular list of words to measure their cognitive ability. The number of correctly recalled words from a 10 or 20-word list divided by the total number of words in the list provides a measure of immediate word recall. In couple-households, each spouse was assigned a different list. The words in the list are different in each wave.

Table 2.4: Summary statistics

| | Male | | | | Female | | | |
|---|---|---|---|---|---|---|---|---|
| | mean | st.dev | min | max | mean | st.dev | min | max |
| *Panel A: time-constant variables (at entry into panel)* | | | | | | | | |
| Log of income | 10.252 | 1.065 | 0 | 14.297 | 10.247 | 1.056 | 0 | 14.297 |
| Ever smoked | 0.697 | 0.459 | 0 | 1 | 0.461 | 0.499 | 0 | 1 |
| Functional limitations | 0.195 | 0.691 | 0 | 5 | 0.185 | 0.6632 | 0 | 5 |
| Chronic conditions | 1.193 | 1.175 | 0 | 7 | 1.109 | 1.127 | 0 | 8 |
| High school | 0.316 | 0.465 | 0 | 1 | 0.378 | 0.485 | 0 | 1 |
| College | 0.426 | 0.495 | 0 | 1 | 0.407 | 0.491 | 0 | 1 |
| Hispanic | 0.113 | 0.317 | 0 | 1 | 0.117 | 0.322 | 0 | 1 |
| African American | 0.131 | 0.338 | 0 | 1 | 0.128 | 0.334 | 0 | 1 |
| Born before 1930 | 0.312 | 0.463 | 0 | 1 | 0.233 | 0.423 | 0 | 1 |
| Born between 1931 and 1945 | 0.383 | 0.486 | 0 | 1 | 0.389 | 0.487 | 0 | 1 |
| *Panel B: time-varying variables* | | | | | | | | |
| Prop. multiples 50 | 0.648 | 0.336 | 0 | 1 | 0.647 | 0.335 | 0 | 1 |
| Immediate word recall | 0.492 | 0.189 | 0 | 1 | 0.554 | 0.19 | 0 | 1 |
| First wave dummy | 0.067 | 0.25 | 0 | 1 | 0.059 | 0.235 | 0 | 1 |

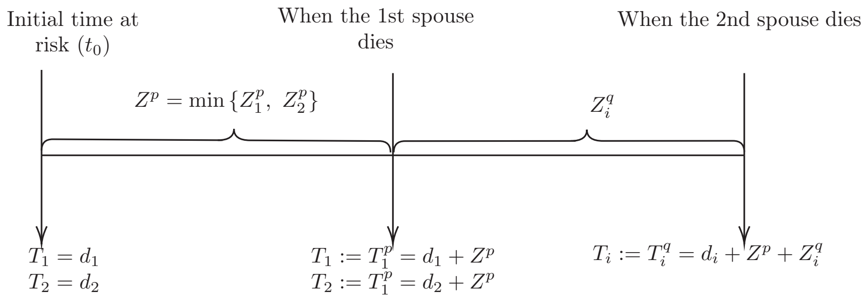
## 2.3 Econometric model and estimation strategy

In this section, we introduce our econometric model for actual mortality (*objective survival*) and reported survival probabilities (*subjective survival*). Section 2.3.1 discusses the general structure of the joint distribution of remaining lifetimes of spouses in a couple that we will use to model objective as well as subjective survival probabilities. Section 2.3.2 presents the likelihood contribution of objective survival part of the model. Section 2.3.3 consists of two subsections. First, we link the survival probability structure in Section 2.3.1 to the conditional subjective survival probabilities in the survey. Then we discuss how respondents report their subjective survival probabilities, focusing on rounding behaviour. Section 2.3.4 links the likelihood parts of objective and subjective survival, allowing the unobserved factors of these to be correlated, and describes our estimation strategy.

### 2.3.1 Joint distribution of the remaining lifetimes

Consider a couple with two spouses: spouse 1 (male), and spouse 2 (female). In our sample, spouses are first observed when the older spouse is aged 50 or older. Thus, we set the first time the spouses are at risk of mortality to the point in time when the older spouse reaches age 50. Moreover, we only consider spouses who already were a couple before the older spouse reached age 50.

Figure 2.2: Potential lifetimes of spouses




*Note:* After the death of the first spouse, spouse $i$ is the surviving spouse. $i = 1$ ($i = 2$) if the male (female) spouse is surviving spouse.

Figure 2.2 illustrates the potential lifetimes of the two spouses. $d_1$ and $d_2$ are their ages at the initial time of risk ($t_0$); if spouse 1 is older than spouse 2, then $d_1 = 50$ and $d_2 \leq 50$. $Z_1^p$ and $Z_2^p$ are partially observed random variables representing the remaining lifetimes of spouses 1 and 2 as of $t_0$ if their spouse is alive. The first spouse dies at time $t_0 + Z^p = t_0 + \min\{Z_1^p; Z_2^p\}$. After one spouse's death, there can be a change in the surviving spouse's residual lifetime distribution due to the bereavement effect. Let the remaining lifetime of spouse 1 (spouse 2) after the death of the other spouse be $Z_1^q$ ($Z_2^q$). Then the total lifetimes of both spouses are:

$$T_1 = d_1 + Z^p + Z_1^q \cdot 1\{Z^p = Z_2^p\} \tag{2.1}$$

$$T_2 = d_2 + Z^p + Z_2^q \cdot 1\{Z^p = Z_1^p\} \tag{2.2}$$

Here $1\{\cdot\}$ is the indicator function (1 if the argument is true and 0 otherwise). Assuming time to be continuous, our model does not allow the possibility that both spouses die at the same moment.

Let $x = (x_1, x_2)$ be a vector of observed initial conditions or other time-invariant regressors (not including an intercept) and let $\eta = (\eta_1, \eta_2)$ be time-invariant unobserved frailty terms, with $\eta_1$ driving $Z_1^p$ and $Z_1^q$, and $\eta_2$ driving $Z_2^p$ and $Z_2^q$. Spouses' remaining lifetimes can be correlated via the observed regressors and the frailty terms. We assume that at $t_0$, the population distribution of unobserved frailty terms $\eta = [\eta_1, \eta_2]$ is bivariate normal with mean zero and arbitrary covariance matrix. We assume $Z_1^p, Z_2^p, Z_1^q$ and $Z_2^q$ are mutually independent conditional on observed regressors and unobserved frailty terms.

With this assumption, the joint distribution of $T_1, T_2$ given $(x, \eta)$ can be fully characterized by the conditional hazard rates of both spouses at each age for each given $(x, \eta)$. We impose the mixed-proportional hazards (MPH) structure on the conditional hazard rates. Moreover, we assume that the baseline hazard rates follow a Gompertz specification, depending on two unknown parameters: an intercept and a duration dependence parameter. Previous studies have shown that the Gompertz specification approximates the mortality rates of the elderly reasonably well (Frees, Carriere, & Valdez, 1996; Carriere, 2000; Luciano, Spreeuw, & Vigna, 2008).

The hazard rates driving $Z_i^p, i = 1, 2$ at age $t_i$, conditional on $(x_i, \eta_i)$, are:

$$\lambda_i^p(t_i|x_i, \eta_i) = \underbrace{\exp(\alpha_i^p t_i + \beta_i^p)}_{\text{baseline hazard rate}} \cdot \exp(x_i \beta_i + \eta_i), \text{ for } d_i \leq t_i < d_i + Z^p \tag{2.3}$$

These are the relevant hazard rates as of $d_i$ as long as both partners are alive.

Suppose that spouse $i$ lives longer than the partner, so $Z^p = Z_{3-i}$. Then the hazard rate of widow(er) $i$ at age $t_i \geq d_i + Z^p$, conditional on $(x_i, \eta_i)$ is:

$$\lambda_i^q(t_i|x_i, \eta_i) = \underbrace{\exp(\alpha_i^q t_i + \beta_i^q)}_{\text{baseline hazard rate}} \cdot \exp(x_i \beta_i + \eta_i), \text{ for } t_i \geq d_i + Z^p \tag{2.4}$$

In other words, bereavement can change both the level (through $\beta_i$) and the slope ($\alpha_i$) in the surviving spouse's log baseline hazard rates.[13].

Together with the conditional independence assumptions, the four hazard rates determine the joint distribution of the lifetimes of both partners given $(x_i, \eta_i)$. For example, the joint survival probability of reaching ages $t_1 = d_1 + z$ and $t_2 = d_2 + z$ conditional on $(x, \eta)$ is:

$$\begin{aligned}
S_0(t_1, t_2|x, \eta) &= P(Z_1^p > z, Z_2^p > z|x, \eta) && (2.5)\\
&= P(Z_1^p > z|x_1, \eta_1) \cdot P(Z_2^p > z|x_2, \eta_2) && (2.6)\\
&= P(Z_1^p + d_1 > z + d_1|x_1, \eta_1) \cdot P(Z_2^p + d_2 > z + d_2|x_2, \eta_2) && (2.7)\\
&= P(T_1^p > t_1|x_1, \eta_1) \cdot P(T_2^p > t_2|x_2, \eta_2) && (2.8)\\
&= \exp(-[\Lambda_1^p(t_1|x_1, \eta_1) + \Lambda_2^p(t_2|x_2, \eta_2)]), && (2.9)
\end{aligned}$$

[13] One interpretation of the changes in the baseline hazard rate parameters is that they result from changes in the observed characteristics of the surviving spouse before and after experiencing spousal bereavement. For example, when the male spouse passes away first, the surviving female spouse may experience a permanent drop in income, which could affect her hazard rates. Our model captures such permanent changes in income by increasing the level changes of the baseline hazard rates of female spouses (i.e., by having $\beta_2^q$ to be larger than $\beta_2^p$).

where $\Lambda_i^p(t_i|x_i,\eta_i)$ is the integrated hazard from age $d_i$ to $t_i$ corresponding to $\lambda_i^p(t|x_i,\eta_i)$, $i=1,2$.

The probability that spouse $i$ survives until at least age $t_i > t_i^p = d_i + z^p$ as a widow(er), given that spouse $3-i$ died at age $t_{3-i}^p = d_{3-i} + z^p$ and was the first who died, and given $(x_i, \eta_i)$, is:

$$S_{i|3-i}(t|t_i^p, x_i, \eta_i) = P(T_i^q > t | T_i^q > t_i^p, x_i, \eta_i) \tag{2.10}$$

$$= \exp(-\Lambda_i^q(t|t_i^p, x_i, \eta_i)), \tag{2.11}$$

where $\Lambda_i^q(t|t_i^p, x_i, \eta_i)$ is the integrated hazard from age $t_i^p$ to $t_i$ corresponding to $\lambda_i^q(t|x_i,\eta_i)$, $i = 1, 2$.

### 2.3.2 Objective survival probabilities

The objective survival probability is estimated using the actual mortality experience of married couples observed in the HRS during the period of interest. The spouses in a couple entered the survey at ages $a = (a_1, a_2)$. The conditional likelihood contribution $L^o$ of the objective part of the model, given $a$ and frailty terms $\eta^o = (\eta_1^o, \eta_2^o)$ and covariates $x$, depends on which of the following five possible situations occurs.

- (1) husband died first, at age $t_1$, and wife died second, at age $t_2$.

$$L^o(x,\eta^o) = \lambda_1^p(t_1|x_1,\eta_1^o)\lambda_2^q(t_2|x_2,\eta_2^o)S_0(t_1, t_1 + a_2 - a_1|x,\eta^o)S_{2|1}(t_2|t_1 + a_2 - a_1, x_2, \eta_2^o)$$

- (2) husband died at age $t_1$, wife is still alive in last survey wave, and has age $t_2$ at that time.

$$L^o(x,\eta^o) = \lambda_1^p(t_1|x_1,\eta_1^o)S_0(t_1, t_1 + a_2 - a_1|x,\eta^o)S_{2|1}(t_2|t_1 + a_2 - a_1, x_2, \eta_2^o)$$

- (3) wife died first, at age $t_2$, husband died second, at age $t_1$.

$$L^o(x,\eta^o) = \lambda_2^p(t_2|x_2,\eta_2^o)\lambda_1^q(t_1|x_1,\eta_1^o)S_0(t_2, t_2 + a_1 - a_2|x,\eta^o)S_{1|2}(t_1|t_2 + a_1 - a_2, x_1, \eta_1^o)$$

- (4) wife died at age $t_2$, husband still alive in last survey wave, and has age $t_1$ at that time.

$$L^o(x,\eta^o) = \lambda_2^p(t_2|x_2,\eta_2^o)S_0(t_2, t_2 + a_1 - a_2|x,\eta^o)S_{1|2}(t_1|t_2 + a_1 - a_2, x_1, \eta_1^o)$$

- (5) both spouses still alive in last survey wave, with ages $t_1$ and $t_2$.

$$L^o(x, \eta^o) = S_0(t_1, t_2|x, \eta^o)$$

Let's use $o$ to denote the parameters of the objective survival. The unknown parameters of the objective survival are $\alpha_i^{p,o}, \alpha_i^{q,o}$, $\beta_i^{p,o}, \beta_i^{q,o}$, and $\beta_i^o$ for $i = \{1, 2\}$.

### 2.3.3 Subjective joint survival and reporting subjective probabilities

#### 2.3.3.1 True subjective survival probabilities

This section models how married and widowed respondents formulate their subjective probability to reach a certain target age, conditional on their age at a given survey wave.

*Married respondents:* Let $a = (a_1, a_2)$ be the ages of the two spouses at the time of the survey, and let $ta_i$ be the target age in the survival question asked to spouse $i$. We consider the question for spouse $i$ with partner $j = 3 - i$. The age of spouse $j$ when spouse $i$ reaches age $ta_i$ is $ta_j = ta_i + a_j - a_i$.

We assume that a married respondent $i$ accounts for the fact that losing their partner changes the hazard from $\lambda_i^p$ into $\lambda_i^q$. Moreover, since we only observe partners' own subjective survival probabilities, we assume that both partners agree on each others survival chances.

Following this structure, spouse $i$'s subjective probability of reaching age $ta_i$ conditional on $(T_1^s > a_1, T_2^s > a_2, x, \eta^s)$ is then given by the following equation:

$$\begin{aligned}
&P(T_i^s \geq ta_i | T_1^s \geq a_1, T_2^s \geq a_2, x, \eta^s) \\
&\quad = \frac{P(T_i^s \geq ta_i \cap T_j^s \geq a_j | x, \eta^s)}{P(T_1^s \geq a_1 \cap T_2^s \geq a_2 | x, \eta^s)} = \frac{\int_{a_j}^{\infty} P(T_i^s \geq ta_i \cap T_j^s = \tau_j | x, \eta^s) d\tau_j}{P(T_1^s \geq a_1 \cap T_2^s \geq a_2 | x, \eta^s)} \\
&\quad = \frac{\int_{a_j}^{ta_j} P(T_i^s \geq ta_i \cap T_j^s = \tau_j | x, \eta^s) d\tau_j + P(T_1^s \geq ta_1 \cap T_2^s \geq ta_2 | x, \eta^s)}{P(T_1^s \geq a_1 \cap T_2^s \geq a_2 | x, \eta^s)} \\
&\quad = \frac{\int_{a_j}^{ta_j} \lambda_j^p(\tau_j | x_j, \eta_j^s) S_0(\tau_1, \tau_2 | x, \eta^s) S_{i|j}(ta_i | \tau_i, x_i, \eta_i^s) d\tau_j + S_0(ta_1, ta_2 | x, \eta^s)}{S_0(a_1, a_2 | x, \eta^s)}
\end{aligned} \tag{2.12}$$

where $\tau_i = \tau_j + a_i - a_j$. The first line of Eq. 2.12 is obtained using Bayes rule. In the second line, the integral in the numerator is separated into two additive terms: the first is an integral where

$\tau_j$ goes from $a_j$ to $ta_j$, and the second one is integral where $\tau_j$ goes from $ta_j$ to infinity. The second additive term has a closed-form solution. In the third line, the probabilities are replaced by their definitions in Eq. 2.3, 2.4, 2.9 and 2.11.

*Widowed respondents:* We assume that widowed individuals expect to remain widowed until they pass away.[14] Thus, if spouse $i$ is a widow(er) at age $a_i$, his or her survival probability of reaching age $ta_i$ conditional on $(T_i^s \geq a_i, x_i, \eta_i)$ is:

$$P(T_i^s \geq ta_i | T_i^s \geq a_i, x_i, \eta_i) = \exp\Big( - \Lambda_i^q(ta_i | a_i, x_i, \eta_i)\Big) \tag{2.13}$$

As shown in Eq. 2.13, the subjective integrated hazard rate of widowed spouse $i$ depends on $\Lambda_i^q(\cdot)$ rather than $\Lambda_i^p(\cdot)$.

#### 2.3.3.2 Reporting subjective survival probabilities

We follow the approaches proposed by De Bresser and Van Soest (2013); Kleinjans and Van Soest (2014); Bissonnette et al. (2017) and De Bresser (2019) to account for rounding behavior, incorporating possible dependence between spouses' reporting behaviors in a couple.

In each wave, respondents answered at most two subjective survival expectation questions with different target ages. We use subscript $k \in \{1, 2\}$ to denote the question and subscript $w \in \{1, 2, .., 13\}$ to denote the wave. Let $P_{iwk}$ be the observed response of spouse $i$ question $k$ in survey wave $w$. Let $S_{iwk}$ be the true survival probability that spouse $i$ with age $a_{iw}$ in wave $w$ reaches target age $ta_{iwk}$. If spouse $i$'s partner is alive at wave $w$, then $S_{iwk}$ is given by Eq. 2.12, otherwise $S_{iwk}$ is given by Eq. 2.13.

We do not directly observe $S_{iwk}$. First, there can be noise:

$$P^*_{iwk} = S_{iwk} + \varepsilon^*_{iwk}, \qquad \text{where } \varepsilon^*_{iwk} \sim N(0, \sigma^{2*}_{iw}), \text{ and } \sigma^*_{iw} = \exp(z_{iw}\beta^\sigma_i). \tag{2.14}$$

Here $\varepsilon^*_{iwk}$ are noise terms, assumed to be independent of each other and of everything that drives the objective survival probabilities and the true survival probability, conditional on $(a_{j\jmath}, x_j, z_{j\jmath}, \eta^s_j)$ for $j = 1, 2$, and $\jmath = 1, ..., 13$. $z_{iw}$ contains, for example, a measure of cognition that may drive the precision of the answers to the subjective questions; it also includes an intercept term.

If respondents decide to report their survival probabilities precisely they round their answer to the nearest integer, the highest precision allowed by the answer scale. On the other hand, they

[14] In our sample, the total number of widowed people is 5,699, and 386 of them (around 6.7%) married again between 1992 and 2016.

can report a coarser answer that is rounded to a multiple of five or ten. For example, suppose the perceived survival probability is 65.3%. A respondent providing a precise answer would report 65%, the nearest multiple of 1. Instead, if the respondent rounds to the nearest multiple of 10, the answer will be 70%. As an extreme example, if the respondent rounds to the nearest multiple of 50, the answer will be 50%.

Let $R_{iwk}$ be the rounding decision of spouse $i$ for question $k$ in wave $w$. We assume that there are five possible rounding rules, $r \in \{1,2,3,4,5\}$, to multiples of five different integers $\delta_r$, resulting on answers in a set $\Omega_r$:

- $R_{iwk} = 1$: Multiples of $\delta_1 = 1$; $\Omega_1 = \{0, 1, ..., 99, 100\}$
- $R_{iwk} = 2$: Multiples of $\delta_2 = 5$; $\Omega_2 = \{0, 5, ..., 95, 100\}$
- $R_{iwk} = 3$: Multiples of $\delta_3 = 10$; $\Omega_3 = \{0, 10, ..., 90, 100\}$
- $R_{iwk} = 4$: Multiples of $\delta_4 = 25$; $\Omega_4 = \{0, 25, 50, 75, 100\}$
- $R_{iwk} = 5$: Multiples of $\delta_5 = 50$; $\Omega_5 = \{0, 50, 100\}$

Since the rounding rules can be ordered in terms of precision, we model $R_{iwk}$ with an ordered response equation:

$$R_{iwk} = r, \text{ if } m_{i,r-1} < z_{iw}\beta_i^R + \eta_i^R + \varepsilon_{iwk}^R \leq m_{i,r}. \tag{2.15}$$

Here $m_{i,0}, m_{i,1}, ..., m_{i,5}$, $i = 1, 2$ are the threshold parameters, with $m_{i,0} = -\infty$ and $m_{i,5} = \infty$. $m_{i,1}$ is normalized to zero as $z_{iw}$ includes a constant. The random component $\eta_i^R$ is independent of $(a_{j\jmath}, x_j, z_{j\jmath})$ for all $j = 1, 2$, and $\jmath = 1, ..., 13$, and captures the unobserved time-invariant effects that determine spouse $i$'s rounding decision. The idiosyncratic rounding shock $\varepsilon_{iwk}^R$ follows an i.i.d. standard normal distribution and independent of $(\varepsilon_{j\jmath k}^*, a_{j\jmath}, x_j, z_{j\jmath}, \eta_j, \eta_j^R)$ for all $k$, $j = 1, 2$, and $\jmath = 1, .., 13$. $\varepsilon_{iwk}^R$ is also independent of $\varepsilon_{i\jmath q}^R$ for $q \neq k$ for all $\jmath = 1, .., 13$.

With these assumptions on $\varepsilon_{iwk}^R$, the probability of spouse $i$ choosing rounding rule $r$ conditional on $(z_{iw}, \eta_i^R)$ is:

$$P(R_{iwk} = r | z_{iw}, \eta_i^R) = \Phi(m_{i,r} - z_{iw}\beta_i^R - \eta_i^R) - \Phi(m_{i,r-1} - z_{iw}\beta_i^R - \eta_i^R), \text{ for } r \in \{1,2,3,4,5\}. \tag{2.16}$$

Choosing a specific rounding rule implies an interval for the perturbed probability $P^*_{iwk} = [LB_{iwk}, UB_{iwk})$. The conditional probability that $P^*_{iwk}$ is in this interval is given by

$$P(LB_{iw1} \leq P^*_{iw1} < UB_{iw1}|a_{iw}, x_i, z_{iw}, \eta^s_i) = \\ \Phi\Big(\frac{UB_{iw1} - S_{iw1}}{\sigma^*_{iw}}|a_{iw}, x_i, z_{iw}, \eta^s_i\Big) - \Phi\Big(\frac{LB_{iw1} - S_{iw1}}{\sigma^*_{iw}}|a_{iw}, x_i, z_{iw}, \eta^s_i\Big). \tag{2.17}$$

Respondents answer at most two survival expectation questions with different target ages in each survey wave. Given that the first reported probability is $P_{iw1}$, if a respondent chooses rounding rule $R_{iw1} = r$, the upper and lower boundaries in Eq. 2.17 are equal to

$$P(LB_{iw1} \leq P^*_{iw1} < UB_{iw1}|a_{iw}, x_i, z_{iw}, \eta^s_i) = \\ \begin{cases} P(100\% - 0.5\delta_r \leq P^*_{iw1}|a_{iw}, x_i, z_{iw}, \eta^s_i) & \text{if } P_{iw1} = 100\% \\ P(P_{iw1} - 0.5\delta_r \leq P^*_{iw1} \leq P_{iw1} + 0.5\delta_r|a_{iw}, x_i, z_{iw}, \eta^s_i) & \text{if } 0\% < P_{iw1} < 100\% \\ P(P^*_{iw1} \leq 0.5\delta_r|a_{iw}, x_i, z_{iw}, \eta^s_i) & \text{if } P_{iw1} = 0\% \end{cases} \tag{2.18}$$

Intuitively speaking, in the first question, if a perturbed probability 10% is rounded to a multiple of 5%, then the interval is $[7.5\%, 12.5\%)$. Since survival probabilities are bounded between 0% and 100%, we take account of censoring as shown in Eq. 2.18.

Following De Bresser (2019), whether a perturbed probability of the second question $P^*_{iw2}$ is censored or not depends on the degree of the rounding and on the reported probability in the first question. Since the second question's target age is higher than in the first question, the perturbed probability of the second question should be lower or equal to that of in the first question. Thus, for a given response of the second question $P_{iw2}$ and a given rounding rule $R_{iw2} = r$, the lower and upper boundaries are defined as:

$$P(LB_{iw2} \leq P^*_{iw2} < UB_{iw2}|a_{iw}, x_i, z_{iw}, \eta^s_i) = \\ \begin{cases} P(P_{iw1} - 0.5\delta_r \leq P^*_{iw2}|a_{iw}, x_i, z_{iw}, \eta^s_i) & \text{if } P_{iw2} \geq P_{iw1} - 0.5\delta_r \\ P(P_{iw2} - 0.5\delta_r \leq P^*_{iw2} \leq P_{iw2} + 0.5\delta_r|a_{iw}, x_i, z_{iw}, \eta^s_i) & \text{if } 0.5\delta_r \leq P_{iw2} < P_{iw1} - 0.5\delta_r \\ P(P^*_{iw2} \leq 0.5\delta_r|a_{iw}, x_i, z_{iw}, \eta^s_i) & \text{if } P_{iw2} < 0.5\delta_r. \end{cases} \tag{2.19}$$

Since we do not directly observe which rounding rules respondents choose, a reported probability $P_{iwk}$ may result from different degrees of rounding. For example, the observed response of 10% can be rounded to a multiple of 1 (interval: $[9.5\%, 10.5\%)$), a multiple of 5 (interval: $[7.5\%, 12.5\%)$), or a multiple of 10 (interval: $[5\%, 15\%)$). Thus, the probability of observing $P_{iwk}$ conditional on $(x_i, z_{iw}, \eta_i^R, \eta_i^s)$ is:

$$\begin{aligned} P(P_{iwk}|a_{iw},&x_i, z_{iw}, \eta_i^R, \eta_i^s) \\ &= \sum_{r=1}^{5} 1\{P_{iwk} \in \Omega_r\} P(R_{iwk} = r|z_{iw}, \eta_i^R) P(LB_{iwk} \leq P^*_{iwk} < UB_{iwk}|a_{iw}, x_i, z_{iw}, \eta_i^s). \end{aligned} \tag{2.20}$$

The conditional likelihood contribution for subjective question $k$ given $(a_{iw}, x_i, z_{iw}, \eta_i^s, \eta_i^R)$ equals the probability of observing the reported probability $P_{iwk}$ and is given by:

$$L^s_{iwk}(\eta_i^s, \eta_i^R) = P(P_{iwk}|a_{iw}, x_i, z_{iw}, \eta_i^R, \eta_i^s) \tag{2.21}$$

We set the subjective likelihood contribution to 1 if a response is invalid (i.e, answered "Don't know" or "Refused to answer") or if a respondent did not answer the subjective survival probability question or passed away at a given wave .

The conditional likelihood contribution of a couple, combining all waves and questions, is:

$$L^s(\eta^s, \eta^R) = \prod_{w=1}^{13} \prod_{i=1}^{2} \prod_{k=1}^{2} L^s_{iwk}(\eta_i^R, \eta_i^s) \tag{2.22}$$

We use superscript $s$ to denote the parameters of the subjective survival. The unknown parameters are $\alpha_i^{p,s}, \alpha_i^{q,s}$, $\beta_i^{p,s}, \beta_i^{q,s}$, $\beta_i^s$, $\beta_i^\sigma, \beta_i^R$, $m_{i,2}$, $m_{i,3}$, and $m_{i,4}$ for $i = \{1, 2\}$.

### 2.3.4 Likelihood contributions and unobserved heterogeneity

For the complete model, the conditional likelihood contribution of couple $n$ is given by:

$$L_n(\eta^o, \eta^s, \eta^R) = L^o(\eta^o) \cdot L^s(\eta^s, \eta^R) \tag{2.23}$$

We allow the random components of the objective and subjective models to be correlated and assume that $[\eta_1^o, \eta_2^o, \eta_1^s, \eta_2^s]^T$ follows a four-dimensional i.i.d. normal distribution with zero means and arbitrary covariance matrix, $\Sigma_1$. Moreover, we allow the random components of the reporting models $[\eta_1^R, \eta_2^R]^T$ to be correlated between spouses in a couple and follows a bi-variate i.i.d.

normal distribution with zero means and arbitrary covariance matrix, $\Sigma_2$. However, we restrict the model such that the random components of the reporting models and the other random components of the model are mutually independent. $[\eta_1^o, \eta_2^o, \eta_1^s, \eta_2^s, \eta_1^R, \eta_2^R]$ are independent of $(x_j, z_{j\jmath}, \varepsilon^*_{j\jmath k}, \varepsilon^R_{j\jmath k})$ for all $k$, $j = 1, 2$, and $\jmath = 1, ..., 13$.

Let $\eta = [\eta^o, \eta^s, \eta^R]$, where $\eta^o = [\eta_1^o, \eta_2^o]$, $\eta^s = [\eta_1^s, \eta_2^s]$, and $\eta^R = [\eta_1^R, \eta_2^R]$. Let $\Sigma$ be the covariance matrix of $\eta^T$ such that:

$$\Sigma = \begin{bmatrix} \Sigma_1 & \mathbf{0} \\ \mathbf{0}^T & \Sigma_2 \end{bmatrix} \tag{2.24}$$

where $\mathbf{0}$ is a zero matrix with dimensions $4 \times 2$.

The interpretations of some elements of $\Sigma$ are worth noting. Let $\sigma_{x,y}$ be the covariance between $x$ and $y$. Following the common lifestyle argument, we expect positive signs in $\sigma_{\eta_1^o,\eta_2^o}$ and $\sigma_{\eta_1^s,\eta_2^s}$. We also expect positive signs from $\sigma_{\eta_1^o,\eta_2^o}$ and $\sigma_{\eta_1^s,\eta_2^s}$ if people mate based on their similar characteristics that are not controlled for via observed characteristics, which is known as the theory of homogamy (Hollingshead, 1950). It is also possible that $\sigma_{\eta_1^o,\eta_2^o}$ and $\sigma_{\eta_1^s,\eta_2^s}$ to be negative if people select mates with complementary needs, which is known as the theory of heterogamy. If respondents' subjective and objective survival expectations are correlated after controlling for observed factors, as noted by Smith et al. (2001), then we expect the estimates of $\sigma_{\eta_1^o,\eta_1^s}$ and $\sigma_{\eta_2^o,\eta_2^s}$ to be positive and significant. In a couple's household, if two spouses tend to elicit their subjective responses with a similar degree of precision, we expect $\sigma_{\eta_1^R,\eta_2^R}$ to be positive.

Since the random components are unobserved, we need each couple's unconditional likelihood contribution. Moreover, the average of the unobserved frailty terms of the sample decreases as the average age of the population increases because people with higher values of $\eta^o$ die sooner than people with low values of $\eta^o$. This implies that the distribution of unobserved frailty terms depends on the entry ages of couples (Lancaster, 1990). Accounting for this, the (unconditional) likelihood contribution of couple is given by:

$$\begin{aligned} L_n &= \int_{R^6} L_n(\eta|T_1^o > a_1^*, T_2^o > a_2^*) g(\eta|T_1^o > a_1^*, T_2^o > a_2^*) d\eta \\ &= \int_{R^6} \frac{L_n(\eta)}{P(T_1^o > a_1^*, T_2^o > a_2^*|\eta^o)} \frac{g(\eta) P(T_1^o > a_1^*, T_2^o > a_2^*|\eta^o)}{P(T_1^o > a_1^*, T_2^o > a_2^*)} d\eta \qquad (2.25) \\ &= \frac{\int_{R^6} L_n(\eta) g(\eta) d\eta}{P(T_1^o > a_1^*, T_2^o > a_2^*)} \qquad (2.26) \\ &= \frac{\int_{R^6} L_n(\eta) g(\eta) d\eta}{\int_{R^2} S_0(a_1^*, a_2^*|\eta^o) g(\eta^o) d\eta^o} \qquad (2.27) \end{aligned}$$

Here $g(\eta)$ is a six-variate probability density function of $\eta$, and $g(\eta^o)$ is the bivariate probability density function of $\eta^o$. In the first line of Eq. 2.27, both the conditional likelihood function, and the density function of $\eta$ are conditional on spouses surviving until ages $(a_1^*, a_2^*)$. The second line of the equation is obtained using Bayes rule. Note that the conditional objective probability that spouses survive until ages $(a_1^*, a_2^*)$, $P(T_1 > a_1^*, T_2 > a_2^*|\eta^o)$, does not depend on $(\eta^s, \eta^R)$. Because of the common multipliers in denominator and numerator, we obtain the third line. Finally, the joint probability in the denominator is replaced by its definition in Eq. 2.9.

Eq. 2.27 does not have a closed-form expression; thus, we rely on numerical methods. First, we use the mid-point approximation rule to numerically approximate the integral in the numerator of Eq. 2.12.[15] Second, we approximate the integral over unobserved random components using a simulation method, rewriting the unobserved factors as follows:

$$[\eta_1^o, \eta_2^o, \eta_1^s, \eta_2^s, \eta_1^R, \eta_2^R]^T = \Lambda u \tag{2.28}$$

where $u$ is a column vector of six independent standard normal random variables. Here $\Lambda$ is a Cholesky lower-triangular matrix with $\Sigma = \Lambda(\Lambda)^T$.

We can now approximate Eq. 2.27 with:

$$L_n \approx \frac{\frac{1}{M}\sum_{m=1}^{M} L_n(\Lambda u)}{\frac{1}{M}\sum_{m=1}^{M} S_0(a_1^*, a_2^*|\Lambda^o u^{o,m})} \tag{2.29}$$

where $M$ is the number of simulations drawn for each couple. $u^m$ is $m$th simulation draw with six elements, and $u^{o,m}$ is the first two elements of $u^m$. In the denominator, $\Lambda^o u^{o,m}$ is the first two elements of vector $\Lambda u^m$. We use Halton draws to generate pseudo-random simulated draws to reduce the variance induced from the simulation procedure.[16] The model is estimated by the Maximum Simulated Likelihood (MSL) method, where the number of simulation draws for each couple is set to be $M = 100$.[17]

[15] The integral of the first additive term in the numerator of Eq. 2.12 is approximated as follows. First, we partition interval $[a_j, ta_j]$ by ten equidistant intervals. Second, we evaluate the function under the integral at each interval's mid-point. Finally, the approximation of the integral equals the sum of all function values evaluated at ten mid-points multiplied by $\frac{(ta_j - a_j)}{10}$.

[16] The Halton sequences are generated with prime bases 3, 5, 7, 11, 13, and 17. The elements of the first 17 six-pairs of the sequence are discarded since the early elements appear to be correlated (Train, 2009).

[17] If the number of simulation draws for each observation -$M$ goes to infinity, the MSL estimator is asymptotically equivalent to the Maximum Likelihood estimator (Train, 2009).

# 2.4 Results

## 2.4.1 Objective hazard rates

Columns (1) and (4) of Table 2.5 show the estimation results for the objective hazard rates of men and women, respectively. Using the estimates of the baseline hazard parameters $\beta^p, \beta^q, \beta, \alpha^p$ and $\alpha^q$, we predict the objective log hazards for "average" individuals whose regressors are equal to the sample averages and whose unobserved frailty equals zero. The predictions are shown in subfigures (a) and (b) of Figure 2.3. The solid and dashed lines in these figures depict the predicted log hazard rates if respondents' partners are alive and deceased, respectively. The observed characteristics and frailties are the same whether partners are alive or dead; the only difference is the bereavement effect on the baseline hazards. The dotted lines are the 95% confidence intervals calculated using a parametric bootstrap method with 500 iterations.[18]

Subfigures (a) and (b) of Figure 2.3 show that the objective log hazard rates of people whose partners are alive are lower than those of widowed individuals with the same average characteristics. The confidence intervals of married and widowed individuals overlap for males, but those for married and widowed females do not overlap for females who are 57 or older. We therefore conclude that there exists a significant negative bereavement effect on female surviving spouses who are 57 or older. These results align with the findings of Van den Berg et al. (2011) and Spreeuw and Owadally (2013). On the other hand, while the hazard rate does increase for male spouses who experience spousal bereavement, this increase is not statistically significant.

A positive coefficient on a covariate implies a higher mortality risk and a lower survival probability if the covariate increases.[19] According to the results in Columns (1) and (4) of Table 2.5, observed mortality risks covary in expected ways with demographics and associations are similar for men and women. For example, if household-size adjusted income increases by 1%, mortality hazards decrease by 0.05%. Ever smoking is associated with a 40% higher mortality rate compared to never smokers. If the number of functional limitations increases by one, the

[18] Since our model is highly non-linear, we use the parametric bootstrap to compute standard errors and confidence intervals for functions of estimators. The method is implemented as follows. Let $\hat{\zeta}$ and $\widehat{Cov}(\hat{\zeta})$ be a vector of estimated parameter values and the covariance-variance matrix of $\hat{\zeta}$, respectively. The bootstrap samples can be taken by generating $N$ random draws of the parameter vector, which follows a normal distribution $\mathcal{N}(\hat{\zeta}, \widehat{Cov}(\hat{\zeta}))$. Then with $N$ random draws, the statistics of interest $f(\hat{\zeta})$ are computed, where $f(\cdot)$ is a continuous function of $\hat{\zeta}$. The sample standard deviation of $f(\hat{\zeta})$ is an estimate of the standard error of $f(\hat{\zeta})$. In this paper, we use $N = 500$.

[19] The parameters of the hazard rates can be interpreted as relative effects. Following the MPH specification:

$$\frac{\partial\lambda(t|x,\eta)}{\partial x} = \frac{\partial\lambda(t)\exp(x\beta+\eta)}{\partial x} = \beta\lambda(t|x,\eta) \rightarrow \beta = \frac{\partial\lambda(t|x,\eta)/\partial x}{\lambda(t|x,\eta)}$$

where $\lambda(t)$ is the baseline hazard.

mortality hazards increase by around 20%. If the number of ever-diagnosed chronic conditions increases by one, the mortality hazards increase by 29%.

Compared to individuals with less than high-school education, high-school education is associated with 8% lower mortality hazards. The magnitude of this difference is even larger for college-educated individuals, who have a 23% lower hazard than their less than high-school counterparts. Hispanics have around 15% lower mortality hazards than non-Hispanics. African Americans have higher mortality hazards than the other racial groups. Cohort differences vary between men and women. Women born before 1930 and between 1931 and 1945 have 46% and 24% lower mortality hazards, respectively, than women born after 1945. On the other hand, we do not find any significant differences in objective mortality hazards for men from different birth cohorts.

### 2.4.2 Subjective hazard rates

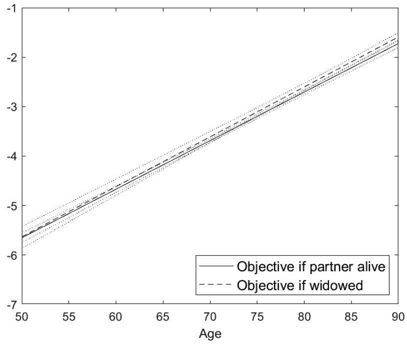
Columns (2) and (5) of Table 2.5 show the estimation results for the subjective hazard rates of men and women, respectively. Sub-figures (c) and (d) of Figure 2.3 show the log subjective hazard rates for an average individual. The results show that the perceived likelihood of death increases significantly once one encounters a spousal bereavement, but the magnitude of the bereavement effect differs between men and women. Females' perceived mortality risk increases irrespective of their age. For males, the perceived bereavement effect is significant until age 86 but insignificant at older ages.

To test whether the relation between observables and mortality is the same for actual and subjective survival, we report the estimated differences between the parameters of objective and subjective hazard rates in Columns (3) and (6) of Table 2.5. Looking at income and education, we cannot reject that the relation between socio-economic status and the mortality hazard is the same for actual and subjective survival for both men and women. We do find discrepancies along racial lines. Hispanic people tend to have lower actual mortality than non-Hispanic. While African Americans face around 13-14% higher mortality hazards, their subjective hazard is 38-50% below that of non-African Americans. The impact of smoking, functional limitations, and chronic conditions is much stronger for actual than for subjective mortality.

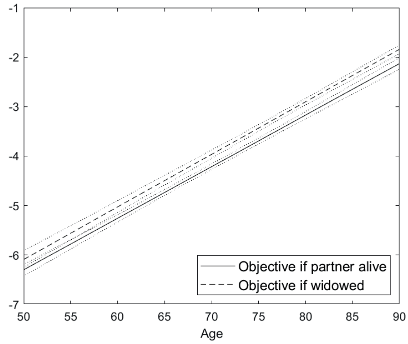
### 2.4.3 Reporting subjective survival probabilities

The estimation results of the reporting model are shown in Columns (7) to (10) of Table 2.5. Columns (7) and (9) show the results for the log of the variance of the measurement error that

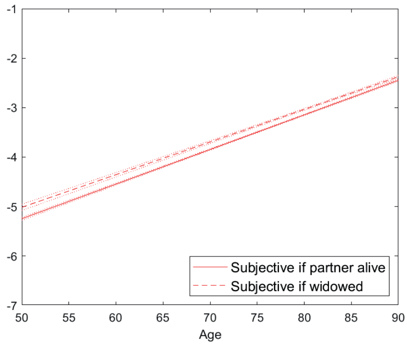
Figure 2.3: Predicted log hazard rates for an average individual, conditional on partner's vital status



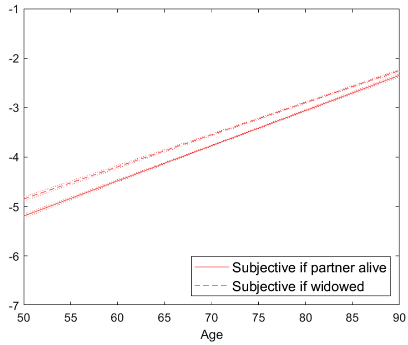

(a) Male, objective




(b) Female, objective




(c) Male, subjective




(d) Female, subjective

Note: The log hazard rates are linear, due to the assumption that the baseline hazards follow a Gompertz specification. The dashed and the solid lines are the spouses' log hazards if partners are alive versus if partners died at a given age. The dotted lines around the dashed and solid lines represent 95% confidence intervals reflecting estimation uncertainty, calculated using a parametric bootstrap method with 500 iterations.

drives deviations between reported probabilities and underlying Gompertz distributions. Positive parameters imply more noisy answers if the regressor increases.

The results show that people who correctly recall a higher number of words tend to report probabilities that line up better with Gompertz distributions than those who recall fewer words. Moreover, if individuals more often choose a multiple of 50 in other subjective expectation questions, their responses are noisier. High-school or college-educated people report with less measurement error than lower educated individuals do. African Americans and Hispanics and individuals born before 1945 tend to deviate more strongly from the assumed Gompertz

Table 2.5: Estimation results, part 1

| *Column* | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | | **MALE** | | | **FEMALE** | |
| | **Objective** | **Subjective** | **Difference (obj-subj)** | **Objective** | **Subjective** | **Difference (obj-subj)** |
| Constant-married ($\beta^p$) | -10.538 | -8.094 | -2.444 | -11.191 | -7.835 | -3.356 |
| | (0.231) | (0.082) | (0.24) | (0.295) | (0.092) | (0.307) |
| Constant-widowed ($\beta^q$) | -10.675 | -7.663 | -3.013 | -11.079 | -7.194 | -3.885 |
| | (0.376) | (0.114) | (0.392) | (0.343) | (0.091) | (0.353) |
| Alpha-married ($\alpha^p$) | 0.098 | 0.070 | 0.027 | 0.104 | 0.071 | 0.033 |
| | (0.002) | (0.001) | (0.002) | (0.003) | (0.001) | (0.003) |
| Alpha-widowed ($\alpha^q$) | 0.101 | 0.066 | 0.033 | 0.106 | 0.065 | 0.042 |
| | (0.003) | (0.001) | (0.004) | (0.003) | (0.001) | (0.004) |
| Log of income | -0.051 | -0.066 | 0.014 | -0.052 | -0.095 | 0.043 |
| | (0.016) | (0.006) | (0.017) | (0.021) | (0.006) | (0.022) |
| Ever smoked | 0.396 | 0.09 | 0.305 | 0.425 | 0.084 | 0.341 |
| | (0.036) | (0.011) | (0.037) | (0.036) | (0.011) | (0.037) |
| Functional limitations | 0.191 | 0.093 | 0.097 | 0.252 | 0.107 | 0.145 |
| | (0.016) | (0.009 ) | (0.018) | (0.018) | (0.01) | (0.021) |
| Chronic conditions | 0.275 | 0.179 | 0.096 | 0.286 | 0.143 | 0.143 |
| | (0.011) | (0.005) | (0.012) | (0.014) | (0.005) | (0.015) |
| High-school | -0.079 | -0.015 | -0.064 | -0.09 | -0.199 | 0.109 |
| | (0.036) | (0.018) | (0.04) | (0.042) | (0.02) | (0.045) |
| College | -0.226 | -0.194 | -0.031 | -0.234 | -0.333 | 0.099 |
| | (0.04) | (0.017) | (0.042) | (0.049) | (0.02) | (0.051) |
| Hispanic | -0.178 | 0.001 | -0.179 | -0.135 | 0.301 | -0.436 |
| | (0.058) | (0.024) | (0.061) | (0.069) | (0.024) | (0.072) |
| African American | 0.143 | -0.504 | 0.647 | 0.129 | -0.379 | 0.508 |
| | (0.041) | (0.019) | (0.045) | (0.053) | (0.021) | (0.056) |
| Born before 1930 | -0.126 | -0.251 | 0.125 | -0.462 | 0.172 | -0.634 |
| | (0.085) | (0.02) | (0.086) | (0.095) | (0.025) | (0.098) |
| Born between 1931 and 1945 | 0.091 | -0.101 | 0.192 | -0.240 | 0.095 | -0.335 |
| | (0.073) | (0.011) | (0.074) | (0.079) | (0.011) | (0.079) |

*Note:* Standard errors in parentheses, calculated using the outer-product gradient estimates. We use 100 Halton draws for each observation. The estimated log-likelihood is -503,523.6. The total number of parameters is 115. The sample consist of 11,043 couples. The total number of observations (spouses × waves × valid responses) is 126,250.

distribution.

Columns (8) and (10) of Table 2.5 show the estimation results of the rounding equation. A positive parameter implies coarser rounding if the covariate increases. If a respondent's proportion of choosing multiples of 50 in other expectation questions is higher, the probability of coarser rounding is also higher. If the number of correctly recalled words increases, the probability of reporting more precisely increases. College-educated and Hispanic people appear to answer more precisely than their counterparts. People born before 1945 are more likely to give imprecise answers than their counterparts.

The estimated parameters of the first survey wave dummy are positive in Columns (7) to (10), due to the fact that the first wave responses were asked on a different scale (and multiplied by 10 to make them comparable with the responses in other waves; cf. Section 2.3). This made first wave responses coarser than those in other waves.

Table 2.5 continued, part 2.

| *Column* | (7) | (8) | (9) | (10) |
|---|---|---|---|---|
| | **MALE** | | **FEMALE** | |
| | **log of variance of measurement error** | **rounding equation** | **log of variance of measurement error** | **rounding equation** |
| Constant | -2.758 | 1.622 | -2.55 | 1.833 |
| | (0.022) | (0.024) | (0.02) | (0.024) |
| Prop. multiples of 50 | 0.511 | 0.708 | 0.488 | 0.658 |
| | (0.014) | (0.016) | (0.012) | (0.014) |
| Immediate word recall | -0.8 | -0.025 | -0.765 | -0.092 |
| | (0.029) | (0.03) | (0.025) | (0.028) |
| High-school | -0.268 | 0.025 | -0.434 | 0.023 |
| | (0.013) | (0.014) | (0.012) | (0.014) |
| College | -0.532 | -0.118 | -0.645 | -0.143 |
| | (0.013) | (0.014) | (0.012) | (0.014) |
| Hispanic | 0.496 | -0.061 | 0.463 | -0.148 |
| | (0.015) | (0.018) | (0.013) | (0.018) |
| African American | 0.61 | 0.019 | 0.646 | -0.023 |
| | (0.014) | (0.015) | (0.012) | (0.016) |
| Born before 1930 | 0.163 | 0.032 | 0.197 | 0.152 |
| | (0.016) | (0.015) | (0.017) | (0.017) |
| Born between 1931 and 1945 | 0.083 | 0.078 | 0.023 | 0.102 |
| | (0.009) | (0.01) | (0.007) | (0.01) |
| First wave dummy | 0.097 | 0.179 | 0.247 | 0.086 |
| | (0.022) | (0.028) | (0.02) | (0.027) |
| $m_1$ | | 1.162 | | 1.21 |
| | | (0.012) | | (0.012) |
| $m_2 - m_1$ | | 1.425 | | 1.480 |
| | | (0.009) | | (0.008) |
| $m_3 - m_2$ | | 0.532 | | 0.595 |
| | | (0.008) | | (0.007) |

### 2.4.4 Estimated variances and correlation coefficients of unobserved factors

Columns (11) to (16) of Table 2.5 show the estimated variances (the diagonal entries) and the estimated correlation coefficients (off-diagonal entries) of unobserved factors.

We find significant variation in the unobserved factors of both objective and subjective hazard rates, both for males and females ($\widehat{Var}(\eta_i^o)$ and $\widehat{Var}(\eta_i^s)$ for $i = 1, 2$). The estimated variances are much larger for subjective hazards (around 0.85-0.90) than for objective hazards (0.02-0.03). This shows that conditional on demographics respondents' perceived mortality varies much more than do actual mortality rates.

The estimated correlations between the frailty terms of husband and wife are positive and significant, but weak ($\widehat{Corr}(\eta_1^o, \eta_2^o) = 0.09$, and $\widehat{Corr}(\eta_1^s, \eta_2^s) = 0.21$). Hence, once we control observed regressors, spouses' objective and subjective mortality hazards are weakly positively correlated. Moreover, the correlations between objective and subjective frailty terms are strong, positive, and significant for males ($\widehat{Corr}(\eta_1^o, \eta_1^s) = 0.99$) and females ($\widehat{Corr}(\eta_2^o, \eta_2^s) = 0.97$). This is in line with Smith et al. (2001), who conclude that even after controlling for the main observed mortality predictors, there is a positive correlation between subjective survival responses and the objective survival rates. The reason could be that people are aware of factors that affect their mortality rates that are unobserved to the econometrician and take account of those factors when they formulate their survival expectations.

There is significant variation in unobserved factors of the rounding decisions, both for males and females ($\widehat{Var}(\eta_i^R)$ for $i = 1, 2$). The estimated correlation between the unobserved factors of males' and females' rounding decisions is positive, significant, and moderately strong ($\widehat{Corr}(\eta_1^R, \eta_2^R) = 0.61$). The explanation could be that spouses in a couple have intrinsically similar rounding behaviors and/or spouses interfere with each other's reporting decisions during an interview. The latter is plausible if couples are interviewed together.

Table 2.5 continued. part 3

| *Column* | (11) | (12) | (13) | (14) | (15) | (16) |
|---|---|---|---|---|---|---|
| *Estimated variances and correlation coefficients of unobserved factors* | | | | | | |
| | $\eta_1^o$ | $\eta_2^o$ | $\eta_1^s$ | $\eta_2^s$ | $\eta_1^R$ | $\eta_2^R$ |
| $\eta_1^o$ | 0.018 | | | | | |
| | (0.002) | | | | | |
| $\eta_2^o$ | 0.094 | 0.032 | | | | |
| | (0.022) | (0.028) | | | | |
| $\eta_1^s$ | 0.994 | -0.015 | 0.853 | | | |
| | (0.003) | (0.016) | (0.042) | | | |
| $\eta_2^s$ | 0.32 | 0.973 | 0.214 | 0.898 | | |
| | (0.002) | (0.021) | (0.008) | (0.028) | | |
| $\eta_1^R$ | 0 | 0 | 0 | 0 | 0.06 | |
| | - | - | - | - | (0.013) | |
| $\eta_2^R$ | 0 | 0 | 0 | 0 | 0.61 | 0.118 |
| | - | - | - | - | (0.02) | (0.011) |

*Notes:* The diagonal elements are the estimated variances and the off-diagonal elements are the estimated correlation coefficients of unobserved factors. Standard errors are calculated using a parametric bootstrap method with 500 iterations.

### 2.4.5 Comparing predicted objective and subjective survival curves

In applied work on, e.g., life-cycle saving decisions, researchers need a proxy for people's perceived survival probabilities (French, 2005; De Nardi, French, & Jones, 2009). We show predicted survival probabilities in Figure 2.4, presenting median survival curves but also illustrating heterogeneity.

We first predict the posterior means of unobserved frailties of each couple.[20] We predict these survival curves separately for men and women who survived to age 70. The black dashed lines and solid red lines are the median predictions of the objective and subjective survival curves.

We predict the subjective and objective survival curves for 70-year-old median males and females, considering whether their partner is alive or deceased. The results show that 70-year-old median males overestimate their chances of survival, regardless of their partner's status. On the other hand, 70-year-old median females underestimate their probability of surviving for another 15 years but overestimate their chances of surviving beyond 15 years.

The blue and red areas reflect the 10th and 90th percentiles of the objective and subjective curves, illustrating the heterogeneity in survival functions.[21] In the top sub-figures, only unobserved frailties are accounted for: to shut down the dispersion due to observed regressors, the values of observed regressors are set equal to their sample averages. These sub-figures show that subjective survival curves are more dispersed than their objective counterparts, as expected from the estimated variances of the unobserved heterogeneity terms.

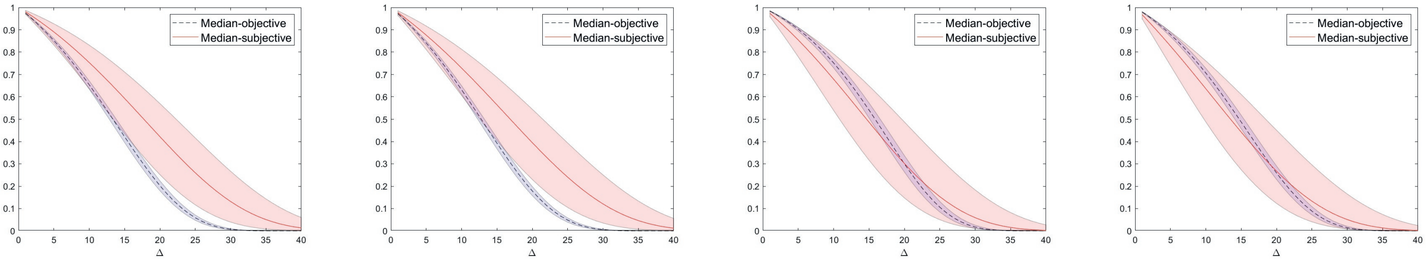
In the bottom part of Figure 2.4, the blue and red areas reflect the 10th and 90th percentiles accounting for both unobserved frailties and observed characteristics. Here the objective and subjective survival curves are much more dispersed than in the top part of the figure. The relative increase in the objective curves is much larger than that of the subjective curves. This can be explained by the fact that the estimated impact of most observed characteristics is much larger for objective than for subjective hazards. For example, the ever-smoking males' objective hazard rates are, on average, 39% higher than the objective hazard rates of never-smoking males. In contrast, the ever-smoking males' subjective hazard rates are, on average, only 9% higher than the subjective hazard rates of never-smoking males. Although the opposite is true for some groups of people (e.g., African Americans and males born before 1945), the overall impact of observed characteristics leads to much more variation in the predictions of the objective than in the subjective survival curves.

[20] Appendix 2.6.1 shows a detailed explanation of how we predicted each couple's unobserved frailties.

[21] The survival curves are predicted at estimated values of parameters; thus, the blue and red areas do not reflect the estimation uncertainty.

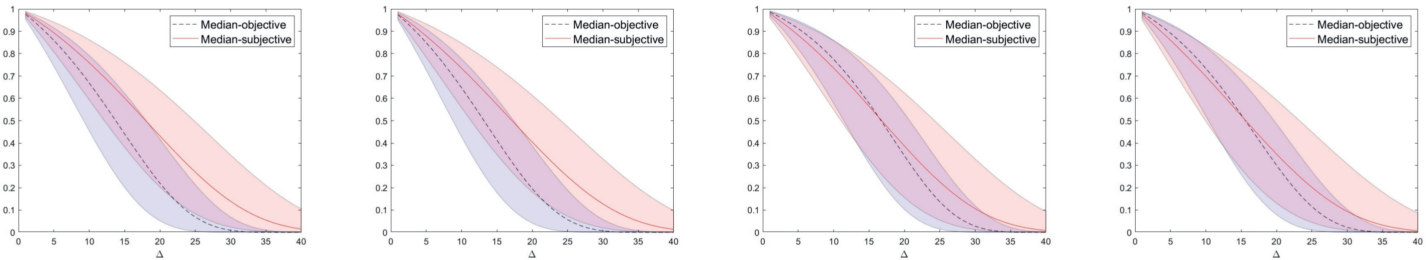
Figure 2.4: Predicted survival probabilities of 70-year-old people to survive for a certain number of years ($\Delta$), conditional on their partners' vital status

A. Dispersion in unobserved frailties




Males with partner alive | Males whose partner died | Females with partner alive | Females whose partner died

B. Dispersion in unobserved frailties and observed factors




Males with partner alive | Males whose partner died | Females with partner alive | Females whose partner died

*Note:* The left- and right-hand sides of the figure illustrate the predicted values of $P(T_i \geq 70 + \Delta | T_i \geq 70, T_{3-i} \geq 70 + d_{3-i} - d_i, x, \hat{\eta})$ if partners are alive, and $P(T_i \geq 70 + \Delta | T_i \geq 70, T_{3-i} = 70 + d_{3-i} - d_i, x, \hat{\eta})$ if partners died. Here $d_{3-i} - d_i$ is the age difference between spouse $3 - i$ and $i$, and $\hat{\eta}$ are the predicted values of unobserved frailties. $i = 1$ for males and $i = 2$ for females. The blue and red areas reflect the prediction heterogeneity induced via unobserved frailties in the top sub-figures, and via unobserved frailties and observed characteristics in the bottom sub-figures. In the top sub-figures, we set the values of the observed regressors equal to the sample average.

### 2.4.6 Share of optimistic individuals in the sample

In the previous sub-section, we compared the subjective and objective survival probabilities of 70-year-old median males and females to analyze whether they over or underestimate their survival probabilities. In this section, we analyze whether people over or underestimate their expected remaining life years conditional on their current age, gender, and marital status. The expected remaining life years can be calculated using the predicted survival curves. Once we compared the subjective and objective remaining life years of each individual for each year they observed in our sample, we computed the share of people who are optimistic regarding their remaining life years.

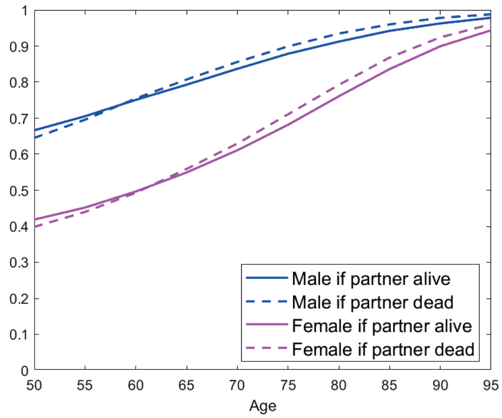
Figure 2.5 shows the share of people in our sample who are optimistic based on gender, age, and marital status. Our findings indicate that males exhibit higher levels of optimism than females across all age groups. For example, at age 70, approximately 82% of married males express optimism about their remaining life expectancy, compared to around 58% of 50-year-old married females. Furthermore, the prevalence of optimism increases with age, particularly among older individuals. This trend is consistent with the findings of Heimer et al. (2019) and O'Dea and Sturrock (2023), who also observed a rise in optimism among older individuals with regard to their survival. Additionally, our study reveals that the proportion of optimistic individuals among widowed and married people does not show significant differences for a given age and gender.

### 2.4.7 Dependent remaining lifetimes

The remaining lifetimes of spouses in a couple at a given age can be related through two different channels: (1) bereavement effects and (2) correlation between observed and unobserved factors that affect spouses' individual mortality hazards. We compare the expected remaining life years of people whose partners are alive with those whose partners died at a certain age and compute some counterfactuals to analyze the importance of the two different channels.[22] Figure 2.6 shows predicted expected remaining life-years conditional on surviving to a certain age, separately for males and females. The black and red lines are the objective and subjective expected remaining life years, respectively. The solid lines refer to the situation where the partner is alive, and the dashed lines refer to the case where the partner died.

[22] Gourieroux and Lu (2015) propose an index that measures the remaining lifetime dependency of spouses by comparing the hazard rates of spouses whose partners are alive with those whose partners died at a certain age. This index focuses only on the immediate changes in the hazard rates at the time of bereavement. Our approach is more general because it also considers the longer term effects of bereavement.

Figure 2.5: Share of optimistic people at given age, gender, and marital status




*Note:* The figure plots the share of optimistic people in the sample conditional on age, gender, and marital status. We define people as optimistic if their predicted subjective remaining life years are larger than their objective remaining life years.

The left-hand panels of Figure 2.6 depict the expected remaining life-years of average individuals if spouses' remaining lifetimes only depend on (un)observed factors. We set the baseline hazards of widowed people equal to those of married people, shutting down the bereavement effect channel.[23] The results show that, at a given age, if the partner is alive, expected remaining life years are slightly larger than if the partner died.

The middle panel of Figure 2.6 adds the bereavement effect. Once we introduce bereavement effects, there is a clear difference between the expected remaining lifetimes of individuals whose partners are alive and those whose partners are deceased. The bereavement effect reduces the predictions of widowed as well as married individuals, since the married people are at risk of losing their partner and facing a future increase in the mortality hazard due to bereavement.

On the right-hand side of Figure 2.6, we show the differences between the expected remaining lifetimes of those whose partners are alive and those whose partners are dead. The positive differences imply that spouses' remaining lifetimes are positively dependent because people whose partner is alive tend to live longer than those whose partner is dead. For example, males (females) who survived until age 60 would live on average 0.9 (1.5) more years if their partners were alive than if they died. Around 47% (35%) of this difference is explained by the correlated

[23] We have also analyzed scenarios in which either the channel via observed characteristics or the channel via unobserved frailties is present, and the other one is shut down. However, the impact of unobserved characteristics on the expected remaining life years was negligible, for males and females and for objective and subjective survival curves. We, therefore, do not show these results.

observed and unobserved factors, and the rest is explained by the fact that married people have not (yet) encountered any spousal bereavement. The difference falls as people age (see black solid and dotted lines in the right hand panel of Figure 2.6). As shown in the figures, if males (resp. females) survive to age 85 with their partners, they would live on average six (resp. eight) more months compared to males (resp. females) who lost their partners, and around 78% (resp. 87%) of this is explained by the bereavement effects. The relative importance of the bereavement effect thus increases with age, and its impact is more substantial for females than for males.

The right-hand panel of Figure 2.6 also shows that spouses' *perceived* remaining lifetimes are positively correlated. This implies that individuals whose partners are alive perceive that they would live longer than those whose partners are dead, keeping other variables constant. For example, males (resp. females) who reached age 60 perceive that they would live on average 1.5 (resp. 1.8) more years if their partners were alive compared to males who lost their partners at age 60. Around 64% (resp. 75%) of this perceived life-years gain is explained by the fact that they have not encountered any spousal bereavement. The rest is explained by the correlated (un)observed factors of both spouses. Compared to the impact of the bereavement effect on the actual remaining lifetimes, the relative importance of the bereavement effect in explaining the correlation in perceived remaining lifetimes falls as people get older. For example, if males (females) survive to age 85 with their partners, they perceive they would live on average six more months than males (females) whose partner died. Around 52% (65%) of this difference in perceived expected life-years at age 85 is explained by the fact that spouses have not encountered any spousal bereavement (yet).

Comparing the solid black and red lines on the right-hand side of Figure 2.6, we conclude that the magnitudes of the impact of having the partner alive on subjective and objective remaining life years differ. For example, males (females) younger than 90 (68) overestimate the impact of having their partner alive on their remaining life years. In contrast, older males (resp. females) underestimate the true impact of having their partner alive.

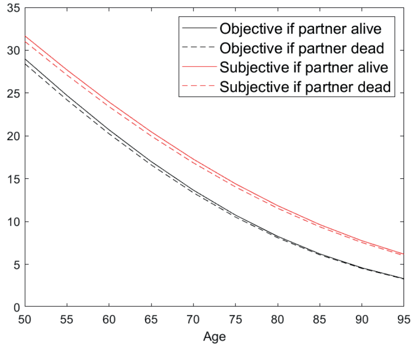
These differences in actual and *perceived* life expectancy can have important implications for understanding the demands of joint and survival annuities.[24] For example, if these annuity prices are actuarially fair and based on the actual life expectancy,[25] the couples who overestimate their expected number of years of living together would demand more joint and less survivor annuities keeping all else constant.

[24] The joint annuity makes an annual payment as long as both spouses are alive. The survival annuity makes an annual payment from the first spouse's death until the surviving spouse's death.

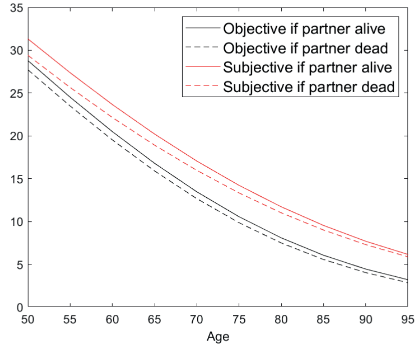
[25] For example, the value of the actuarially fair joint annuity is $\sum_{s=0}^{T} \frac{P(T_1 \geq t_1+s, T_2 \geq t_2+s | T_1 \geq t_1, T_2 \geq t_2)}{(1+r)^s}$, where we set $T = 100$ - the maximum age the individuals can reach. If $r = 0$, the value of the joint annuity equals the expected remaining life years conditional on male and female spouses aged $(t_1, t_2)$.

Figure 2.6: Expected remaining life years conditional on surviving to a certain age

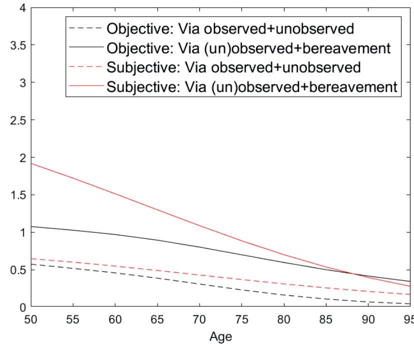
A. Males




dependent via observed + unobserved factors

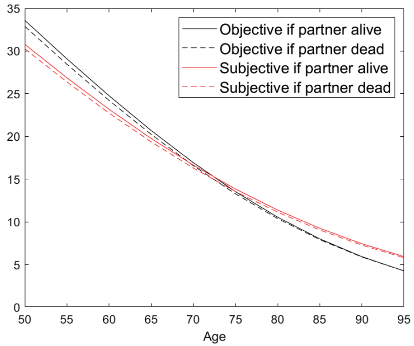



dependent via (un)observed+bereavement

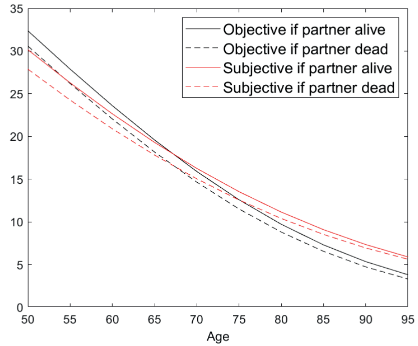



Difference between if a partner is alive & if dead

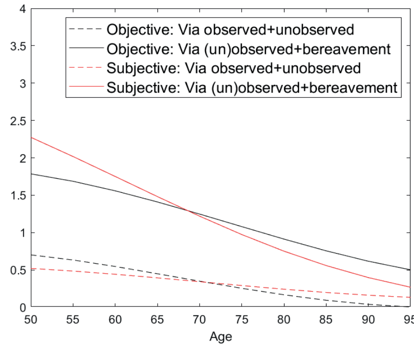
B. Females




dependent via observed + unobserved factors




dependent via (un)observed+bereavement




Difference between if a partner is alive & if dead

## 2.5 Conclusion

This paper estimates a model for married couples' joint actual and perceived survival probabilities using longitudinal data. We jointly estimate objective hazard rates using couples' actual, in-sample mortality and subjective hazard rates based upon reported subjective expectations to survive to certain target ages. Our model captures the dependence between the remaining life years of spouses by allowing for correlation between the observed and unobserved factors that explain mortality, as well as a structural change in the surviving spouse's baseline hazard rate when the first spouse dies, interpreted as a "bereavement effect".

We find that the remaining actual and perceived lifetimes of spouses are positively correlated. Subjective remaining lifetimes are more strongly dependent than objective remaining lifetimes, but this pattern reverses as couples age. At age 50, the bereavement effect accounts for approximately 34% and 68% of the immediate increase in objective hazard rates for males and females, respectively. The remaining part is explained by correlations between observed and unobserved factors. As couples age, the bereavement effect becomes the dominant factor in explaining the dependence of remaining objective lifetimes. However, the percentage of immediate increases in subjective log hazard rates explained by bereavement effects decreases as couples age.

There is a significant difference between actual and perceived survival probabilities for both males and females, as well as for married and widowed individuals. For example, 70-year-old median males overestimate their chances of survival, while 70-year-old median females underestimate their probability of surviving for another 15 years but overestimate their chances of surviving beyond 15 years. Misinterpreting their remaining survival probabilities could result in individuals allocating their assets sub-optimally over their lifetime. For instance, when all other factors are constant, young couples who are optimistic about their survival may consume too little than the optimal level, depleting their wealth too slowly.

Furthermore, the actual and perceived survival curves have substantial dispersion around their corresponding medians for a given age, gender, and partner's vital status. Most of the dispersion in actual survival curves is explained by variation in observed characteristics, while unobserved frailties explain only a small part. In contrast, both observed and unobserved factors explain substantial dispersion in perceived survival curves, resulting in more heterogeneity in people's subjective survival probabilities than in their actual survival rates at given observed characteristics.

Our predictions of married couples' survival probabilities can be used to predict couples' life-cycle choices. Since we propose predictions based on couples' elicited survival expectations, it is more credible to use our model to compute the aspects of the joint posterior distribution of survival that captures perceived dependence instead of using observed mortality data. Researchers can then relate the predicted perceived survival probabilities to some aspects of married couples' life-cycle decisions, especially their decisions before and after one of the spouses enters widowhood.

Throughout the paper, we have assumed that both spouses' subjective survival probabilities are common knowledge, and both spouses have the same expectations regarding both spouses' survival probabilities. In future research, these assumptions could be relaxed, e.g., by collecting more information on respondents' expectations on the survival chances of their spouses. In addition, in the paper, we assume that only baseline hazard parameters differ between married and widowed spouses. However, this assumption may be restrictive as it is possible that the impacts of other regressors, such as income, vary between married and widowed individuals. An interesting extension can be analyzed to relax this assumption by allowing for the possibility of varying impacts of observed regressors between the two groups.

Moreover, our empirical analysis aggregated eight chronic conditions and functional limitations. In future research, it would be interesting to explore the impact of each chronic condition and functional limitation individually, considering their unique contributions. This would provide a more comprehensive understanding of the specific effects of each factor on subjective survival probabilities.

## 2.6 Appendix

### 2.6.1 Predicting unobserved factors

Once we have estimated the parameters, we can impute the posterior means of the unobserved factors, using the algorithm in Chapter 12 of Train (2009). This is implemented as follows:

1. For each couple, generate 500x6 i.i.d. draw from a standard normal distribution. Let $Q$ be the matrix of generated random draws with dimensions 500x6. Calculate $\tilde{\eta} = Q\hat{\Lambda}$. Here $\hat{\Lambda}$ is the estimated lower-triangular Cholesky matrix of the covariance matrix of $\eta$.

2. Let $\tilde{\eta}_q$ be row $q$ of $\tilde{\eta}$, and define $\tilde{\eta}_q = [\tilde{\eta}_q^o, \tilde{\eta}_q^s, \tilde{\eta}_q^R]$. Then for each $q$, predict the conditional likelihood contribution of couple $n$ as follows:

$$L_{n,q}(\tilde{\eta}_q^o, \tilde{\eta}_q^s, \tilde{\eta}_q^R) = L_q^o(\tilde{\eta}_q^o) \cdot L_q^s(\tilde{\eta}_q^s, \tilde{\eta}_q^R) \tag{2.30}$$

   The conditional likelihood of couple $n$ is shown in Eq. 2.23.

3. Generate the weighting vector for each couple as

$$w_{n,q} = \frac{L_{n,q}(\tilde{\eta}_q^o, \tilde{\eta}_q^s, \tilde{\eta}_q^R)}{\sum_{\iota=1}^{500} L_{n,\iota}(\tilde{\eta}_q^o, \tilde{\eta}_q^s, \tilde{\eta}_q^R)} \tag{2.31}$$

4. Calculate the posterior mean of unobserved frailties of couple $n$ as

$$\hat{\eta}_n = \sum_{q=1}^{500} w_{n,q}\tilde{\eta}_q \tag{2.32}$$

Here $\hat{\eta}_n$ is a vector with 6 elements. We use these posterior means, $\hat{\eta}_n$, to predict each couple's survival probabilities and their expected remaining life years.

### 2.6.2 Dependence index of Gourieroux and Lu (2015)

To simplify the notation, let $\theta_i = (x_i, \eta_i)$ for $i = 1, 2$ and $\theta = [\theta_1, \theta_2]$. Here, we do not make a distinction between the objective and subjective hazards. The dependence index is calculated for both objective and subjective models and the results are reported in Section 2.4.

Let $g(\theta)$ be the p.d.f of $\theta$. Let $\gamma_1^{GL}(t_1, t_2)$ and $\gamma_2^{GL}(t_1, t_2)$ be the dependence index of Gourieroux and Lu (2015) from the perspective of male and female spouses when spouses have ages $(t_1, t_2)$. Without loss of generality, we show that the derivation of the index from the perspective of a male spouse (aka. spouse 1). The mortality hazards of spouse 1 unconditional on $\theta$

- if both spouses are alive at $(t_1, t_2)$, then

$$\lambda_1(t_1|T_1 \geq t_1, T_2 \geq t_2) = \left(\frac{\partial S(t_1,t_2)}{\partial t_1}\Big/ S(t_1,t_2)\right) \equiv \frac{S_1(t_1,t_2)}{S(t_1,t_2)} \tag{2.33}$$

- if spouse 2 dies at age $t_2$ and spouse 1 survives at age $t_1$, then

$$\lambda_{1|2}(t_1|T_1 \geq t_1, T_2 = t_2) = \left(\frac{\partial S(t_1,t_2)}{\partial t_1 \partial t_2}\Big/ \frac{\partial S(t_1,t_2)}{\partial t_2}\right) \equiv \frac{f_{1|2}(t_1,t_2)}{S_2(t_1,t_2)} \tag{2.34}$$

$\gamma_1^{GL}(t_1, t_2)$ is defined as the ratio of mortality hazard in 2.34 to 2.33. This implies

$$\begin{aligned}
\gamma^{GL}(t_1,t_2) &= \frac{\lambda_{1|2}(t_1|T_1 \geq t_1; T_2 = t_2)}{\lambda_1(t_1|T_1 \geq t_1; T_2 \geq t_2)} = \frac{f_{1|2}(t_1,t_2)}{S_1(t_1,t_2)} \cdot \frac{S(t_1,t_2)}{S_2(t_1,t_2)} && (2.35)\\
&= \frac{\mathbb{E}_\theta(\lambda_1^q(t_1|\theta_1)\lambda_2^p(t_2|\theta_2)S_0(t_1,t_2|\theta))}{\mathbb{E}_\theta(\lambda_1^p(t_1|\theta_1)S_0(t_1,t_2|\theta))} \cdot \frac{\mathbb{E}_\theta(S_0(t_1,t_2|\theta))}{\mathbb{E}_\theta(\lambda_2^p(t_2|\theta_2)S_0(t_1,t_2|\theta))} && (2.36)
\end{aligned}$$

Let $\mathbf{S}_0(t_1,t_2|\theta) = \frac{S(t_1,t_2|\theta))}{\mathbb{E}_\theta(\mathbf{S}(t_1,t_2|\theta))}$, then we can re-define the index in Eq. 2.36 as:

$$\begin{aligned}
\gamma^{GL}(t_1,t_2) &= \frac{\mathbb{E}_\theta(\lambda_1^q(t_1|\theta_1)\lambda_2^p(t_2|\theta_2)\mathbf{S}_0(t_1,t_2|\theta))}{\mathbb{E}_\theta(\lambda_1^p(t_1|\theta_1)\mathbf{S}_0(t_1,t_2|\theta))} \cdot \frac{1}{\mathbb{E}_\theta(\lambda_2^p(t_2|\theta_2)\mathbf{S}_0(t_1,t_2|\theta))} && (2.37)\\
&= \frac{\mathbb{E}_{\theta|T\geq t}(\lambda_1^q(t_1|\theta_1)\lambda_2^p(t_2|\theta_2))}{\mathbb{E}_{\theta|T\geq t}(\lambda_1^p(t_1|\theta_1))\,\mathbb{E}_{\theta|T\geq t}(\lambda_2^p(t_2|\theta_2))} && (2.38)
\end{aligned}$$

In the last line, $(T \geq t)$ stands for $(T_1 \geq t_1, T_2 \geq t_2)$ and the p.d.f $\theta$ conditional on $T \geq t$ is

$$g(\theta|T \geq t) = \frac{S_0(t_1,t_2|\theta)}{\mathbb{E}_\theta(S_0(t_1,t_2|\theta))} g(\theta). \tag{2.39}$$

After re-arranging the term in the second line of Eq. 2.38, one obtains the following:

$$\gamma_1^{GL}(t_1,t_2) = \frac{\mathbb{E}_{\theta|T\geq t}\left(\frac{\lambda_1^q(t_1|\theta_1)}{\lambda_1^p(t_1|\theta_1)} \frac{\lambda_1^p(t_1|\theta_1)\lambda_2^p(t_2|\theta_2)}{\mathbb{E}_{\theta|T\geq t}(\lambda_1^p(t_1|\theta_1)\lambda_2^p(t_2|\theta_2))}\right)\mathbb{E}_{\theta|T\geq t}(\lambda_1^p(t_1|\theta_1)\lambda_2^p(t_2|\theta_2))}{\mathbb{E}_{\theta|T\geq t}(\lambda_1^p(t_1|\theta_1))\,\mathbb{E}_{\theta|T\geq t}(\lambda_2^p(t_2|\theta_2))} \tag{2.40}$$

Using the assumption that conditional on $\theta$ the hazard rates follow the MPH form, Eq. 2.40 can be simplified further as the following way:

$$\gamma^{GL}(t_1,t_2) = \frac{\exp(\beta_1^q + \alpha_1^q t_1)}{\exp(\beta_1^p + \alpha_1^p t_1)} \cdot \frac{\mathbb{E}_{\theta|T\geq t}\Big(\exp(x_1\beta_1+\eta_1)\cdot\exp(x_2\beta_2+\eta_2)\Big)}{\mathbb{E}_{\theta|T\geq t}(\exp(x_1\beta_1+\eta_1))\,\mathbb{E}_{\theta|T\geq t}(\exp(x_2\beta_2+\eta_2))} \tag{2.41}$$

$$= \underbrace{\frac{\exp(\beta_1^q + \alpha_1^q t_1)}{\exp(\beta_1^p + \alpha_1^p t_1)}}_{\equiv A} \cdot \underbrace{\Big[\frac{COV_{\theta|T\geq t}\Big(\exp(x_1\beta_1+\eta_1)\cdot\exp(x_2\beta_2+\eta_2)\Big)}{\mathbb{E}_{\theta|T\geq t}(\exp(x_1\beta_1+\eta_1))\,\mathbb{E}_{\theta|T\geq t}(\exp(x_2\beta_2+\eta_2))} + 1\Big]}_{\equiv B} \tag{2.42}$$

In Section 2.4, we report the log of $\gamma^{GL}(t_1,t_2)$ because the log version of the index can be decomposed as a summation of the following two terms:

$$\ln \gamma^{GL}(t_1,t_2) = \ln A + \ln B \tag{2.43}$$

The first multiplier $\ln A$ captures the magnitude of the dependence due to a bereavement effect. Because for any relation between $\theta_1$ and $\theta_2$, the first multiplier equals zero if there is no bereavement effects. The value of the first multiplier positive (resp. negative) implies that bereavement effect increases (resp. decreases) the mortality hazard rates of surviving spouses. The second multiplier, $\ln B$ captures the dependence via the correlated (un)observed factors that affect spouses' mortality hazard rates. The second multiplier equals zero if there is no dependence via (un)observed factors. The value of the second multiplier that is positive (resp. negative) implies a positive (resp. negative) correlated (un)observed factors.

# Chapter 3.

# Heterogeneous response in labor supply to anticipated pension reforms

## 3.1 Introduction

In the past decades, concerns about ageing populations and the financial sustainability of pension schemes have pressured many European governments to raise the retirement age (OECD, 2017). However, the implementation of pension reforms often involves a long-drawn discussion among the various stakeholders with opposing interests and faces fierce public resistance (Immergut et al., 2007; Ciani et al., 2019). Discussions and debates about pension reforms usually attract intense mass media coverage, allowing people to anticipate the reforms. In response to their anticipation, people may then change their behavior if there is a benefit to doing so before the reform is adopted. Not accounting for such anticipatory behavior can substantially affect the estimated impact of the reforms (Malani & Reif, 2015).

We aim to answer the following two main questions in this paper: First, to what extent does anticipating a pension reform make individuals adjust their behaviour, particularly their employment status? Second, if the reform is actually implemented, does it affect people's labor

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supply differently depending on how strongly people anticipated the reform?

We focus on reforms that increased the statutory retirement age (SRA) because they were the most common type of pension reform in the past two decades in Europe (Carone et al., 2016).[1] The outcome of interest is the decision on when to change from employment to retirement, because the primary aim of these pension reforms was to delay the retirement of older workers. Compared to the previous literature on the importance of financial incentives for the retirement decisions and the effectiveness of pension reforms (see, e.g., Gruber and Wise (2002); Bozio (2008); Bernal and Vermeulen (2014); Carone et al. (2016); Lüthen (2016); Scharn et al. (2018)), we are the first to consider anticipatory behavior explicitly.

Our analysis starts by building a conceptual framework of forward-looking agents with heterogeneous anticipation regarding the timing of a reform that may increase their retirement age, à la Caliendo et al. (2019). The primary focus of our model is to investigate how individuals' expectations of imminent reforms affect their employment decisions. Specifically, we concentrate on individuals who are currently 50 years old, employed, and in the process of planning their retirement. These individuals already possess positive assets and are eligible for retirement benefits at the Statutory Retirement Age (SRA) of 65. However, the government is considering a proposal to increase the SRA before they reach the age of 65. If this happens, they would only be entitled to pension benefits after reaching the new SRA, without any adjustments to the level of monthly pensions they receive. To explore the various possibilities, we examine a range of anticipation levels among individuals, from no anticipation of the reform to complete certainty that it will be implemented, which reflects the heterogeneity in people's awareness regarding this potential SRA increase.

We derive two main predictions from our model on the relation between people's employment decisions and anticipation. First, keeping everything else constant, the more strongly people anticipate they will be affected by the reform, the longer they will remain employed. The intuition of this prediction is that increasing SRA decreases employed individuals' total discounted value of their future pension. To self-insure themselves against income loss (i.e., a decrease in the expected value of the total pension benefits) due to potential pension reform, risk-averse people who strongly anticipate the reform are the ones that are more likely to remain employed at older ages.

Secondly, we predict that the impact of the reform on the likelihood of remaining employed

[1] During the observed period, we identified thirteen major pension reforms in nine countries. Six of these reforms increased the SRA, while the remaining seven discouraged early retirement, decreased pension benefits, or lowered the SRA. Since the SRA-increasing reforms were the most frequent, we concentrated solely on this type of reform. This approach simplifies our analysis as different types of reforms could have different impact on labor supply.

is smaller for those who strongly anticipated the reform before its implementation. The rationale behind this prediction is that people who strongly anticipate the reforms are more likely to stay employed in the pre-reform period. Once they are affected by the reform, on average, the change in their employment rate induced by the reform will be smaller than for people who anticipated it less strongly.

To test the predictions of our economic model, we combine the Survey of Health, Ageing and Retirement in Europe (SHARE) with hand-collected detailed records on pension reforms in nine European countries. The former is representative data that provides information on the employment history of individuals aged between 50 and 64 and their elicited anticipation of changes in their SRA. The latter provides information on the history of individuals' SRA.

The main novelty of the paper is that we account for people's reform anticipation using elicited expectations data available in SHARE. Using direct data on anticipation allows us to take into account heterogeneity in anticipation that may not be captured by other observables. It is crucial to control for heterogeneity in anticipation because depending on how strongly people anticipate imminent reforms, the way they respond to reforms can be different. Indeed, several recent studies show that people form heterogeneous expectations for a given random process due to differences in processing and acquisition of information (Pfajfar & Žakelj, 2014; Armantier, Nelson, Topa, Van der Klaauw, & Zafar, 2016; Coibion & Gorodnichenko, 2015; Ciani et al., 2019).

We consider potential endogeneity and measurement issues in the elicited anticipation by implementing an instrumental variable approach. Our main instrument is the Google Trends index constructed with the keyword "pension reform." This index measures online information searches about pension reforms for each country. We rely on the identification strategy that the country-level online search intensity regarding pension reforms affects individuals' employment decisions only by changing their anticipation of their future retirement ages.

Since we combine information on multiple reforms that were implemented in different periods and countries, we observe variation in the timing of pension reforms. This allows us to identify the impact of the reforms while simultaneously controlling for age and year effects. This is an important advantage as governments tend to define the treatment assignment rule based on people's birth year, which is jointly determined by individuals' age and calendar year. Hence, if researchers focus on one pension reform, they are not able to identify the impact of the reform while controlling for age and year effects.

Our main findings are as follows. First, when all else is kept constant, people who strongly anticipate being affected by future pension reforms are more likely to remain employed. For example, among people who are employed at age 58, the average probability of remaining employed in the next two years is around 77% if they did not at all expect to be affected by a reform (i.e., reported anticipation is 0%), and 92% if they are certain that they will be affected by a reform (i.e., reported anticipation is 100%).

Next, the magnitude of the impact of the actually implemented reforms varies substantially depending on anticipation. For instance, when the SRA increases by one year, the probability that 58-year-old employees remain employed in the next two years increases by about eight percentage points if they did not anticipate this increase in SRA at all. In contrast, the same reform has no statistically significant impact on 58-year-old employees who were certain about the increase in SRA. These results are congruent with the prediction of our economic model that the reform impacts people's employment decisions less the more they anticipated the reform.

Individuals may opt to use disability insurance or unemployment insurance schemes as pathways into early retirement. Therefore, an increase in the SRA may raise the use of social insurance schemes.[2] Following this concern, we extend our baseline specification such that workers can use disability or unemployment insurance as alternative pathways into retirement. We do not find statistically significant evidence that reforms that increased the SRA affected people's use of alternative pathways to retirement. There is also no evidence that people respond to their anticipation by transitioning to states other than employed or retired. These results suggest that people act on their anticipation primarily by prolonging employment and delaying retirement instead of strategically transitioning to registering as disabled or becoming unemployed. One reason why we find these results is that several countries (e.g., the Netherlands, and Belgium) implemented regulations to limit the possibility of this type of substitution before or when increasing SRA.

We find that reforms that increased the SRA affected workers' employment decisions irrespective of their employment sector or whether they work full-time or part-time. On the other hand, older or at least college-educated workers respond more strongly than their counterparts. Furthermore, our results are robust under various alternative scenarios. For example, the point estimates of the effects of the reform and its anticipation on labor supply remain similar if we exclude people who are potentially exempted from the reforms because their job was physically demanding or one of the work, income, or asset-related variables is missing. Similar results are also obtained if we remove people 50% probabilities, which could indicate people's inability to reason in terms of probabilities (Bruine de Bruin et al., 2002).

[2] See, e.g., Atav, Jongen, and Rabaté (2019) analyzed the impact of Dutch pension reform that increased the SRA on labor supply.

The paper is structured as follows. Section 3.2 presents the economic model of forward-looking agents with heterogeneous anticipation of pension reforms. Section 3.3 describes our data construction procedure. The econometric model is discussed in Section 3.4. Section 3.5 shows the estimation results. The last section concludes.

# 3.2 Life-cycle model of older workers

## 3.2.1 Conceptual framework

In this section, we build a simple model to analyze the qualitative relationship between an economic agent's anticipation of an imminent reform that may increase her SRA and her employment decision.

The agent starts at age $\underline{\tau}$ in the model. She works at age $\underline{\tau}$ and plans when to retire. She lives until age $\bar{\tau}$ and dies with certainty before age $\bar{\tau}+1$: there is no mortality risk. The only uncertainty in the model is whether the agent is affected by the pension reform that increases her SRA. An increase in the SRA implies an increase in the age when the agent is eligible for pension benefits.

We formulate our model as one where the agent faces a sequential problem in a discrete finite-horizon setting starting from age $\underline{\tau}$ until she passes away. The main decision of the agent is when to retire and retirement is an absorbing state. Thus, the agent's problem can be described as an optimal stopping problem (i.e., finding an optimal age to stop working).

*Pension system and reform:* Let $\Omega_\tau$ be the state of the pension system when the agent is $\tau$ years old, where $\underline{\tau} \leq \tau \leq \bar{\tau}$. The pension system is summarized by the statutory retirement age (SRA), $R(\Omega_\tau)$, and benefit, $b(\Omega_\tau)$. There are two types of pension systems: $\Omega_\tau \in \{\omega_1; \omega_2\}$. At age $\underline{\tau}$, the pension system is $\omega_1$. Between ages $\underline{\tau}+1$ and $R(\omega_1)-1$, the agent is at risk of encountering a reform that shifts the system from $\omega_1$ to $\omega_2$ such that the reform increases the SRA, i.e., $R(\omega_1) < R(\omega_2)$. If the system shifts to $\omega_2$, the system stays at $\omega_2$ forever. The reform may be implemented, but the agent can be exempted from the reform if the agent is $R(\omega_1)$ or older by the time the reform is implemented.[3] If the agent is exempted, she is eligible to receive benefits according to the old system $\omega_1$, and she will not face any more uncertainty after the reform.

[3] It is common in Europe that governments exempt certain groups of people from pension reforms, e.g., those who have many years of pension contributions, who work(ed) in physically demanding jobs, or who are already retired.

Prior to the reform, the agent has some knowledge that system $\omega_1$ is unsustainable. She knows that if the system shifts to $\omega_2$, the retirement age increases to $R(\omega_2)$. She assumes that once the system is in $\omega_2$, the pension system will always remain in that state. She is also aware that she will be exempted from the reform once she passes age $R(\omega_1)$. If the system at age $\tau$ is $\Omega_\tau = \omega_q$, $q = \{1, 2\}$, the retired agent is eligible to receive benefit $b(\Omega_\tau)$ according to the following schedule:

$$b(\Omega_\tau) = \begin{cases} 0, & \text{if } \tau < R(\omega_1) \\ 0, & \text{if } R(\omega_1) \leq \tau < R(\omega_2) \text{ and the system shifted to } \omega_2 \text{ before the agent reaches age } R(\omega_1) \\ B, & \text{if } R(\omega_1) \leq \tau < R(\omega_2) \text{ and the system remains at } \omega_1 \text{ until the agent reaches age } R(\omega_1) \\ B, & \text{if } R(\omega_2) \leq \tau \end{cases} \tag{3.1}$$

where $B$ is a per-period pension benefit that can be obtained if the agent stops working. Eq. 3.1 shows that the benefit scheme is designed such that in state $\Omega_\tau = \omega_q$, $q = \{1, 2\}$, if the agent retires before reaching age $R(\omega_q)$, she does not receive any benefit. Once she reaches age $R(\omega_q)$, she is eligible to receive the pension benefit $B$ every year from period $R(\omega_q)$ until the end of her lifetime.[4]

*Anticipation of pension reform:* The agent is uncertain but anticipates the timing of the reform implementation. Let $T$ be the duration that the pension system remains in system $\omega_1$ from age $\underline{\tau}$ according to the agent's perspective. Let $P_{\underline{\tau}}^{R(\omega_1)}$ be the agent's subjective probability at age $\underline{\tau}$ that the system shifts to $\omega_2$ before the agent reaches age $R(\omega_1)$:

$$P_{\underline{\tau}}^{R(\omega_1)} = \mathsf{P}(T \leq R(\omega_1) | T > \underline{\tau}) \tag{3.2}$$

There are two reasons why we choose to measure the agent's anticipation via $P_{\underline{\tau}}^{R(\omega_1)}$. Firstly, we observe an elicited probability that people are affected by the reform before they retire in our data. Hence, we choose the probability in Eq. 3.2 as it connects the economic model to our empirical analysis. Secondly, since the agent is at risk of being affected by the reform until she

[4] For simplicity, we assume that $B$ is independent of the number of years the agent has worked until retirement, assets, and labor income. This assumption abstracts from the penalties on pension benefits for retiring earlier than $R(\omega_q)$. Since we aim to analyze the qualitative relationship between the agent's employment decisions and her SRA, this simplification serves our purpose. If the early and statutory retirement ages increase simultaneously with the same number of years and the rest of the pension system remains the same, the qualitative relations between the employment decisions and the SRA remain the same.

reaches age $R(\omega_1) - 1$, the primary concern for her is what the state of the pension system at age $R(\omega_1) - 1$ would be, instead of when exactly the reform is implemented. Here, $P_{\underline{\tau}}^{R(\omega_1)}$ is the most relevant measure of the agent's degree of anticipation because $P_{\underline{\tau}}^{R(\omega_1)}$ measures the agent's subjective probability that the system will be in $\omega_2$ by the time before she reaches age $R(\omega_1)$.

We assume $P_{\underline{\tau}}^{R(\omega_1)}$ is a function of a time-invariant hazard rate $\pi$: The probability that the system shifts to $\omega_2$ at age $s+1$ given that the system is in $\omega_1$ at age $s$, $\forall s$, $\underline{\tau} \leq s \leq R(\omega_1) - 1$. Under the time-invariant hazard rate assumption, there is a one-to-one relationship between $P_{\underline{\tau}}^{R(\omega_1)}$ and $\pi$:[5]

$$\pi = 1 - (1 - P_{\underline{\tau}}^{R(\omega_1)})^{\frac{1}{R(\omega) - \underline{\tau} - 1}}. \tag{3.3}$$

*Preferences and budget constraints:* At each age $\tau$, the agent receives utility $u(c_\tau, h_\tau)$ which is a function of consumption $c_\tau$ and labor supply $h_\tau$, where labor is a binary choice. Following French (2005), we assume that the flow utility of the agent at $\tau$ is represented by the constant relative risk aversion (CRRA) function:

$$u(c_\tau, h_\tau) = \frac{\left(c_\tau^\nu \cdot (\bar{L} - h_\tau \cdot \underline{L})^{1-\nu}\right)^{1-\gamma}}{1-\gamma}. \tag{3.4}$$

Here $\gamma > 0, \gamma \neq 1$ and $0 < \nu < 1$. These conditions are supported by empirical studies (see, e.g., French (2005); French and Jones (2011)) and used in various calibration studies as well (see e.g., Lusardi, Michaud, and Mitchell (2017)). At every age, the agent is endowed with leisure hours $\bar{L}$. If she works at age $\tau$, her leisure is reduced by the amount of work-hours $\underline{L}$.[6]

The agent can leave a non-negative bequest at the end of her lifetime, $a_{\bar{\tau}} \geq 0$, but she cannot die with debt.[7] The utility obtained from bequest $a_{\bar{\tau}}$ is as follows:

$$\eta(a_{\bar{\tau}}) = \theta_B \frac{(a_{\bar{\tau}} + K)^{\nu(1-\gamma)}}{1-\gamma}. \tag{3.5}$$

Here $K$ determines the curvature of the bequest function. If $K = 0$, there is infinite disutility of leaving a non-positive bequest. If $K > 0$, it can be optimal not to leave a bequest. $\theta_B$ is the bequest weight.

At age $\underline{\tau}$, the agent is endowed with non-negative assets. The agent only has access to a

5 See Appendix 3.7.1.2 for the derivation.

6 When we solve the model at given values of primitives, we set $\bar{L} = 4,000$ and $\underline{L} = 3,000$.

7 Since the agent is assumed to live with certainty until the end of age $\bar{\tau}$, there is no accidental bequest in this model. If the mortality risk is incorporated, it is necessary to impose that the agent's wealth cannot be negative for each period, see, e.g., French (2005). Otherwise, the agent may die in debt.

single risk-free bond, and her wealth is raised by an interest rate of $r$ each year. She is allowed to save and borrow.

In every period, the agent faces the following budget constraint:

$$a_{\tau+1} = h_\tau \cdot w + (1 - h_\tau) \cdot b(\Omega_\tau) + (1 + r)a_\tau - c_\tau \tag{3.6}$$

where $a_{\tau+1}$ is the savings at age $\tau$ and $w$ is the annual net labor income. The agent is eligible to receive the benefit $b(\Omega_\tau)$ only if she does not work at that age.

*Timing of the model and agent's problem:* At the beginning of each age, an individual observes the pension state $\Omega_\tau = \omega_q, q = \{1, 2\}$. Conditional on the realized pension system, she decides to work or retire $h_\tau$, and save $a_{\tau+1}$ (once $h_\tau$ and $a_{\tau+1}$ are determined, the consumption level $c_\tau$ is determined from the budget constraints). Retirement is a discrete choice that is modeled as a binary decision between working and retiring. Retirement is assumed to be an absorbing state; thus, if an individual decides to stop working at age $\tau$, she will not work from age $\tau$ until the end of age $\bar{\tau}$.

The agent is assumed to be an expected discounted utility maximizer. Following Rust and Phelan (1997) and Bernal and Vermeulen (2014), we formulate the agent's problem in terms of value functions of working $V^W(a_\tau, \Omega_\tau, \pi)$ and retirement $V^S(a_\tau, \Omega_\tau, \pi)$ which summarize the future consequences of choosing each alternative employment decision while accounting for the pension reform uncertainty the agent faces. The agent's expectation of future pension states is determined by her subjective hazard rate $\pi$.[8]

The agent's problem can be solved recursively according to the following two phases of her life:

1. *From age $R(\omega_1)$ to $\tau = \bar{\tau}$:* If the agent is affected by the reform before she reaches age $R(\omega_1)$, the system will remain in $\omega_2$. Otherwise, the agent will receive benefits according to system $\omega_1$. Thus, there will not be any uncertainty after the agent surpasses age $R(\omega_1)$. This implies that her decisions do not depend on her reform anticipation during this period.

2. *From age $\underline{\tau}$ to $R(\omega_1) - 1$*: Independent of whether the agent works or not at age $\underline{\tau} \leq \tau \leq R(\omega_1) - 1$, she is still at a risk of being affected by the reforms that may occur before she reaches age $R(\omega_1)$.

*Solution of the model:* Since this type of problem generally does not have a tractable analytical

[8] Equivalently, the agents' expectation of future pension states is determined by her subjective probability $P_{\underline{\tau}}^{R(\omega_1)}$ since there is a one-to-one relation between $P_{\underline{\tau}}^{R(\omega_1)}$ and $\pi$ shown in Eq. 3.3

solution, we follow the typical approach that is based on Bellman's optimality principle. The model is solved by backward recursion after discretizing assets, the only continuous state variable. We solve for optimal decisions on each point in the grid of assets for each period. At each point in the state space, we use a grid-search method to find the optimal solution of savings given that the agent is employed or retired at given age. Piece-wise cubic Hermite interpolation is used to find the value function when assets at $\tau + 1$ fall off the grid. Appendix 3.7.1.3 shows the value functions and explains the backward induction.

### 3.2.2 Comparative statics analysis of the relationship between reform anticipation and labor supply

In this subsection, we examine the retirement decision of a 50-year-old employed agent who is at risk of encountering a reform that increases her SRA from 65 to 70 (i.e., $R(\omega_1) = 65$ and $R(\omega_2) = 70$).[9] The agent's degree of anticipation at age 50 is $P_{\tau}^{R(\omega_1)} = P_{50}^{65}$: the subjective probability that the reform would hit her before she reaches age 65. In the comparative statics analysis, we set $P_{50}^{65} \in \{0; 0.25; 0.5; 0.75; 1\}$. To simplify the solution for the economic model, we do not consider the possibility that the agent would update her subjective probability $P_{\tau}^{R(\omega_1)}$ over time. However, our empirical analysis allows these probabilities to be time-varying.

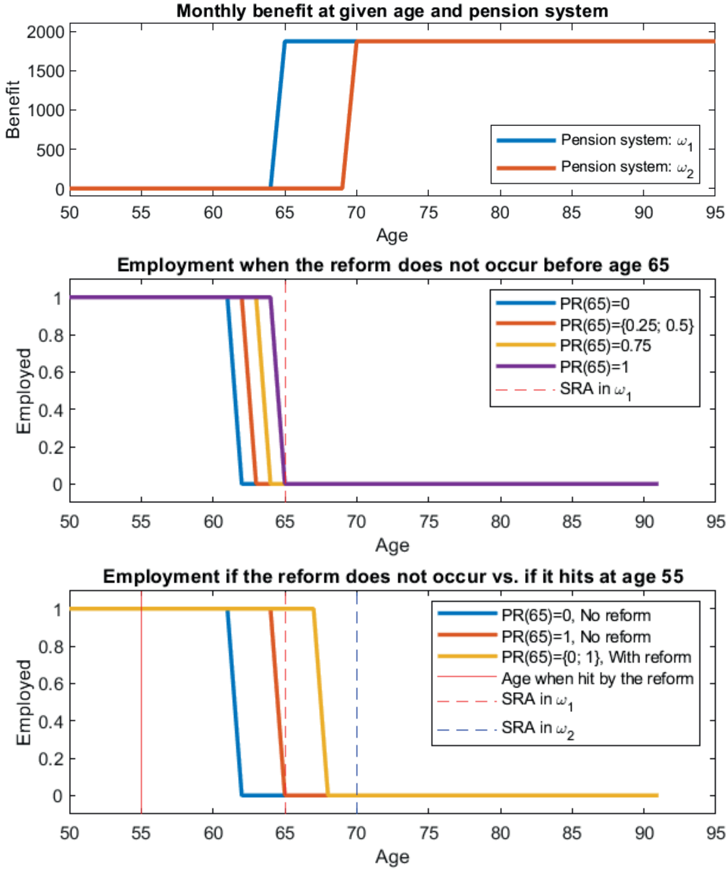
For the analysis in this sub-section, we set the monthly pension benefit to 1,700 euros. Table 3.7 in Appendix 3.7.1 shows the values set for the preference parameters and financial variables. The values for the preference parameters are obtained from the estimation results of French (2005). The values for initial assets and per-period income are based on the sample that we use for our empirical analysis. We set these financial values by rounding the sample averages to the nearest thousands.

Figure 3.1 illustrates the predicted labor supply of the agent conditional on her degree of anticipation and whether she is affected by the reform before she reaches age 65. The top of the figure shows the pension benefit scheme when the system is either $\omega_1$ or $\omega_2$ at a given age. Following Eq. 3.1, the agent is eligible for pension benefits starting from age 65 if the system remains in $\omega_1$ until the agent reaches age 65, or from age 70 if the reform is implemented before the agent reaches age 65.

The second sub-figure of Figure 3.1 illustrates four profiles of the agent with the degree of anticipation $P_{50}^{65} \in \{0; 0.25; 0.5; 0.75; 1\}$. Here $P_{50}^{65} = 0$ implies the agent does not anticipate any

[9] To demonstrate the model's predictions, we examine a hypothetical scenario with a reform that leads to a 5-year increase in the agent's SRA. Other increases (with, e.g., increases of 1, 2, or 3 years) may be more realistic but would lead to qualitatively similar responses.

Figure 3.1: Benefit scheme and employment decisions under different pension systems and degree of anticipation




*Note:* The top figure shows the benefit path when the pension system is in $\omega_1$ and $\omega_2$. In the old system, the age when an individual is eligible to obtain the full pension is 65, and in the new system, that age is 70. In the figure, $PR(65)$ refers to $P_{50}^{65}$. The middle figure shows the employment decisions of five individual profiles if they are not affected by the reform conditional on their degree of anticipation, given as $P_{50}^{65} = \{0; 0.25; 0.5; 0.75; 1\}$. In the bottom figure, we show the two profiles where the anticipation is $P_{50}^{65} = \{0; 1\}$. The bottom figure shows the scenarios if the reform does not affect the individual until they reach age 65 versus the reform hits them at age 55.

reform at all, whereas $P_{50}^{65} = 1$ implies the agent believes that the reform would occur before age 65 with certainty from her perspective at age 50. This sub-figure shows the agent's labor supply if she has not *actually* encountered any reform until she reaches age 65. The comparative statics analysis shows that if the degree of anticipation $P_{50}^{65}$ is $\{0; 0.25; 0.5; 0.75; 1\}$, the corresponding ages when the agent stops working are $\{62; 63; 63; 64; 65\}$. Following this result, we construct our first hypothesis as follows:

- *Hypothesis 1:* people with a higher degree of anticipation are more likely to remain employed

The rationale behind this hypothesis is the more strongly individuals anticipate the reform, the lower the expected value of their pension. Therefore, to self-insure themselves from income loss (i.e., decrease in the expected value of the total pension benefits) due to potential pension reform,[10] people who strongly anticipate the reform are the ones that are more likely to remain employed.

The bottom sub-figure of Figure 3.1 shows the agent's employment dynamics if she has not encountered any reform until she reaches age 65 vs. if she encounters the reform at age 55 when her subjective probability is either $P_{50}^{65} = 0$ or $P_{50}^{65} = 1$. It is shown that if no reform is realized, the corresponding retirement ages when $P_{50}^{65} \in \{0; 1\}$ are $\{62; 65\}$. However, if the agent is affected by the reform at age 55, she will retire at age 68 irrespective of her degree of anticipation. These results imply that if $P_{50}^{65} = 0$, the retirement age changes from 62 to 68. In contrast, if $P_{50}^{65} = 1$, the retirement age changes from 65 to 68. In other words, the stronger the reform anticipation, the lesser the impact of the reform. Based on this theoretical prediction, we construct our second hypothesis as follows:

- *Hypothesis 2:* The magnitude of the impact of increasing SRA on the probability of remaining employed is smaller for those who anticipated a reform more strongly.

The next two sections discuss our data set and our empirical strategy to test these hypotheses.

# 3.3 Data

This section discusses the datasets that we use for our empirical analysis. First, we discuss how we combine datasets from different sources. Second, we will discuss our sample selection procedure. Then we will explain our main variables of interest. For the rest of the paper, $i$ indexes individuals, $j$ indexes countries, and $t$ indexes survey waves.

## 3.3.1 Data construction

The dataset used in our study is constructed based on three sources. The first is the "Survey of Health, Aging and Retirement in Europe" (SHARE). In 2004/05, SHARE started collecting data on a representative sample of individuals aged 50 and over as well as their partners across twelve

[10] As shown in Eq. 3.4, the agents are risk-averse because their utilities are strictly concave in $c_t$ at given $h_t$.

European countries. Since then, 16 additional countries have joined the survey, and the next seven waves of data have been collected at approximately two-year intervals (2004/05, 2006/07, 2008/09, 2011, 2013, 2015, 2017, 2019). Wave 3 (2008/09) contains mostly retrospective data on sample members' lives.

SHARE contains information on employment status and the elicited anticipation regarding pension reforms that increase the retirement age. Moreover, SHARE has comprehensive information on each respondent's annual income, wealth, marital status, socioeconomic characteristics, education, numeracy, and self-reported health. Section 3.3.3 explains the definitions of the variables we use in detail.

We start with countries that participated continuously in the survey from wave one (2004/2005) until wave eight (2019). Furthermore, we selected the countries for which we can recover the SRA of respondents. Following these criteria, the selected countries are Austria, Belgium, Denmark, Germany, the Netherlands, Spain, France, Sweden, and Switzerland.

Our second dataset contains the history of pension reforms and the official SRA of each respondent from the selected countries. We retrieved the official dates of the major pension reforms in the selected countries from Immergut et al. (2007) for the reforms before Dec 31, 2007,[11] from Ciani et al. (2019) for the reforms after Jan 1, 2008. After constructing the information on the official dates of major reforms, we selected the reforms that increased the SRA between 2005 and 2019.

One shortcoming of the datasets provided by Immergut et al. (2007) and Ciani et al. (2019) is that they do not mention which groups of people from country $j$ were affected and how they were affected. This information is crucial to construct the official SRA of each panel member over time. We use various sources, including European Union reports, Organisation for Economic Co-operation and Development (OECD) publications, and online articles to determine who is treated by each reform and how their pension age has changed during the period of interest. For most reforms that increased the SRA, the treatment assignments were based on birth year/month and gender. Since we observe this information from SHARE, we can distinguish between treated and untreated groups for each reform for the selected countries.

The third dataset is Google Trends, which is the total number of searches for predefined keywords from the selected country and time horizon using a random sample from the complete database. The raw search counts data are not publicly available. Instead, Google scales the index to 100 in the month it reaches its maximum level, while the index in the other months is

[11] Immergut et al. (2007) describe the pension reforms in West Europe from early 1990 until 2007. Their dataset is available on the following link: `https://cadmus.eui.eu/handle/1814/64604`. Retrieved on September 10, 2021.

expressed as a proportion of the maximum. We used the keyword "pension reform" and retrieved the index from each country for each official language of that country during the period of interest.[12] We match SHARE respondents with the Google Trends index based on their countries, interview languages, years, and months.

### 3.3.2 Sample selection

By merging the data sets described in the previous subsection, we build a panel that contains the information we need for our estimation. Table 3.8 in Appendix 3.7.3 shows our sample selection procedure with the remaining observations after each selection step. The initial sample consists of 421,143 observations for 143,004 individuals. After keeping the countries of interest, 228,827 observations remained. We connect the employment state at wave $t+1$ to the reported anticipation at wave $t$. Thus, we select those who participated in SHARE for at least two consecutive waves. After this selection, 201,346 observations for 50,351 individuals remained. The drop at this step is mainly due to attrition in SHARE (Börsch-Supan, 2015).[13]

Our main interest is to analyze the transitions from employment to retirement. Thus, we select the respondents who were either employed or retired in wave $t+1$ and employed in wave $t$. This step excludes respondents who are permanently disabled, unemployed, homemakers, or whose employment states are unobserved either in wave $t$ or $t+1$ and retired in both $t$ and $t+1$.[14] After these selections, we are left with 59,132 observations for 17,915 individuals. Next, we selected individuals aged between 50 and 64 in wave $t$ because our interest is to analyze the behavior of older workers close to their retirement. We also dropped 58 respondents who were not citizens of the countries in which they were interviewed. After these steps, 50,230 observations for 16,711 individuals remained.

Next, we selected individuals who reported their anticipation of being affected by the future pension reforms in wave $t$. This selection reduced the sample to 35,317 observations for 14,730 individuals. The substantial decrease in sample size at this step is mainly due to the following

[12] Google Trends index is not available for country $j$ in a given language if the number of online articles in that language is too small. This can happen if the language is spoken by a small fraction of people and online articles are not published in the local languages. We encountered this problem when retrieving the index from Belgium in German, Switzerland in Italian and Romansh, and Spain in Galician and Basque. If the interview was conducted using the local languages in these countries, the corresponding Google Trends indices are replaced by the index in the major language. For example, it is replaced by Dutch, German, and Castilian Spanish for Belgium, Switzerland, and Spain, respectively.

[13] For example, the retention rate of SHARE between two waves, on average, was 73% between 2004 and 2013.

[14] Since wave three is mostly about respondents' retrospective data, whether the respondents were employed in that wave is missing. We set the respondents' employment states in wave three the same as in wave two if the respondents reported that their employment states did not change since wave two. We dropped those observations if we could not impute the employment state at wave three.

two reasons related to the survey design of SHARE. Firstly, since wave three focused on the retrospective data, SHARE did not ask about the reform anticipation in this wave. Secondly, starting from wave six, SHARE asked the reform anticipation only from the newly recruited respondents. Therefore, we observe few responses of reform anticipation in waves three, six, seven, and eight.

Finally, some countries have implemented multiple reforms between 2005 and 2019. If there were pension reforms in country $j$ that are not of our interest (for example, those that decreased the pension benefit or increased the early retirement age), we select the waves of country $j$ that are *around* the SRA reforms. Suppose other pension reforms that are unrelated to SRA, which are qualitatively different than our reforms of interests, were implemented in country $j$ in wave $\bar{t}$, and the SRA reform was implemented in wave $t^*$. If $\bar{t} < t^*$ (resp. $\bar{t} > t^*$), we drop the observations before (resp. after) and at wave $\bar{t}$. If the SRA is the only major reform of country $j$ during the period of interest, we use all available waves of that country.

After this selection, our sample consists of 29,309 observations for 12,215 individuals. In this sample, 68% of individuals were observed twice, 24% observed thrice, and the rest were observed at least four times.

Figure 3.2 describes the sample size at the relevant survey waves (i.e., survey years and months) for each country. Tables 3.9 and 3.10 in Appendix 3.7.3 show the descriptive statistics and the definition of the variables, respectively. In the following subsection, we describe the main variables of interest in detail.

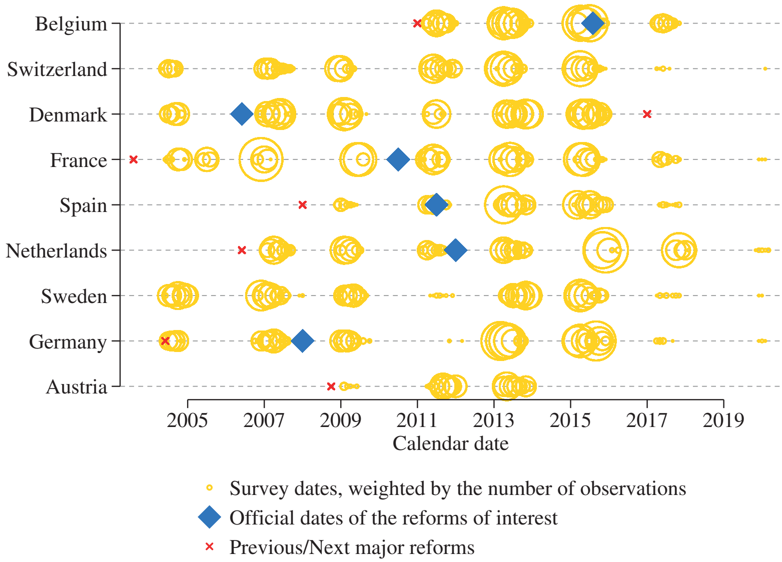
### 3.3.3 Main variables of interest

*Employment state at $t+1$:* Our main outcome is the employment state. Similar to previous studies on retirement behavior (Rust & Phelan, 1997; Karlstrom, Palme, & Svensson, 2004; Bernal & Vermeulen, 2014), in the main analysis, we define our outcome variable as a dummy indicating whether an individual is employed or retired in wave $t+1$ conditional on being employed in wave $t$. This variable is binary, which equals one if the respondent is employed or self-employed, or part-time employed in wave $t+1$; and zero if the respondent is fully or partially retired in wave $t+1$.[15]

*Anticipation at $t$:* SHARE asks the following question from the respondents who are employed or self-employed:

[15] Unfortunately, the SHARE does not have information on which respondents are fully and partially retired.

Figure 3.2: Pension reform dates and the number of observations for each country




Note: Figure depicts the sample sizes, shown in yellow circles, at the given year and month of the interview for each country. The smallest yellow circle is if one observation and the largest is if 442 observations at a given month, year, and country. The blue diamonds are the official dates when the pension reforms of interest. The red crosses indicate the official dates of the other major reforms that are not of interest. Our sample consists of 29,309 observations (individual $\times$ wave) for 12,215 individuals. The total number of households is 11,411. 68% of individuals were observed for two consecutive waves.

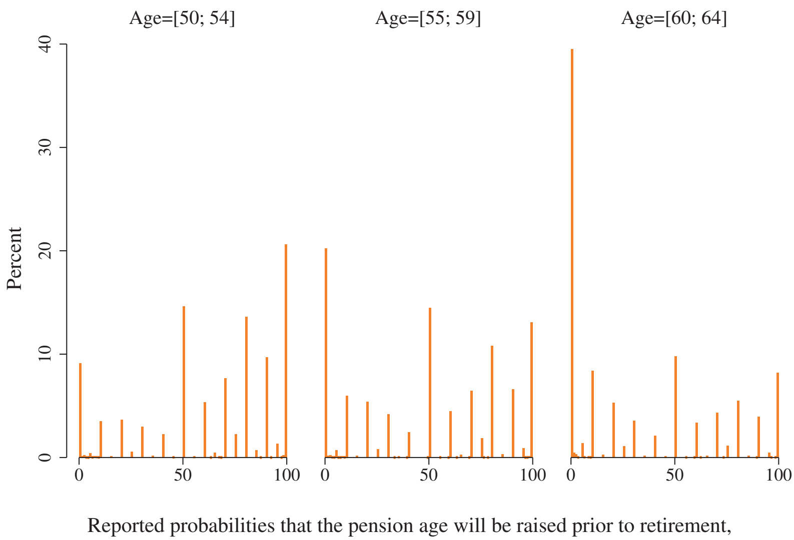
"*What are the chances that before you retire the government will raise your retirement age?*"

The respondents can choose a value between 0% and 100%, where 0% means absolutely no chance, whereas 100% means absolutely certain. It is also possible to choose not to respond, for example, by choosing "Don't know" or "Refuse to answer" options. We dropped those non-responses since fewer than 3% of the respondent chose these options.

Figure 3.3 shows the frequency of reported probabilities of anticipation by three age groups: people who are aged between 50 and 54, 55 and 59, and 60 and 64. The figure shows that as age increases, the frequency of reporting 100% decreases; whereas the frequency of reporting 0% increases. Moreover, the sample average of the elicited probabilities decreases as respondents' age increases. For example, the sample averages of the elicited probabilities are 63%, 49%, and 32% for people who are aged 50 to 54, 55 to 59, and 60 to 64, respectively. This negative correlation between the average elicited expectations and age is intuitive because most reforms are designed such that people who are close to their pension age are less likely to be affected by the reforms than younger people. Another reason why this negative relation makes sense is that the frequency of government intervention in the pension system has been increasing due to increasing insolvency (Caliendo et al., 2019; Carone et al., 2016). Thus, if individuals are far from their retirement, they stay longer periods at risk of encountering a reform compared to those who are close to their retirement.

As shown in Figure 3.3, around 17% of the respondents exhibit no uncertainty at all by reporting a 0% chance (certainty there will be no reform) and around 14% report a 100% chance (certainty there will be a reform) of a policy change before their retirement. Around 14% report 50%, which is substantially larger than the other responses, except those of 0% and 100%. A high concentration of responses at 50% could indicate people's inability to reason in terms of probabilities, also known as epistemic uncertainty, rather than expressing their uncertainty regarding the underlying process (Bruine de Bruin et al., 2002). In the main analysis, we do not exclude the responses of 50%. The robustness analysis will show the results where we exclude these responses.

Figure 3.3: Frequency of responses of the elicited anticipation in wave $t$ conditional on age groups




Note: Figure depicts the frequency of responses to the reform anticipation question conditional on respondents' age. The frequencies shown conditional on respondents' age at the interview are between 50 and 54, 55 and 59, and 60 and 64.

*Statutory retirement age.* We construct the SRA of each respondent using data from various sources. Appendix 3.7.2 shows the official implementation dates of pension reforms, which group of people was affected by the reforms, and to what extent their SRA has changed.

Figure 3.2 shows that only some countries of our interest had a reform that increased the SRA between 2005 and 2019. The major reforms were implemented in Belgium, Denmark, France, Spain, the Netherlands, and Germany. No major reforms that increased the SRA were implemented in Switzerland and Sweden. In Austria, the government increased the SRA in early 2005. Since the first wave of SHARE started in 2004/2005, most Austrian respondents are observed after 2005; thus, we do not consider the Austrian reform as of our interest.

Figure 3.4 shows the empirical distribution of the increase in SRA, relative to its pre-reform level, which is defined as:

$$\Delta\mathrm{SRA}_{ijt} = \mathrm{SRA}_{ijt} - \mathrm{SRA}_{ij,\mathrm{pre}}. \tag{3.7}$$

Here $\mathrm{SRA}_{ijt}$ is the official SRA of individual $i$ from country $j$ in wave $t$, and $\mathrm{SRA}_{ij,\mathrm{pre}}$ is that of in the pre-reform periods. For most countries, $\mathrm{SRA}_{ij,\mathrm{pre}}$ equals to 65. In France, $\mathrm{SRA}_{ij,\mathrm{pre}}$ is 60.

Figure 3.4 uses the observations if the increase in SRA is strictly positive. Following the definition in Eq. 3.7, SRA does not change for respondents who were not affected by the reform. SRA also does not change for respondents from countries that did not experience any reform during the period of interest, e.g., Switzerland, Sweden, and Austria.[16]

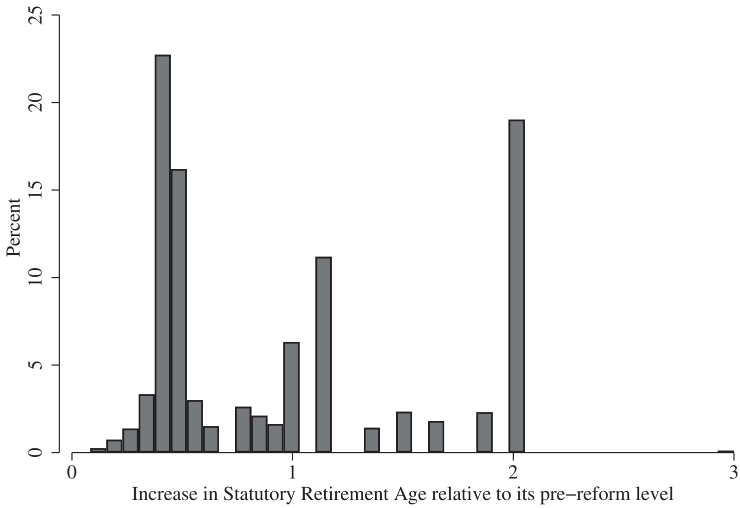
As shown in the figure, around 62% the respondents' SRA increased between 0.1 to 1 year. Around 37% of the treated respondents' SRA increased between 1.1 to 2 years, and for very few treated respondents' SRA increased by 3 years.

### 3.3.4 Descriptive evidence on the relationship between the probability of remaining employed and reported anticipation

Figure 3.5 shows the empirical probabilities of remaining employed at age $a + 2$ conditional on being employed at age $a$ following the fact that the average duration between two waves in SHARE is around two years. The x-axis shows age $a$, and the y-axis shows the empirical probability of remaining employed at age $a + 2$. In the figure, the empirical probabilities are calculated conditional on the reported anticipation at age $a$ being (1) below 20%, (2) between 21% and 79%, and (3) at least 80%. These cutoffs were chosen such that the sample is divided into three approximately equally sized sub-samples.

[16] Sweden did not implement any reforms. Switzerland implemented one reform in May 2019, but the reform was immediately abolished. Thus, we consider that Switzerland did not implement any reform during the period of interest. Austria increased the SRA of females in 2005, and no reform has been implemented since then.

Figure 3.4: Increase in SRA relative to its pre-reform level, restricted to the sample of respondents who experienced a reform



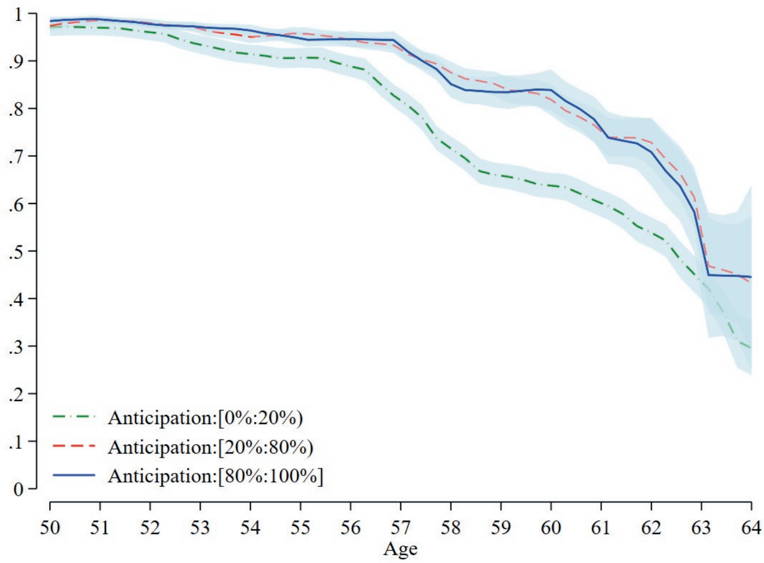

Note: The figure illustrates the increase in SRA relative to its pre-reform level using the working sample. We use 15,072 observations (around 51% of the main sample) of respondents who were affected by the reforms during the period of interest.

The figure exhibits no distinguishable difference between the employment rates of people whose anticipation degrees are 21-79% and 80%+. However, compared to the group of people with less than 20% of anticipation, people who have 21% or more anticipation have significantly higher employment rates, on average. The descriptive evidence is consistent with our hypothesis that people with higher anticipation regarding pension reforms are more likely to remain employed because they prepare more against the negative impact of the pension reforms on their financial well-being.[17]

Figure 3.7 in Appendix 3.7.3 shows the relation between the empirical probability of remaining employed and reported anticipation after controlling for various socio-demographic characteristics and the country and year effects. The positive association between the reported anticipation at age $a$ and employment rate at age $a + 2$ still holds even if we control for the effects of other observed covariates. However, we should be careful to establish the causality of the expectations on the labor market outcome since there can be multiple confounding factors. Section 3.4.2 discusses our strategy for solving potential endogeneity issues in anticipation.

[17] As illustrated in Figure 3.8 in Appendix 3.7.5, our results remain consistent when we plot the empirical probabilities of transitioning from employment to retirement at a given age, conditional on reported anticipation being within the following ranges: [0, 20%), [20%, 40%), [40%, 60%), [60%, 80%), and [80%, 100%].

Figure 3.5: Empirical probability of remaining employed for the next two years conditional on reported reform anticipation probability and age




*Note:* Working sample. The lines show the empirical probabilities of remaining employed at given age $a + 2$ conditional on respondents being employed at age $a$. The x-axis shows age $a$ and the y-axis shows the empirical probability of remaining employed at age $a + 2$. The empirical probabilities are calculated conditional on respondents' reported anticipation in the previous survey. The cutoffs of the reported anticipation (i.e., <20%, 21%-79%, and 80%+) were chosen such that the sample is divided into 3 approximately equally sized sub-samples. We use kernel-weighted local polynomial smoothing with the Epanechnikov kernel. 95% of CIs are depicted around their means.

### 3.3.5 Other variables

As shown in Table 3.9, in our sample, the average age is 56 years. 51% of the sample respondents are female. 75% of the respondents are married, 12% divorced, 0.3% widowed, and the rest never-married. Around 18% of the respondents evaluated their health state as excellent, 30% very good, 36% good, and the rest as either fair or poor. On average, out of 5 numerical skill questions, the respondents answered 3.7 of them correctly.

In the main analysis, we include several characteristics of the jobs in wave $t$ as explanatory variables. For example, we include whether the respondents were self-employed, employed in the private or public sector, and whether the job was full-time or part-time. We could not recover some respondents' work sector at $t$. We create a dummy for those individuals and treat them as a fourth job sector in the main analysis. About 52% of the respondents work in the private sector, 24% in the public sector, 13% are self-employed, and 11% of the respondents' work sector is missing in wave $t$.

We define the respondent as working full-time if the average number of hours worked per week is 36 or above in wave $t$. Around 78% of the respondents have a full-time contract, and the rest had a part-time contract.

In terms of the highest obtained educational degree, about 40% of the sample has a college or higher degree, 42% has an upper-secondary degree, 12% has a lower-secondary degree, and the rest has basic education.

We use the imputed annual household income and asset data available in SHARE. To make the income and asset data comparable across countries and different years, we first multiply their values by the Purchasing Power Parity index, where Germany in 2015 is the base. Next, we adjusted for household size following the OECD equivalence scale method (Burniaux et al., 1998). In our sample, the average annual log household income is around 10.24 (around 28 thousand euros), whereas the average annual log household real asset value is around 10.66 (around 43 thousand euros). If we exclude non-positive assets from the sample, the average of log assets is 11.3 (around 81 thousand euros).[18]

In waves 6 and 7, the Netherlands did not participate in the regular SHARE waves but conducted an experiment using an online survey or telephone interviewing instead of face-to-face interviews as conducted in the rest of SHARE countries. In these waves, the information on income, assets, and numeracy scores was missing if the respondent participated in Dutch Mixed Mode Interview. The information on income and assets were missing because their imputed versions are not available in the main SHARE, and the data with raw reported income and assets suffer from a high share of missing or unusual values. Furthermore, the questionnaires related to the numeracy scores were adapted and became incomparable to the regular SHARE questionnaire. Instead of dropping these observations, we generate a dummy "Dutch Mixed" which equals 1 if the respondents are interviewed in the Netherlands in waves 6 and 7, and zero otherwise. When "Dutch Mixed" equals one, the corresponding values of the income, assets, and numeracy scores are set to zero. In the robustness analysis, we check the sensitivity of our results if we exclude the observations of respondents who participated in "Dutch Mixed" interview.

[18] To make the annual income and assets comparable across countries and time, we adjusted the income and assets as follows: $f_{ijt}^{real} = \frac{f_{ijt}^{nominal} \cdot NE_{jt}}{PPP_{jt}} \cdot \frac{1}{\sqrt{hhsize_{ijt}}}$, where $f_{ijt}^{nominal}$ is the reported household income or assets of respondent $i$ from country $j$ at wave $t$. $NE_{jt}$ is the nominal exchange rate and $PPP_{jt}$ is the purchasing power parity index of country that $i$ is from at wave $t$. Both $NE$ and $PPP$ are available in SHARE. Germany 2015 is the base of the PPP. We also adjust the income and assets by household size. This procedure is done by dividing the financial variable by the square root of the number of people living together with $i$ at $t$. The minimum value the income can take is zero; whereas, the real asset can take a negative value. To convert these variables into logged form, we use the following monotone transformation rule: $\ln(1 + f_{ijt}^{real})$ if $f_{ijt}^{real} \geq 0$ and $-\ln(1 - f_{ijt}^{real})$ if $f_{ijt}^{real} < 0$.

## 3.4 Econometric model

### 3.4.1 Baseline specification

We estimate a binary outcome model where the transition from employed to retired can occur at discrete points in time corresponding to the individuals' ages. $y_{ij,t+1}$ is a dummy, which equals one if individual $i$ from country $j$ is employed in wave $t+1$ such that:

$$y_{ij,t+1} = \begin{cases} 1 & \text{if } y^*_{ij,t+1} \geq 0 \\ 0 & \text{if } y^*_{ij,t+1} < 0 \end{cases} \tag{3.8}$$

where

$$\begin{aligned} y^*_{ij,t+1} = \beta_0 + \underbrace{\beta_1}_{>0} \text{Ant}_{ijt} + \underbrace{\beta_2}_{>0} \Delta\text{SRA}_{ij,t+1} + \underbrace{\beta_3}_{<0} \text{Ant}_{ijt} \cdot \Delta\text{SRA}_{ij,t+1} ... \\ + \beta_4 \text{SRA}_{ij,\text{pre}} + \mathbf{a}_{ijt}\gamma_a + \mathbf{Z}_{ijt}\gamma_Z + \delta_{\mathbf{jt}} + \varepsilon_{\mathbf{ij,t+1}} \end{aligned} \tag{3.9}$$

The independent variables of primary interests are as follows. First, $\Delta\text{SRA}_{ij,t+1}$ equals:

$$\Delta\text{SRA}_{ij,t+1} = \text{SRA}_{ij,t+1} - \text{SRA}_{ij,\text{pre}}, \tag{3.10}$$

which is the difference between the SRA of respondent $i$ from country $j$ in wave $t+1$ and his/her pre-reform SRA. We subtract $\text{SRA}_{ij,\text{pre}}$ to ease the interpretation of parameters $\beta_2$ and $\beta_3$. By construction, $\Delta\text{SRA}_{ij,t+1}$ is positive if respondent $i$ from country $j$ is affected by the reform and $t+1$ is the post-reform period. Otherwise, $\Delta\text{SRA}_{ij,t+1}$ is zero. $\text{SRA}_{ij,\text{pre}}$ is included as an additional independent variable.

The second main independent variable is $\text{Ant}_{ijt}$: the perceived anticipation of $i$ that the government of country $j$ would increase his/her retirement age before $i$ retires. The variable $\text{Ant}_{ijt}$ is measured between 0 and 100. We also include the interaction between $\Delta\text{SRA}_{ij,t+1}$ and $\text{Ant}_{ijt}$ because our economic theory predicts that the magnitude of the impact of increasing the statutory retirement age depends on people's anticipation.

In our specification, the duration dependence in age is captured via age dummies, $\mathbf{a}_{ijt}$. We expect that the probability of transitioning from employed to retired is increasing in age. The additional covariates are summarized in vector $\mathbf{Z}_{ijt}$ including dummies for gender, for work sector (e.g., worked in the private or public sector or self-employed), for working full or part-time, highest obtained educational level, marital status, marital status interacted with gender, and a numeracy skill to control for the cognitive ability of the respondents. The time-varying variables in $\mathbf{Z}_{ijt}$ are from wave $t$. $\delta_{\mathbf{jt}}$ includes country and year effects to control for the time and country-specific conditions that affect individuals' labor market decisions, such as business cycles. We assume that $\varepsilon_{ij,t+1}$ follows a standard normal distribution. This implies a standard probit specification based on the latent variable defined in Eq. 3.9.[19]

The theory outlined in Section 3.2 has several implications for the signs of the parameters in this probit model. Firstly, ceteris paribus, the probability of remaining working increases if people anticipate the reform more strongly: $\beta_1 > 0$. Secondly, we expect that an increase in SRA increases the probability of remaining employed, i.e., $\beta_2 > 0$. The second hypothesis states that the magnitude of the impact of increasing the SRA on the probability of remaining working decreases if the anticipation is stronger. Since $\beta_2$ is expected to be positive, the second hypothesis is justified if $\beta_3 < 0$.

### 3.4.2 Solving measurement and endogeneity issues in anticipation

A critical issue in estimating the model in Eq. 3.9 is that the model specification can be incorrect in that it could have omitted some important variables. To address this issue, we account for a variety of individual-specific observed characteristics, as well as country and year effects. Yet concerns may remain about unobserved differences across individuals, e.g., motivation, ability, etc. The time-invariant unobserved factors can be controlled by including individual fixed effects (FE). However, including FE is not suitable in our context because 68% of the respondents in our sample are observed only twice, and the econometric model specification is defined such that variables at $t$ and $t+1$ explain a variable at $t+1$. Thus, including individual fixed effects would lead us to lose 68% of the sample.

Another issue in estimating the model is that the reported expectations can suffer from reporting bias and measurement error. Such bias and error may induce a correlation between anticipation and the error terms. In the main analysis, we assume the reporting bias and measurement error are additive and independent of the instrument variables.

To address these issues, we use an instrumental variable (IV) approach for the probit model. Our potentially endogenous regressors are anticipation- $\mathrm{Ant}_{ijt}$, and its interaction with $\Delta\mathrm{SRA}_{ij,t+1}$.

[19] A linear probability model gives similar results; see Table 3.15 in Appendix 3.7.5.

In the IV-probit model, we specify the first-stage equation as:

$$
\begin{aligned}
X_{ijt} = {} & \kappa_1^X Google_{jt} + \kappa_2^X Google_{jt} \times Read_{ijt} ... \\
& + \kappa_3^X Google_{jt} \times \Delta\mathrm{SRA}_{ij,t+1} + \kappa_4^X Google_{jt} \times Read_{ijt} \times \Delta\mathrm{SRA}_{ij,t+1} ... \\
& + \kappa_5^X Read_{ijt} + \kappa_6^X \Delta\mathrm{SRA}_{ij,t+1} + \kappa_7^X \mathrm{SRA}_{ij,\mathrm{pre}} + \mathbf{a}_{ijt}\kappa_a^X + \mathbf{Z}_{ijt}\kappa_Z^X + \delta_{\mathbf{jt}}^{\mathbf{X}} + \mathbf{u}_{\mathbf{ijt}}^{\mathbf{X}} \qquad (3.11)
\end{aligned}
$$

where $X_{ijt} = [\mathrm{Ant}_{ijt}, \quad \mathrm{Ant}_{ijt} \cdot \Delta\mathrm{SRA}_{ij,t+1}]$. The main equation remains the same; see Eq. 3.9. We assume $[\varepsilon_{ij,t+1}, u_{ijt}^{\mathrm{Ant}}, u_{ijt}^{\mathrm{Ant}\cdot\mathrm{SRA}^{\mathrm{norm}}}]$ follow tri-variate normal distribution, and $Var(\varepsilon_{ij,t+1}) = 1$ to identify the model.

As shown in Eq. 3.11, our excluded instruments in the first-stage are: Google Trends index with a keyword "pension reform" $Google_{jt}$,[20] its interaction with whether individuals' frequency of reading or watching news $Google_{jt} \times Read_{ijt}$, and their interactions with $\Delta\mathrm{SRA}_{ij,t+1}$. The reading activity $Read_{ijt}$ is a proxy for each individual's degree of exposure to publicly available information at a given time.[21] Interacting the reading activities with the country-level instruments generates individual-level variation in the instruments with sufficiently strong power to explain the endogenous regressors.

Why do we think our instruments are valid? Most pension reforms were preceded by several years of parliamentary debates and strikes before their implementation. Such events tend to attract mass media attention, and the public media are likely the primary information source to most individuals and are salient to individuals' beliefs (Jun, Yoo, & Choi, 2018). Furthermore, the exclusion restriction holds in our context under the assumption that country-level policy uncertainties affect the individuals' labor market outcomes only by changing their expectations regarding their own prospects.

One caveat of using the Google Trends index with the keyword "pension reform" is that the index is based on all online articles with the same keywords. Therefore, the index may be based on articles about increasing or decreasing SRA or reforms unrelated to SRA. However, since we construct the Google Trends index based on the months near our reforms of interest, most articles counted in our index should be about *the reforms that increase the SRA*. Hence, a priori, we expect a positive correlation between the anticipation $\mathrm{Ant}_{ijt}$ and Google Trends index $Google_{jt}$.

We include the interactions between the country-level indices with individuals' reading activities as shown in Eq. 3.11 to increase the strength of our instruments. The main motivation

[20] We chose the keyword "pension reform" because we need a reliable Google Trends Index based on a substantial number of online articles. Using more specific keywords, such as "reform that increases SRA," would lead to fewer relevant articles and a less powerful instrument.

[21] $Read_{ijt}$ equals two if a respondent reported that between wave $t-1$ and $t$, he or she read or watched news daily, one if monthly, and zero otherwise.

for including these interactions is that the country-level indices could have insufficient variation across individuals from the same country because the country-level indices only vary across time for a given country and language.

Instruments that are the interactions between the country-level and the individual-specific variables are also known as Bartik instruments, named after Bartik (1991), and popular in applied economic studies, see, e.g., Acemoglu and Linn (2004) and Card (2009). One may question the validity of the reading activities as these variables may be correlated with the error term of the structural equation, i.e., $\varepsilon_{ij,t+1}$. Following this concern, we include the reading activity in the structural equation in Eq. 3.9 as additional independent variables, but they are not considered as excluded instruments. Only the interactions between reading activity and Google Trends are excluded instruments. Our approach is valid if the interactions between reading activities and country-level uncertainties do not have a direct impact on the employment decision other than via anticipation, conditional on controls.

## 3.5 Results

This section discusses the estimation results. First, we select our main model specifications based on several model selection tests. Second, we interpret the estimation results of our main model specification. More specifically, we concentrate on interpreting the estimated impacts of an increase in SRA and anticipation on the probability of remaining employed in wave $t + 1$ conditional on being employed in wave $t$. The third subsection focuses on the other estimates.

In subsection four, we extend our baseline model specification such that there can be more than two transition states in wave $t+1$ conditional on being employed in $t$. We estimate the model with multiple transition states using the multinomial probit model. The fifth subsection analyzes the heterogeneous effects of an increase in SRA and anticipation conditional on respondents' gender, age, education, marital status, work sector, whether having full or part-time jobs, and numeracy score. The final subsection contains several robustness checks.

### 3.5.1 Model selection

Table 3.1 shows the estimated effects of the main regressors for the probit and IV-probit models, together with several model specification tests. Anticipation is excluded in the specification of the first column but included in the second and third columns. The first two columns follow the probit model, and the last column is the IV-probit model. In the IV-probit model, we consider the anticipation and its interaction with ΔSRA as potentially endogenous regressors. All specifications in the table include age dummies, country and year effects, and additional covariates. The standard errors are clustered at the household level. In Appendix 3.7.5, we show the estimated parameters of age dummies and of additional covariates, and the first-stage regression results of the IV-probit model.

Before we interpret our results, we run several model specification tests for the IV-probit model to determine whether we prefer probit or IV-probit model specification. First, the Kleibergen-Paap rk LM statistics test rejects the null that the IV-probit model is under-identified at a 1% significance level. Second, we run the weak instruments test proposed by Cragg and Donald (1993) and Sanderson and Windmeijer (2016). The null of these tests is that the IV-probit instruments are weak after controlling for additional covariates. If the instruments are weak, the conventional approximations to the distributions of the IV estimators are unreliable (Andrews, Stock, & Sun, 2019). We reject the null of these weak instrument tests at a 1% significance level for all specifications. Moreover, the first-stage regression results in Table 3.11 in Appendix 3.7.5 show that Google Trends have statistically significant and positive effects on the respondents' reform anticipation probabilities, which aligns with our intuition.

Third, the Sargan over-identifying restrictions test does not reject the null that our instruments are valid at 5% significance level. Note that we run a linear probability IV model to obtain the under-identification, over-identification, and weak instrument tests. Therefore these tests are illustrative since our structural equation is nonlinear. However, we suspect the results of these tests are informative about the strength and validity of our instruments.

Fourth, according to the Wald-exogeneity test, we do not reject the null hypothesis - that anticipation and its interaction with ΔSRA are exogenous after controlling for other covariates - at a 5% significance level. Therefore, we prefer the probit model specification because it is consistent and more efficient than the IV-probit.

The estimation results are robust if we exclude the additional covariates, as shown in Table 3.12 in Appendix 3.7.5. However, the log-likelihood test suggests that for each specification of Table 3.1, including additional covariates improves the predictive power of the model significantly. Therefore, we decide to keep the additional covariates and select the specification in the second column of Table 3.1 as our baseline specification. We provide the estimation results of both probit and IV-probit models throughout the following subsection for robustness purposes.

Table 3.1: Baseline estimation results

| VARIABLES | M1: Probit (1) | M2: Probit (2) | M3: IV-probit (3) |
|---|---|---|---|
| Anticipation | | 0.007*** | 0.015 |
| | | (0.001) | (0.01) |
| Anticipation × ΔSRA | | -0.005*** | -0.022 |
| | | (0.001) | (0.017) |
| ΔSRA | 0.15** | 0.392*** | 1.434 |
| | (0.056) | (0.092) | (1.05) |
| Pre-reform SRA | 0.089*** | 0.079*** | 0.058 |
| | (0.021) | (0.022) | (0.038) |
| Read | -0.041 | -0.038 | -0.022 |
| | (0.027) | (0.027) | (0.032) |
| Log-likelihood | -4,535.7 | -4,452.3 | -161,078.9 |
| Number of parameters | | | |
| - Probit | 54 | 56 | |
| - IV-probit - structural eq. | | | 56 |
| - First-stage | | | 58×2=116 |
| - (Co)variance of error terms | | | 5 |
| Age dummies | Y | Y | Y |
| Country effects | Y | Y | Y |
| Year effects | Y | Y | Y |
| Additional covariates | Y | Y | Y |
| Under-identification test: | | | |
| : Kleibergen-Paap rk LM (pval.) | | | <0.001 |
| Weak instruments test: | | | |
| : Cragg-Donald, $F_{5\%,rel} = 11.04$ | | | 12.26 |
| : SW (pval.): Anticipation | | | <0.001 |
| : SW (pval.): Anticipation × $\Delta\text{SRA}_{ij,t+1}$ | | | <0.001 |
| Sargan over-identifying restrictions test (pval.) | | | 0.82 |
| Wald-exogeneity test (pval.) | | | 0.65 |

Note: *** p<0.01, ** p<0.05, * p<0.1. Standard errors are clustered at a household level and reported in parentheses. The sample consists of $N = 29,309$ observations of 12,215 individuals from 10,369 households. In the IV-probit model, Anticipation and Anticipation × $\text{SRA}^{\text{norm}}$ are treated as potentially endogenous regressors. All specifications include age dummies, additional covariates, country effects, and year effects. SW stands for Sanderson-Windmeijer multivariate F-test of excluded instruments. The Cragg-Donald critical value when at 5% maximal IV relative bias is $F_{5\%,rel} = 11.04$, and at 10% maximal IV relative bias is $F_{10\%,rel} = 7.56$.

### 3.5.2 Baseline results

In the baseline results, shown in Column (2) of Table 3.1, the estimated coefficients of the main regressors are in line with our theoretical model prediction. More specifically, the estimated effects of ΔSRA and anticipation are positive and statistically significant, and that of the interaction term between these variables is negative and statistically significant. Therefore, according to our baseline estimation results, our hypotheses on the relationship between anticipation and people's decision of transitioning from employed to retired are confirmed.

According to the IV-probit model, shown in Column (3) of Table 3.1, the signs of the estimated parameters of $\Delta$SRA and anticipation are positive, and the interaction between these regressors are negative. These results also align with our economic theory. Compared to the baseline model in Column (2), in the IV-probit model, the magnitudes of the points estimates of the main parameters are larger but statistically insignificant.

To better understand the magnitudes of the estimated effects of anticipation and $\Delta$SRA,

Table 3.2: Predicted probability of 58-year-old average individual remaining employed at age 60 when the SRA remains at 65

| | M1: Probit<br>(1) | M2: Probit<br>(2) | M3: IV-probit<br>(3) |
|---|---|---|---|
| | 0.896*** | | |
| | (0.024) | | |
| Anticipation | | | |
| 0% | | 0.829*** | 0.691*** |
| | | (0.036) | (0.191) |
| 50% | | 0.898*** | 0.901*** |
| | | (0.025) | (0.025) |
| 100% | | 0.945*** | 0.981*** |
| | | (0.016) | (0.027) |
| Diff: 100% - 0% | | 0.116*** | 0.289 |
| | | (0.022) | (0.215) |

Note: Table shows the predicted probabilities of a 58-year-old worker remaining employed for the next two years when SRA remains at 65. The probabilities are computed at the sample averages of other regressors. Anticipation is excluded from the specification in the first column. In Column (3), we follow the two-step instruments variables estimator proposed by Rivers and Vuong (1988) and Wooldridge (2015) to calculate the predicted probabilities of the IV-probit model in this table. The standard errors of the corresponding estimates are calculated by block bootstrap to take into account the dependency among observations from the same households. More detailed discussion on the two-step procedure can be found in Appendix 3.7.4.

Table 3.2 shows the predicted probability of being employed at different degrees of anticipation for *average individuals*. We define the average individual as a German male who was 58 years old in 2015.[22] The predictions in Table 3.2 are based on the estimation results in Table 3.1. Table 3.2 suggests that the model that ignores anticipation (M1: Probit in Column (1)) predicts the probability of being employed at age 60 to be around 89%. However, the models that take into account the anticipation effects (M2: Probit in Column (2) and M3: IV-probit in Column (3))

[22] We set the values of additional covariates for the average individual by finding sample averages of the non-dummy variables and modes of the dummies. For example, the average individual has a college degree, and in 2015, he worked in the private sector with a full-time contract, evaluated his health as very good, and his numeracy score in 2015 was three. His annual income in 2015 was 22,000, and his assets 60,000.

predict substantial heterogeneity among average individuals' probabilities of being employed at age 60 conditional on how strongly they anticipate the pension reforms at age 58. For example, Column (2) shows that if the anticipation is zero, the probability of being employed is predicted to be around 83%. In contrast, if the anticipation is 100%, this probability is predicted to be around 95%. The difference between these probabilities is statistically significantly different from zero, as shown in the last row of the table. A similar conclusion will be drawn if we consider the results in Column (3). This evidence is consistent with the hypothesis that people who strongly anticipate the imminent reforms are the ones who are more likely to remain employed when all else is constant.

Table 3.3 shows the predicted changes in probabilities if the average individuals' SRA

Table 3.3: Predicted change in probability of 58-year-old average worker remaining employed at age 60 when the SRA increases from 65 to 66

| | M1: Probit (1) | M2: Probit (2) | M3: IV-probit (3) |
|---|---|---|---|
| Average effect of increasing SRA by one year | 0.024*** | 0.061*** | 0.197 |
| | (0.011) | (0.019) | (0.124) |
| Average effect of increasing SRA by one year conditional on anticipation | | | |
| 0% | | 0.082*** | 0.286 |
| | | (0.023) | (0.207) |
| 50% | | 0.027** | 0.051** |
| | | (0.012) | (0.023) |
| 100% | | -0.006 | -0.075 |
| | | (0.008) | (0.073) |
| Diff: 100% - 0% | | -0.088*** | -0.361 |
| | | (0.024) | (0.246) |

Note: Table shows the predicted changes in probabilities of a 58-year-old worker remaining employed for the next two years when his SRA increases from 65 to 66. The probabilities are computed at the sample averages of other regressors. Anticipation is excluded from the specification in the first column. See the footnote of Table 3.2 for the estimation methods to compute the predicted probabilities and the standard errors for IV-probit.

increases from 65 to 66 conditional on different degrees of anticipation. Column (1) of the table shows that the estimated effect of increasing SRA from 65 to 66 is around 2.4 percentage points for the model that neglects the anticipation effects. However, for the probit model that incorporates anticipation, the estimated effect rises to around 6.1 percentage points. This suggests that disregarding the anticipation effect would lead to an underestimation of the impact of the reform by around a factor of three.

Moreover, we find substantial heterogeneity in the estimated effect of SRA conditional on people's anticipation. Our baseline model that takes into account the anticipation shows that increasing SRA from 65 to 66 increases the probability of remaining employed by around eight percentage points for people who had no anticipation (i.e., 0% anticipation), but there is no significant effect for people who were completely certain that they would be affected by the reform (i.e., 100% anticipation). The difference in magnitudes of the effects of increasing SRA between those who did not anticipate and those who were completely certain is statistically significantly different from zero, as shown in the last row of the table. Considering IV-probit model estimates, we reach the same conclusions as in our baseline model. Thus, our empirical evidence corroborates our economic model prediction that people who strongly anticipate imminent reforms are less strongly affected by the reforms.

### 3.5.3 Estimated effects of age and additional covariates

According to the estimation results in Table 3.13 in Appendix 3.7.5, we find that the probability of transitioning from employed to retired state increases as people get older when all else is constant.

Table 3.14 in Appendix 3.7.5 shows the estimated coefficients of the additional covariates that are included in the specifications in Columns (1), (2), and (3) of Table 3.1. The signs of the estimated parameters of the additional covariates are as expected, and their magnitudes are similar across different specifications. For example, people who reported having better health are more likely to stay employed when all else is constant. Compared to never-married females, both married females and males are more likely to retire earlier. The parameter estimates for married males and females are not statistically significantly different. However, no significant differences exist between divorced or widowed people and never-married females. High-educated people are more likely to continue being employed than lower-educated people.

Compared to self-employed people, those who worked in both public and private sectors have a significantly higher probability of retiring earlier. Furthermore, people working in the public sector retire earlier on average than those in the private sector. Compared to people with part-time contracts, those with full-time contracts are more likely to remain employed.

We find that if income increases, the probability of remaining employed increases on average. However, the estimated parameter of logged income is statistically significant only at 10% and insignificant at 5%. We do not find any significant effects of assets, numeracy score, or reading activity on decisions of when to retire.

### 3.5.4 Multiple exit routes out of employment

The baseline analysis focused on the transition from employed in wave $t$ to either employed or retired in wave $t+1$. In this section, we extend the analysis such that there are more than two transition states in wave $t+1$ and estimate a multinomial probit (MP) model. The MP is an extension of M2: Probit model in Table 3.1. Appendix 3.7.4 explains the MP model in further detail.

We consider the transitions to the states other than employed and retired, such as disabled or unemployed, because people may use disability or unemployment insurance schemes as pathways into early retirement. To incorporate the transitions other than employment and retirement, we include the observations of people who reported to be disabled or unemployed in wave $t+1$ conditional on being employed in wave $t$. Therefore, the number of observations for this specific analysis increases from 29,309 to 32,625.

Table 3.4 shows predicted average marginal effects (AME: the marginal effects are calculated for each observation in the data and then averaged) of anticipation when SRA remains at 65. The table also shows the AME of ΔSRA when anticipation is either 0% or 100%. As shown in the table, we find no evidence that people respond to their anticipation by changing their behavior of transitioning into either disabled or unemployed states. Therefore, we find that people respond to their anticipation by prolonging their employment and delaying their retirement on average. Furthermore, the table shows that when the anticipation is zero, there is no evidence that the reforms that increase SRA changes the probability of transitioning to the states other than remaining employed or retiring.

Previous studies on whether people use disability or unemployment insurance schemes to transition to early retirement have reached different conclusions. This is mainly because researchers focus on specific reforms from different countries. For example, Rabaté and Rochut (2020) found that the French reform in 2010, which increased the SRA from 60 to 61, not only increased the employment rate but also increased unemployment and disability rates. In contrast, Atav et al. (2019) found no evidence that the Dutch reform in 2011 increased unemployment or disability rates. Our results are in line with Atav Atav et al. (2019). However, we should interpret our results cautiously because we aggregate multiple reforms. Therefore, our results should be interpreted as there being no evidence of an aggregate effect of the reforms in the countries analyzed increasing unemployment or disability rates.

Table 3.4: AME of SRA and anticipation to different transition states

| | Transition to retired in $t+1$ | | |
|---|---|---|---|
| | Retired | Employed | Disabled or unemployed |
| | (1) | (2) | (3) |
| AME | | | |
| $\text{Ant}\|_{\text{SRA}=65}(\cdot 100)$ | -0.083*** | 0.08*** | 0.003 |
| | (0.008) | (0.011) | (0.008) |
| $\Delta\text{SRA}\|_{\text{Ant}=0}$ | -0.079*** | 0.075*** | 0.004 |
| | (0.016) | (0.016) | (0.008) |
| $\Delta\text{SRA}\|_{\text{Ant}=100}$ | 0.002 | 0.002 | -0.004 |
| | (0.009) | (0.01) | (0.007) |

Note: *** p<0.01, ** p<0.05, * p<0.1. The table shows the estimation results of the multinomial probit model, which extends our baseline model M2: Probit. In wave $t$, individuals are employed. In wave $t+1$, they can transition to be (1) retired, (2) remain employed, or (2) become disabled or unemployed. Standard errors are clustered at a household level and reported in parentheses. The estimation used 32,625 observations for 13,483 individuals from 11,411 households.

### 3.5.5 Heterogeneous impacts of reforms and anticipation

To better understand what types of heterogeneity drive the effects of SRA and anticipation, we estimate the main model specification (M2:Probit) conditional on the following observables: (1) education, (2) age group, (3) gender, (4) marital status, (5) numeracy score, (6) work sector, and (7) whether employed full-time or part-time.

To test whether the effects of anticipation and ΔSRA vary across different socio-economic groups, we extend the main specification in Eq. 3.9 in the following way:

$$
\begin{aligned}
y^*_{ij,t+1} =& \beta_0 + \beta_1 \text{Ant}_{ijt} + \beta_2 \Delta\text{SRA}_{ij,t+1} + \beta_3 \text{Ant}_{ijt} \cdot \Delta\text{SRA}_{ij,t+1} + \beta_4 \text{SRA}_{ij,\text{pre}} + \mathbf{a}_{ijt}\gamma_a + \mathbf{Z}_{ijt}\gamma_Z + \delta_{\mathbf{jt}} \ldots \\
&+ \sum_{k=2}^{K} h^k_{ijt} \Big( \beta_0^{\text{h,k}} + \beta_1^{\text{h,k}} \text{Ant}_{ijt} + \beta_2^{\text{h,k}} \Delta\text{SRA}_{ij,t+1} + \beta_3^{\text{h,k}} \text{Ant}_{ijt} \cdot \Delta\text{SRA}_{ij,t+1} + \beta_4^{\text{h,k}} \text{SRA}_{ij,\text{pre}} \ldots \\
&\quad + \mathbf{a}_{ijt}\gamma_a^{\text{h,k}} + \mathbf{Z}_{ijt}\gamma_Z^{\text{h,k}} + \delta_{\mathbf{jt}}^{\text{h,k}} \Big) + \varepsilon_{\mathbf{ij,t+1}}.
\end{aligned}
\tag{3.12}
$$

In this specification, we separate the sample into $K$ groups, such that $h^k_{ijt} = 1$ if respondent $i$ is in the $k$th group, zero otherwise. According to the model in Eq. 3.12, $\beta_1$ captures the effect of anticipation for people from the first group (i.e., $h^1_{ijt} = 1$) and $\beta_1 + \beta_1^{\text{h,k}}$ for the $k$th group (i.e., $h^k_{ijt} = 1$ when $k > 1$) when ΔSRA=0. Similarly, parameters $\beta_2$ and $\beta_2 + \beta_2^{\text{h,k}}$ capture the effects of ΔSRA for groups with $h_{ijt} = 1$ and $h^k_{ijt} = 1$ for $k > 1$, respectively, given that the anticipation is zero. By testing whether $\beta_1^{\text{h,k}}$, $\beta_2^{\text{h,k}}$ and $\beta_3^{\text{h,k}}$ are statistically significantly different from zero, we analyze whether there exist differences in the effects of anticipation and ΔSRA between people from the first and the $k$th groups.

The key estimation results are summarized in Table 3.5. The main regressors are anticipation, $\Delta$SRA, and their interaction term. In Columns (1) and (2), we compare the effects of the main regressors between people with at least a college degree and those with at most an upper secondary degree. Column (2) shows that compared to those with at most an upper secondary degree, people with at least a college degree respond to their anticipation more strongly and get affected by $\Delta$SRA with a larger magnitude. These results can be driven by the fact that compared to the people with at most upper secondary degrees, those with at least college degrees have more flexible jobs in which they can more easily prolong their employment if they anticipate an imminent reform.

Columns (3) to (5) show the estimation results conditional on age groups. We define three groups based on respondents' age at the interview date: people aged between 50 and 54 ({50:54}), 55 and 59 ({55:59}), and 60 and 64 ({60:64}). Column (5) shows the estimated differences in the parameters of the main regressors between those aged {55:59} and {50:54}. We do not find any statistically significant differences in the effects of anticipation and $\Delta$SRA between these groups. Next, Column (6) shows the estimated differences in the parameters of the main regressors between those aged {60:64} and {50:54}. Compared to the group of people aged {50:54}, the oldest group aged {60:64} respond to their anticipation significantly more strongly when $\Delta$SRA=0. In other words, older workers are likely to respond to their anticipation with a larger magnitude compared to their younger counterparts. This can be because older workers may acquire more information on pension reforms since this information is more valuable to them as they approach their retirement (Kézdi & Willis, 2011; Ciani et al., 2019).

Table 3.18 in Appendix 3.7.5 shows the estimated heterogeneous effects of anticipation and $\Delta$SRA conditional on respondents' gender, numeracy score, and marital status. We do not find evidence that responses to anticipation differ between males and females, between married, never-married, divorced, or separated people, and between people with low and high numeracy scores.[23] We also do not find evidence that $\Delta$SRA affects retirement decisions differently depending on people's gender, marital status, and numeracy scores.

The next set of heterogeneity analyses involves with people's work sector. This analysis estimates the multinomial probit model where in wave $t$, people are employed in one of the following sectors: (1) public or (2) private, (3) self-employed, or (4) job sector missing. In wave

[23] To keep the analysis simple, we define numeracy as a dichotomous indicator that takes the value "High" if an individual scored more than or equal to four out of five questions and "Low" otherwise. In this way, around 40% of the responds belong to those with the "Low" numeracy score group, and the rest to those with the "High" numeracy score group.

Table 3.5: Heterogeneous effects of anticipation and ΔSRA conditional on education and age

| | Education | | Age groups | | |
|---|---|---|---|---|---|
| | College+ | Upper secondary - College+ | {50:54} | {55:59}-{50:54} | {60:64}-{50:54} |
| | (1) | (2) | (3) | (4) | (5) |
| Anticipation | 0.008*** | -0.003** | 0.005*** | -0.0001 | 0.003** |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.002) |
| Ant. × ΔSRA | -0.009*** | 0.007*** | -0.003* | 0.001 | -0.008** |
| | (0.002) | (0.002) | (0.002) | (0.002) | (0.003) |
| ΔSRA | 0.718*** | -0.506** | 0.316** | -0.076 | 0.264 |
| | (0.166) | (0.198) | (0.143) | (0.197) | (0.300) |
| Pre-reform SRA | 0.082** | 0.002 | 0.022 | 0.098* | 0.093 |
| | (0.040) | (0.047) | (0.055) | (0.069) | (0.074) |
| Read | 0.029 | -0.086 | -0.033 | 0.121 | -0.127 |
| | (0.056) | (0.064) | (0.030) | (0.111) | (0.095) |
| log-Likelihood | -4,416.6 | | -4,347.9 | | |

Note: *** p<0.01, ** p<0.05, * p<0.1. The table shows the heterogenous effects of anticipation, ΔSRA, and their interaction across certain socio-economic groups. The estimation results for the heterogeneous effects of the main regressors between people with at most upper secondary degree and at least a college degree are in Columns (1) and (2), and across different age groups are in Columns (3), (4) and (5). Standard errors are clustered at the household level and reported in parentheses.

$t+1$, they can transition to one of the following states: (1) being employed in the public sector or (2) private sector, (3) self-employed, or (4) retired.

Panel A of Table 3.16 in Appendix 3.7.5 shows the estimated average marginal effects (AMEs) of ΔSRA and anticipation on the probability of transitioning from a specific work sector in wave $t$ to retired in wave $t+1$. We find that increase in anticipation decreases the probability of retiring irrespective of people's employment sector in wave $t$. We also find that workers from different sectors respond similarly to their anticipation because the AME of anticipation is estimated to be similar across workers from different sectors. Furthermore, the AMEs of ΔSRA are significant and negative when anticipation is 0%. In contrast, the AMEs of ΔSRA are statistically insignificant when anticipation is 100%. The magnitudes of AME of ΔSRA are estimated to be similar across workers from different sectors. Hence, an increase in ΔSRA had a similar impact on workers from different sectors.

The final analysis concerns whether people work full-time or part-time in wave $t$. We estimate the multinomial probit model where in wave $t$ people are working (1) full-time or (2) part-time. They transition into one of the following states in wave $t+1$: (1) working full-time, (2) working part-time, or (3) retired.

Panel A of Table 3.17 in Appendix 3.7.5 shows the estimated AMEs on the probability of retiring in $t+1$. We find that AMEs of anticipation are similar across full-time or part-time workers. Hence, on average, people's response behavior on their anticipation is independent of whether people work full or part-time. Furthermore, the table shows that $\Delta$SRA has a similar impact on full-time and part-time workers.

In sum, how people respond to their anticipation varies substantially across workers' age and education. Older or at least college-educated workers tend to respond to their anticipation with a larger magnitude than their counterparts. However, we do not find substantial differences in workers' responses to their reform anticipation based on their gender, numerical skills, marital status, work sector, and whether they work full-time or part-time.

### 3.5.6 Robustness checks

Table 3.6 shows the estimation results for several robustness checks. All robustness analysis consists of different sample restrictions. The first column of the table shows the estimates of the parameters and the estimated AME of the main regressors when we use the entire sample (i.e., estimation results from Column (2) of Table 3.1).

Our first robustness check relates to the responses of 50% in an elicited anticipation. A high concentration of responses at 50%, relative to other valus, could indicate people's inability to reason in terms of probabilities, also known as an epistemic uncertainty, rather than expressing their uncertainty regarding the underlying process (Bruine de Bruin et al., 2002). Taking into account this concern, we drop the responses of 50% in reform anticipation, leading to around a 9% decrease in sample size. As shown in Column (2) of Table 3.6, the parameter estimates of anticipation, $\Delta$SRA, and the interaction between these variables remain robust if we use the sample that excludes the responses of 50% in reform anticipation.

The second check is related to missing values in work sectors. After dropping the observations where the work sector is missing in wave $t$, our sample decreased by around 5%. As shown in Column (3) of Table 3.6, dropping the observations with missing work sector does not alter the estimates of the parameters of the main regressors. Thus, our results remain robust.

The third check is related to the missing values in income, assets, and numeracy score for the Dutch Mixed Mode Interview. We dropped the observations collected via Dutch Mixed Mode interviews in waves six and seven. The corresponding estimation results after this drop are shown in Column (4) of Table 3.6. Our results remain robust.

The last check is related to the individuals who are *potentially exempted* from the reforms. According to the reforms of our interest, people could have been exempted based on the following two criteria: (1) if they did physically demanding jobs (e.g., miners and armed forces) or (2) if they had a large number of years of pension contribution.[24]

We define that respondents are potentially exempted as follows. Suppose that country $j$ exempts respondents if they were doing physically demanding jobs, and they could have contributed $T^*$ number of years to the pension funds by the time they reach the pre-reform SRA. In that case, we define the respondents from country $j$ are potentially exempted based on the following two criteria:

1. Whether respondents reported that their jobs were physically demanding.[25]

2. Assuming that they continued working non-stop from the last observed wave until their pre-reform SRA, we compute the maximum contribution years the respondents can attain by summing up the followings: (1) self-reported contribution years in their last observed wave and (2) the number of years between their last observed survey year and the year they could have reached their pre-reform.[26] Then, the respondents satisfy the second criterion if their maximum contribution years exceed or equal to $T^*$.

It is possible that country $j$ uses only one of the criteria mentioned above to exempt or does not exempt anyone. Therefore, definitions of the potentially exempted vary across countries.

After dropping the potentially exempted respondents from the reforms, our sample decreased by around 18%. Column (5) of Table 3.6 shows the estimation results when we exclude the potentially exempted individuals' observations. When we exclude the potentially exempted respondents from the sample, the estimates of the parameters of the main regressors remain similar to those in Column (1).

Finally, we dropped observations if they were dropped in at least one of the previous four selections. Following this selection, we dropped around 33% of the sample, and the corresponding results after this selection are shown in Column (6) of Table 3.6. Our results still remain robust.

[24] For example, in France, if an individual's number of contribution years is at least 40 by the time he/she reaches pre-reform SRA, he/she is exempted from the reform. Germany set this year as 41, and Spain set this year as between 36 and 38 depending on individuals' birth cohort. More detailed information on the exemption rules can be found in Appendix 3.7.3.

[25] In each wave, SHARE asks whether the respondents' job is physically demanding. The respondents can answer by choosing one of the following six options: (a) Strongly agree, (b) Agree, (c) Disagree, (d) Strongly disagree, (e) Don't know, and (f) Refuse to answer. We consider that people who answered "strongly agree" to this question are the ones that do physically demanding jobs.

[26] Suppose respondent $i$ with age 55 from country $j$ observed in the survey *last time* in 2005. He/she reported that his/her contribution years be 35. Country $j$ implemented the reform in 2010, exempting those who have 40 years of contributions by age 65. In this case, the respondent $i$ is potentially exempted because his/her "maximum potential years of contribution" for respondent $i$ by age 65 will be 45, assuming that the respondent $i$'s employment status will not be interrupted until he/she reaches 65. If the respondent has never reported his/her contribution years, we imputed that year by subtracting 18 (or 22) from the current age if the respondent's highest obtained education is a high-school degree or below (or bachelor or more).

Table 3.6: Estimation results for robustness check

| | Full sample | Drop if answered 50% as anticipation | Drop if work sector missing | Drop if Dutch mixed | Drop if potentially exempted | Drop if at least one of the conditions in Col. (2) to (4) holds |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Anticipation | 0.006*** | 0.006*** | 0.006*** | 0.006*** | 0.006*** | 0.006*** |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |
| Ant. × ΔSRA | -0.004*** | -0.004*** | -0.004*** | -0.004*** | -0.004*** | -0.003*** |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |
| ΔSRA | 0.393*** | 0.397*** | 0.353*** | 0.376*** | 0.361*** | 0.259** |
| | (0.092) | (0.097) | (0.095) | (0.093) | (0.096) | (0.097) |
| Pre-reform SRA | 0.079*** | 0.079*** | 0.08*** | 0.08*** | 0.075*** | 0.075*** |
| | (0.022) | (0.023) | (0.022) | (0.022) | (0.022) | (0.024) |
| log-Likelihood | -4452.3 | -3899.6 | -3962.7 | -4376.3 | -3626.6 | -2809.3 |
| Observations | 29,309 | 26,820 | 26,935 | 27,975 | 24,238 | 19,746 |
| AME | | | | | | |
| - ΔSRA | 0.032*** | 0.034*** | 0.029*** | 0.032*** | 0.0301*** | 0.022*** |
| | (0.009) | (0.01) | (0.009) | (0.009) | (0.01) | (0.01) |
| - Ant.· 100 | 0.082*** | 0.083*** | 0.08*** | 0.083*** | 0.081*** | 0.082*** |
| | (0.007) | (0.007) | (0.007) | (0.006) | (0.007) | (0.008) |

Note: *** p<0.01, ** p<0.05, * p<0.1. The table shows whether our baseline estimation results remain robust under different samples. The first column shows the baseline estimation results. In Column (2), we drop the responses of 50% in an elicited reform anticipation probabilities. In Column (3), we drop if the respondents' work sector is missing. In Column (4), we drop if the respondents participated in Dutch Mixed interviews. In Column (5), we dropped if the respondents are potentially exempted from the SRA reforms of our interest. The final column shows the results if the respondents' observations dropped in at least one of the previous four selections. Standard errors are clustered at the household level and reported in parentheses.

## 3.6 Conclusion

In this paper, we analyzed how workers' retirement decisions are affected by their anticipation of imminent pension reforms that could increase their statutory retirement age. We propose a novel method to control for people's anticipation using elicited expectation data available in a representative survey.

To understand people's responses to their perceived anticipation, we develop a life-cycle model of the forward-looking agent. The model predicts that people who strongly anticipate that they will be affected by future reforms are more likely to remain employed. Moreover, those people are the ones that are less strongly affected by the reform.

In the following step, we tested the hypotheses obtained from our economic model. We constructed a dataset of the pension reform history of nine European countries and combined it with individual-level data on anticipation and employment history.

Our analysis shows that ignoring people's response to anticipation would result in underestimating the magnitude of the reform effect. For instance, when anticipation is ignored, the estimated impact of increasing SRA from 65 to 66 on the probability that a 58-year-old employee remains employed in the next two years, is approximately two percentage points. However, when accounting for the anticipation mechanism, the estimated total impact of the same reform is approximately six percentage points, an underestimation by a factor three.

Secondly, we find that people respond to their anticipation by prolonging their employment and delaying their retirement. Moreover, people who had strong anticipation in the pre-reform period were affected by the reforms with a lesser magnitude than those who anticipated weakly. For example, we find that the estimated effect of increasing SRA from 65 to 66 increases the probability of remaining employed at age 60, conditional on being employed at age 58, by around eight percentage points if those individuals do not anticipate the reform. In contrast, this effect is estimated to be insignificant for individuals who anticipated that they would certainly be affected by the reform.

Finally, we find that older or at least college-educated workers respond to their anticipation more strongly than their respective counterparts. For robustness purposes, we consider the potential endogeneity issues in reported anticipation using an instrumental variable approach. However, we do not find evidence supporting reported anticipation is endogenous after controlling for respondents' various socioeconomic factors, cognitive ability, job characteristics, and health status.

In this paper, we focus explicitly on the timing uncertainty of pension reforms, i.e., when the reform will be implemented. However, due to the lack of data in SHARE, we do not consider the uncertainty regarding the magnitude of the increase in SRA, i.e., if the reform is implemented, how it would change the SRA relative to its pre-reform level. Further research could investigate the impact of this uncertainty related to the magnitude of the change in SRA, in conjunction with timing uncertainty, on people's retirement decisions.

## 3.7 Appendix

### 3.7.1 Economic model

#### 3.7.1.1 Definition of notations and values used for model solution

Table 3.7: Notations and parameter values used for the economic model prediction

| Notation | Definition | Baseline values |
|---|---|---|
| $\tau$ | a period indicator; one period equals one year of human life | |
| $\bar{\tau}$ | The maximum number of periods the agent lives | 100 |
| $r$ | One-period interest rate of risk-free assets | 0.01 |
| $\beta$ | One-period discount rate | $1/(1+r)$ |
| $\gamma$ | Risk aversion parameter of CRRA utility | 3.2 |
| $\nu$ | Consumption weight | 0.7 |
| $\theta_B$ | Bequest weight | 0.7 |
| $K$ | Bequest utility curvature parameter | 100 |
| $\Omega_\tau; \{\omega_{1,\tau}, \omega_{2,\tau}\}$ | pension system; and realizations of $\Omega_\tau$ | |
| $b(\Omega_\tau)$ | Pension benefit | |
| $v_P$ | The realization of the reform date | |
| $w$ | One period exogenous labor income | 36,000 |
| $\pi$ | Subjective probability that the system would change into | |
| | $\omega_2$ in period $s$ conditional on the system is $\omega_1$ in period $\tau$ | |
| $c_\tau$ | Consumption at period $\tau$ | |
| $l_\tau$ | Leisure state at period $\tau$ | |
| $a_\tau$ | Accumulated asset at period $\tau$ | |
| $a_0$ | Initial endowment | 180,000 |
| $u(c_\tau, l_\tau)$ | Utility function depends on consumption and leisure at $\tau$ | |
| $beq(a_{\bar{\tau}})$ | Bequest function depends on the assets at period $\bar{\tau}$ | |
| $\bar{L}$ | Monetary value of having a leisure for one period | 5200 |
| $\underline{L}$ | Monetary value of not having a leisure for one period | 800 |
| $V^W(a_\tau, \omega_q, \pi)$ | Value function if continues working and if stop working | |
| $V^S(a_\tau, \omega_q, \pi)$ | Value function if stops working | |

#### 3.7.1.2 Derivation of the hazard rate

We assume that the subjective hazard rate is time-invariant, i.e.,

$$\pi = \mathsf{P}(T = s + 1 | T > s) \tag{3.13}$$

Then, one can establish the connection between $P_\tau^{R(\omega_1)}$ and th hazard rate $\pi$ as follows:

$$
\begin{aligned}
P_\tau^{R(\omega_1)} &= \mathsf{P}(T < R(\omega_1)|T > \tau) \\
&= 1 - \mathsf{P}(T \geq R(\omega_1)|T > \tau) \\
&= 1 - \prod_{s=\tau}^{R(\omega_1)-1} \mathsf{P}(T \geq s+1|T > s) \\
&= 1 - \prod_{s=\tau}^{R(\omega_1)-1} (1 - \mathsf{P}(T = s+1|T > s)) \\
&= 1 - \prod_{s=\tau}^{R(\omega_1)-1} (1 - \pi) \\
&= 1 - (1-\pi)^{R(\omega_1)-\tau-1}
\end{aligned}
\tag{3.14}
$$

where the first line of Eq. 3.14 shows the definition of the subjective probability of our interest. The second to fourth lines follow the properties of the conditional probabilities. The last line follows the definition of subjective hazard rate $\pi$, shown in Eq. 3.3.

The result in Eq. 3.14 indicates that at given values of $P_\tau^{R(\omega_1)}$, one can recover $\pi$ as the function of $P_\tau^{R(\omega_1)}$, which is

$$\pi = 1 - (1 - P_\tau^{R(\omega_1)})^{\frac{1}{R(\omega_1 - \tau - 1)}} \tag{3.15}$$

#### 3.7.1.3 Backward induction, discretizing assets and solution of the model

The agent's problem can be solved recursively according to the following two phases of her life. First, from age $R(\omega_1)$ to $\tau = \bar{\tau}$, if the agent is affected by the reform before she reaches age $R(\omega_1)$, the system will remain in $\omega_2$. Otherwise, the agent will receive benefits according to system $\omega_1$. Thus, there will not be any uncertainty after the agent surpasses age $R(\omega_1)$. Second, from age $\underline{\tau}$ to $R(\omega_1) - 1$, independent of whether the agent remains or stops working at age $\underline{\tau} \leq \tau \leq R(\omega_1) - 1$, she is still at risk of being affected by the reforms that may occur before she reaches age $R(\omega_1)$.

Having defined the recursive problem of the agent, we can define the value function for the case the agent still works as follows:

- age $\tau = \bar{\tau}$

$$V^W(a_{\bar{\tau}}, \Omega_{\bar{\tau}}, \pi) = \max_{a_{\bar{\tau}+1}} \Big[ u(c_{\bar{\tau}}, 1) + \beta \cdot \eta(a_{\bar{\tau}+1}) \Big] \tag{3.16}$$

- at age $\tau$ when $R(\omega_1) \leq \tau \leq \bar{\tau} - 1$, and $\forall q$ such that $\Omega_{R(\omega_1)} = \omega_q$, $q = \{1, 2\}$:

$$V^W(a_\tau, \Omega_\tau, \pi) = \max_{a_{\tau+1}} \Big[ u(c_\tau, 1) + \beta \cdot \max \Big\{ V^W(a_{\tau+1}, \omega_q, \pi); V^S(a_{\tau+1}, \omega_q, \pi) \Big\} \Big] \tag{3.17}$$

- at age $\tau$ when $\underline{\tau} \leq \tau \leq R(\omega_1) - 1$:
  $V^W(a_\tau, \Omega_\tau, \pi) =$

$$\begin{cases} \max\limits_{a_{\tau+1}} \Big[ u(c_\tau, 1) + \beta \Big( (1-\pi) \cdot \max \Big\{ V^W(a_{\tau+1}, \omega_1, \pi); V^S(a_{\tau+1}, \omega_1, \pi) \Big\} \quad ... \\ \qquad\qquad + \pi \cdot \max \Big\{ V^W(a_{\tau+1}, \omega_2, \pi); V^S(a_{\tau+1}, \omega_2, \pi) \Big\} \Big) \Big] & \text{if } \Omega_\tau = \omega_1 \\ \max\limits_{a_{\tau+1}} \Big[ u(c_\tau, 1) + \beta \max \Big\{ V^W(a_{\tau+1}, \omega_2, \pi); V^S(a_{\tau+1}, \omega_2, \pi) \Big\} \Big]. & \text{if } \Omega_\tau = \omega_2 \end{cases} \tag{3.18}$$

Following the assumption that the retirement is an absorbing state, the value function of stop working is defined as follows:

- at age $\tau = \bar{\tau}$:

$$V^S(a_{\bar{\tau}}, \Omega_{\bar{\tau}}, \pi) = \max_{a_{\bar{\tau}+1}} \Big[ u(c_{\bar{\tau}}, 0) + \beta \cdot \eta(a_{\bar{\tau}+1}) \Big] \tag{3.19}$$

- at $\tau$ when $R(\omega_1) \leq \tau \leq \bar{\tau} - 1$, and $\forall q$ such that $\Omega_\tau = \omega_q$, $q = \{1, 2\}$:

$$V^S(a_\tau, \Omega_\tau, \pi) = \max_{a_{\tau+1}} \Big[ u(c_\tau, 0) + \beta \cdot V^S(a_{\tau+1}, \omega_q, \pi) \Big] \tag{3.20}$$

- at $\tau$ when $\underline{\tau} \leq \tau \leq R(\omega_1) - 1$:
  $V^S(a_\tau, \Omega_\tau, \pi) =$

$$\begin{cases} \max\limits_{a_{\tau+1}} \Big[ u(c_\tau, 0) + \beta \Big( (1-\pi) \cdot V^S(a_{\tau+1}, \omega_1, \pi) + \pi \cdot V^S(a_{\tau+1}, \omega_2, \pi) \Big) \Big] & \text{if } \Omega_\tau = \omega_1 \\ \max\limits_{a_{\tau+1}} \Big[ u(c_\tau, 0) + \beta V^S(a_{\tau+1}, \omega_2, \pi) \Big] & \text{if } \Omega_\tau = \omega_2 \end{cases} \tag{3.21}$$

In every period, the agent faces the following budget constraints,

$$a_{\tau+1} = h_\tau \cdot w + (1 - h_\tau) \cdot b(\Omega_\tau) + (1 + r) a_\tau - c_\tau \tag{3.22}$$

where $a_{\tau+1}$ is the savings at age $\tau$ and $w$ is the annual net labor income. The agent is eligible to receive the benefit $b(\Omega_\tau)$ only if she does not work at that age.

Moreover, the agent cannot die with debt; thus, at age $\bar{\tau}$ the accumulated asset must be non-negative, i.e., $a_{\bar{\tau}} \geq 0$..

*Discretizing assets:* The conceptual model is solved by backward recursion after discretizing the assets, the only continuous state variable, at every period between bounds $[\underline{a}_\tau; \bar{a}_\tau]$. The lower bound at $\tau$ is determined as:

$$\underline{a}_{\bar{\tau}+1} = 0; \text{ and } \underline{a}_\tau = \sum_{s=\tau+1}^{T} \frac{1}{(1+r)^{\bar{\tau}-(\tau+1)}} (c_{min} - y_{\tau,min}) \quad \text{for } 1 \leq \tau \leq \bar{\tau}. \tag{3.23}$$

The upper bound of the asset at age $\tau$ is as follows:

$$\bar{a}_{\underline{\tau}} = a_0; \text{ and } \bar{a}_\tau = (1+r)(\bar{a}_{\tau-1} - c_{min} + w) \text{ for } \underline{\tau}+1 \leq \tau \leq \bar{\tau} \tag{3.24}$$

where $a_0$ is an endowment at age $\underline{\tau}$.

We set $c_{min} = 10^{-5}$ which is the minimum possible consumption level. The minimum assets is a natural borrowing constraint such that $c_{min}$ is always affordable when the income is at its minimum. We set $y_{\tau,min} = b(\Omega_\tau = \omega_2)$ because this is the minimum possible income stream that the agent can have according to our specifications.

The lower bound is found from the following inequality:

$$a_{\tau+1} + \sum_{s=\tau+1}^{\bar{\tau}} \frac{1}{(1+r)^{\bar{\tau}-(\tau+1)}} y_{\tau,min} \geq \sum_{s=\tau+1}^{\bar{\tau}} \frac{1}{(1+r)^{\bar{\tau}-(\tau+1)}} c_{min}. \tag{3.25}$$

This implies that $c_{min}$ is always affordable when the income is at its minimum from period $\tau+1$ onward. The lower bound of $a_{\tau+1}$ is the value of assets that makes the inequality holds with equality. That value is shown in Eq. 3.23. The maximum is how much one would have if saving everything and consuming $c_{min}$ at every period, conditional on initial assets.

*Backward induction:* The backward inductions starts at period $\bar{\tau}+1$ because the agents are allowed to leave a bequest. Then we calculate the optimal solution for control variables, i.e., consumption and savings, for each possible combination of the state variables at $\bar{\tau}$. We continue the backward induction recursively for previous periods until we reach period $\underline{\tau}$. This results in a decision rule for optimal choices at given degree of anticipation $P_{\underline{\tau}}^{R(\omega_1)}$, initial endowment, and history of pension reform from $\underline{\tau}$ until $R(\omega_1)$.

Next, we compute individuals' age to transition from employed to retired by comparing the value functions for each alternative state, which summarizes the future consequences of choosing each alternative accounting for the reform uncertainty. The optimal retirement age is found if retiring at that age brings the highest expected discounted utility.

We set the initial age $\underline{\tau} = 50$ and the maximum age as $\bar{\tau} = 90$. We set the initial age as 50 since individuals are first observed at age 50 in our empirical data. Furthermore, we set $R(\omega_1) = 65$ and $R(\omega_2) = 70$. In other words, the comparative static analysis examines the impact of increasing SRA from 65 to 70 on the transition from employed to retired state at given age and anticipation.

### 3.7.2 Definition of SRA and pension reforms

#### 3.7.2.1 Definition of Statutory retirement age

European countries differ in defining the legal age when people can access their pension benefits with any reduction. To make the SRA comparable across countries, we adopt the definition of the pensionable age defined by OECD (2017) from different countries. OECD (2017) defined the SRA, or the pensionable age, as the age at which people can first draw full benefits, that is, without actuarial reduction for early retirement. The SRA in most countries is clearly set out in legislation. For example, for most countries in Europe, the SRA is between 65 and 67, and it is (planned to be) linked to life expectancy and other macroeconomic indicators. It is, however, possible in France to retire earlier than SRA without an actuarial reduction in pension benefits. Thus, the OECD defined the SRA of France as 60. Finally, Sweden does not have SRA. Instead, Sweden establishes a range of ages at which the pension can be drawn without reduction. Following the pensionable age definition, the OECD defined the SRA of Sweden as 65.

#### 3.7.2.2 Pension reforms that increased SRA between 2005 and 2019 for the selected countries

This sub-section discusses the pension reforms and the evolution of the official SRA of respondents for each selected country. We started with collecting the official dates of the major pension reforms of the selected European countries from Immergut et al. (2007), and Ciani et al. (2019).

Afterwards, we use OECD (2017), and online articles to determine which groups of people were affected by how and by which reform. This information is crucial to construct the history of the official SRA of each participant because we use the change in SRA to measure the treatment intensity of reforms.

#### 3.7.2.2.1 Belgium

| | |
|---|---|
| Announcement date | NA |
| Implementation date | Aug 1, 2015 |
| Previous major reform date | Dec 1, 2011 |
| Next major reform date | NA |

The first pillar, PAYGO public statutory pension scheme is mandatory for all workers, and it is based on a 45-year career. SRA for women was gradually raised between 1997 and 2008 from 60 to 65.

**Part 1.** Affected group: Women. The SRA of women increased as follows:

| **SRA** | **cohort** |
|---|---|
| $60+0.5 \cdot i$ | born between Jan [1937+$i$] and Dec [1937+$i$], where $i = 1 : 1 : (2008 - 1997 + 1)$ |
| 65 | born after Jan 1943 |

**Part 2.** Under a law passed in July 2015, this will rise to 66 in 2025 and 67 in 2030 for both women and men. There is a plan to link the retirement age to life expectancy. The SRA for each cohort is determined as follows:

| **SRA** | **cohort** |
|---|---|
| 65 | retires before Jan 2025 (born before Jan 1960) |
| 66 | retries between Feb 2025 and Jan 2030 (born between Feb 1960 and Jan 1964) |
| 67 | retires after Feb 2030 (born after Feb 1964) |

#### 3.7.2.2.2 Denmark

The public pension scheme is universal and covers the entire Danish population. Entitlement to pension is acquired on the basis of residence in Denmark and is thus not conditional on payment of contributions. A full public old-age pension requires 40 years of residence until 1 July 2025. Thereafter a full public old age pension requires 9/10 years of residence from the age of 15 to the public retirement age.

**Part 2. Acceleration:**

| | |
|---|---|
| Announcement date | NA |
| Implementation date | Jun 1, 2006 |
| Previous major reform date | NA |
| Next major reform date | Dec 1, 2011 |

| **SRA** | **cohort** |
|---|---|
| 65 | if before Dec 1958 |
| 65.5 | if born in between Jan 1959 and Jun 1959 |
| 66 | if born between Jul 1959 and Dec 1959 |
| 66.5 | if born between Jan 1960 and Jun 1960 |
| 67 | if born between Jul 1960 and Dec 1960 |
| 67+ | if born after Jan 1961. Here, the SRA will be linked to the life expectancy |

| | |
|---|---|
| Announcement date | NA |
| Implementation date | Dec 1, 2011 |
| Previous major reform date | Jan 1, 2006 |
| Next major reform date | Jan 2017 |

The SRA increased from 65 to 67 between 2019-22 and to 68 in 2030. After this increases are directly linked to increases in life expectancy. The SRA for each cohort is defined as follows:

| **SRA** | **cohort** |
|---|---|
| 65 | if before Dec 1953 |
| 65.5 | if born in between Jan 1954 and Jun 1954 |
| 66 | if born between Jul 1954 and Dec 1954 |
| 66.5 | if born between Jan 1955 and Jun 1955 |
| 67 | if born between Jul 1955 and Dec 1962 |
| 68 | if born between Jan 1963 and Dec 1966 |
| 69+ | if born after Jan 1967. Here, the SRA will be linked to the life expectancy |

#### 3.7.2.2.3 France

| | |
|---|---|
| Announcement date | Jun 1, 2010 |
| Implementation date | Nov 1, 2010 |
| Previous major reform date | Jul 1, 2003 |
| Next major reform date | Jan 1, 2014 |

The reform of 2010 provided for a raising of the statutory retirement age from 60 to 62 between 2012 and 2018. The SRA increases four months per year. The cohorts born after Jan 1952 were affected.

In December 2011, the pace of the earlier pension reform was to be accelerated. The SRA is

| SRA | cohort |
|---|---|
| 60 | born before July 1951 |
| $60 + \frac{4}{12}$ | born between August 1951 and Dec 1951 |
| $60 + \frac{4}{12} \cdot i$ | born between Jan [1952+$i$] and Dec [1952+$i$], where $i = 1:1:(2018-2012)$ |
| 62 | born after Jan 1958 |

raised to 62 from 2017, instead of 2018.

| SRA | cohort |
|---|---|
| 60 | born before July 1951 |
| $60 + \frac{4.8}{12}$ | born between August 1951 and Dec 1951 |
| $60 + \frac{4.8}{12} \cdot i$ | born between Jan [1952+$i$] and Dec [1952+$i$], where $i = 1:1:(2017-2012)$ |
| 62 | born after Jan 1957 |

From 2012, **the exemption** rule is applied. François Hollande's government lowered back to 60 for those who could meet the contribution year requirements of 41+ years already at that age.

#### 3.7.2.2.4 Germany

| | |
|---|---|
| Announcement date | Nov 1, 2006 |
| Implementation date | Mar 1, 2007 |
| Previous major reform date | Jun 1, 2004 |
| Next major reform date | Jul 1, 2014 |

The SRA is step by step increased to 67 years of age. Starting in 2012 and ending in 2030. Between 2012 and 2024, the SRA is adjusted first each year by one month from age 65 to 66. Between 2025 and 2030, each year by two months from age 66 to 67. The phase-in is cohort-oriented, it will affect cohorts younger than Jan 1947. For the 1964 and younger cohorts, a statutory retirement age of 67 finally applies.[27]

**Exemptions:** Since there were additional worries about the coverage for workers subject to extreme physical wear and tear due to long years of hard work, a new pension type was introduced making it possible for workers with a service life of at least 45 years to retire two years earlier without any actuarial adjustments (at age 65). Some employees retire on a full pension at 63,

[27] In addition, eligibility ages for disability pensions are raised from age 63 to 65 from 2017 to 2029 for handicapped persons. Early retirement with deductions is raised from age 60 to 62. Maximum deductions for early retirement are thus 10.8%. For long-time insured workers, disability pensions can still be received at age 63 without deductions if workers have at least 35 service years (until 2023) or 40 years (from 2024 on).

| SRA | cohort |
|---|---|
| 65 | born before Dec 1946 |
| $65+\frac{1}{12}\cdot i$ | born between Jan [1947+$i$] and Dec Jan [1947+$i$] where $i=1:1:(2024-2012)$ |
| $66+\frac{2}{12}$ | born between Jan [1959+$i$] and Dec Jan [1959+$i$] where $i=1:1:(2030-2024)$ |
| 67+ | born after Jan 1964 |

provided they have worked for 45 years without claiming jobless benefits for more than a short time.

#### 3.7.2.2.5 Netherlands

| | |
|---|---|
| Announcement date | NA |
| Implementation date | 2012 |
| Previous major reform date | Jan 1, 2006 |
| Next major reform date | NA |

**Phase 1:** The increase of the retirement age was first explicitly proposed by the government in 2009 but only formalized in the summer of 2012 when a law was adopted to gradually raise the statutory pension age from 65 to 66 in 2019 and 67 in 2026 and increase with life expectancy thereafter. Starting from cohorts born after 1948 the SRA increases to 66 by 2019 and to 67 in 2026 Parlevliet (2017). The information on the pension reform in 2012 is obtained from Atav et al. (2019).

| SRA | cohort |
|---|---|
| 65 | born before Dec 1947 |
| $65+\frac{1}{12}$ | born between Jan 1948 and Nov 1948 |
| $65+\frac{2}{12}$ | born between Dec 1948 and Oct 1949 |
| $65+\frac{3}{12}$ | born between Nov 1949 and Sep 1950 |
| $65+\frac{5}{12}$ | born between Oct 1950 and Jul 1951 |
| $65+\frac{7}{12}$ | born between Aug 1951 and May 1952 |
| $65+\frac{9}{12}$ | born between Jul 1952 and Mar 1953 |
| 66 | born between Apr 1953 and Dec 1953 |
| $66+\frac{2}{12}\cdot i$ | born between Jan [1954+$i$] and Dec [1954+$i$] where $i=1:1:(2023-2018)$ |
| 67+ | born after 1959 |

**Phase 2:** In 2015, the government introduced another acceleration. This time, the SRA increased to 66 years in 2018 and to 67 years in 2021. After that, the State Pension age (‘AOW age’) will be linked to the increase in life expectancy. The acceleration will primarily affect

employees born between 30 September 1950 and 1 January 1957.

| SRA | cohort |
|---|---|
| 65 | born before Oct 1948 |
| $65 + \frac{1}{12}$ | born between Jan 1948 and Nov 1948 |
| $65 + \frac{2}{12}$ | born between Dec 1948 and Oct 1949 |
| $65 + \frac{3}{12}$ | born between Nov 1949 and Sep 1950 |
| $65 + \frac{6}{12}$ | born between Oct 1950 and Jul 1951 |
| $65 + \frac{9}{12}$ | born between Aug 1951 and May 1952 |
| 66 | born between Jul 1952 and Mar 1953 |
| $66 + \frac{4}{12} \cdot i$ | born between Jan [1954+$i$] and Dec [1954+$i$] where $i = 1 : 1 : (2021 - 2018)$ |
| 67+ | born after 1957 |

#### 3.7.2.2.6 Spain

| | |
|---|---|
| Announcement date | Jan 2011 |
| Implementation date | Aug 2011 |
| Previous major reform date | Dec 2008 |
| Next major reform date | NA |

In 2011, the statutory retirement age was increased from 65 to 67. The increase is being gradually applied between 2012 and 2027. The cohorts born after Aug 1948 were affected. Between 2013 and 2018, the SRA increased by one month per year. Between 2020 and 2027, the SRA increased by two months per year.

| SRA | cohort |
|---|---|
| 65 | born before Jul 1948 |
| $65 + \frac{1}{12} \cdot i$ | born between Aug [1947+$i$] and Jul [1948+$i$] where $i = 1 : 1 : (2018 - 2013 + 1)$ |
| $65 + \frac{8}{12} + \frac{2}{12}$ | born between Aug [1954+$i$] and Jul [1954+$i$] where $i = 1 : 1 : (2027 - 2019 + 1)$ |
| 67+ | born after Aug 1963 |

**Exemption:** The retirement age of 65 applies only to those with exceptionally long periods of contribution. However, the contribution years are also increasing together with the SRA as shown in the following table:
Early retirement will continue to be possible for people with particularly "hazardous and arduous jobs."

| Contribution years | cohort |
|---|---|
| $35 + \frac{3}{12} \cdot i$ | born between Aug [1947+$i$] and Jul [1948+$i$] where $i = 1 : 1 : (2018 - 2013 + 1)$ |
| $36\ \frac{9}{12} + \frac{3}{12}$ i | born between Aug [1954+$i$] and Jul [1955+$i$] where $i = 1 : 1 : (2026 - 2019 + 1)$ |
| $38 + \frac{6}{12}$ | born after Aug 1963 |

#### 3.7.2.2.7 Austria

By 2022, SRA is 60 for women and 65 for men. No major reform after 2005 and before 2019. The Act on the Harmonisation of Austrian Pension Systems came into effect on 1 January 2005. Women's SRA being adjusted to that of men between 2024 and 2033. During this period, women's SRA increases by half a year each calendar year OECD (2017).

#### 3.7.2.2.8 Sweden

Main reforms took place in 1994 and 1998 made the system stable for the following decades Ciani et al. (2019).

#### 3.7.2.2.9 Switzerland

No major reforms between 2005 and 2019. There were attempts to change the pension system; however, failed eventually. For example, in Dec 2008, the Swiss parliament (Ständerat) agreed the conversion rate of second pillar pensions should be cut to 6.4% by 2015 in light of the financial crisis. The cut in conversion rate was turned down by referendum on 7th March 2010 Ciani et al. (2019).

### 3.7.3 Sample selection and descriptive statistics

Table 3.8: Sample selection and the main sample composition

| | number of individuals | number of individuals × waves |
|---|---|---|
| *The sample selection:* | | |
| the initial sample of waves from one to eight consists of [a] | 143,004 | 421,143 |
| keep the countries of interest [b] | 68,964 | 228,827 |
| keep if observed at least two consecutive waves | 50,351 | 201,346 |
| keep if the employed at $t$ and employed or retired at $t+1$ | 17,915 | 59,132 |
| keep if the age is between 50 and 64 | 16,769 | 50,883 |
| keep if citizen | 16,711 | 50,230 |
| keep if the reform anticipation is reported at $t$ | 14,730 | 35,317 |
| keep if the observations are around the reform of interest | 12,215 | 29,309 |
| *The main sample composition, out of 100%:* | | |
| A. | | |
| observed two times | 68.2 | - |
| observed three times | 23.6 | - |
| observed at least four times | 8.2 | - |
| B. | | |
| treated | 51.7 | 53.7 |
| never-treated | 48.3 | 46.3 |
| C. | | |
| Austria | 5.5 | 4.7 |
| Germany | 13.9 | 13 |
| Sweden | 12.4 | 12.7 |
| Netherlands | 11.9 | 10.8 |
| Spain | 6.9 | 6.8 |
| France | 12.7 | 13.5 |
| Denmark | 14.7 | 15.7 |
| Switzerland | 10.1 | 11.5 |
| Belgium | 11.9 | 11.3 |

*Notes:*

[a]: We did not use the sample from Greece and Israel because they did not participate in all of the subsequent waves. The observations of Italy were dropped because the SHARE does not have variables that help us to distinguish the treated group of people by the reforms implemented in they country between 2004 and 2018. The sample includes the respondents from the "Main interview" of SHARE and the observations from SHARE-LIFE in wave 3.

[b]: Panel C shows the countries of interests. The selection on countries of interested are discussed in Section 3.3 in detail.

Table 3.9: Descriptive statistics of variables

| VARIABLES | Total<br>(1) | AUS<br>(2) | BEL<br>(3) | DK<br>(4) | DEU<br>(5) | FRA<br>(6) | NL<br>(7) | ESP<br>(8) | SWE<br>(9) | CHE<br>(10) |
|---|---|---|---|---|---|---|---|---|---|---|
| *Main variables* | | | | | | | | | | |
| Employed at $t+1$ | 0.881 | 0.821 | 0.892 | 0.917 | 0.887 | 0.845 | 0.901 | 0.852 | 0.898 | 0.876 |
| | (0.323) | (0.383) | (0.310) | (0.276) | (0.317) | (0.362) | (0.299) | (0.356) | (0.303) | (0.330) |
| Anticipation at $t$ | 52.57 | 44.16 | 63.46 | 43.46 | 50.54 | 56.23 | 58.72 | 74.06 | 50.89 | 41.33 |
| | (36.30) | (35.66) | (32.24) | (36.88) | (36.96) | (36.38) | (34.22) | (30.21) | (34.56) | (35.80) |
| ΔSRA | 0.380 | 0 | 0.182 | 0.856 | 0.783 | 0.229 | 0.728 | 0.471 | 0 | 0 |
| | (0.612) | (0) | (0.529) | (0.970) | (0.618) | (0.197) | (0.531) | (0.0787) | (0) | (0) |
| Pre-reform SRA | 64.09 | 62.51 | 65 | 65 | 65 | 60 | 65 | 65 | 65 | 64.48 |
| | (1.858) | (2.501) | (0) | (0) | (0) | (0) | (0) | (0) | (0) | (0.500) |
| Age at $t$ | 55.57 | 55.09 | 54.59 | 55.26 | 55.32 | 54.65 | 55.77 | 56.08 | 57.27 | 56.15 |
| | (3.616) | (3.235) | (3.346) | (3.624) | (3.560) | (3.151) | (3.569) | (3.672) | (3.705) | (3.707) |
| Female | 0.514 | 0.497 | 0.513 | 0.497 | 0.520 | 0.531 | 0.490 | 0.496 | 0.543 | 0.518 |
| *Health at t (base: poor)* | | | | | | | | | | |
| Excellent | 0.179 | 0.158 | 0.126 | 0.305 | 0.104 | 0.133 | 0.135 | 0.0738 | 0.291 | 0.184 |
| Very good | 0.304 | 0.385 | 0.333 | 0.391 | 0.229 | 0.231 | 0.159 | 0.287 | 0.324 | 0.391 |
| Good | 0.364 | 0.335 | 0.430 | 0.214 | 0.453 | 0.483 | 0.319 | 0.448 | 0.295 | 0.350 |
| Fair | 0.109 | 0.104 | 0.0979 | 0.0815 | 0.190 | 0.125 | 0.0914 | 0.176 | 0.0818 | 0.0674 |
| *Marital status at t (base: never-married)* | | | | | | | | | | |
| Married | 0.745 | 0.671 | 0.707 | 0.780 | 0.815 | 0.724 | 0.602 | 0.852 | 0.797 | 0.733 |
| Widowed | 0.0281 | 0.0348 | 0.0237 | 0.0297 | 0.0321 | 0.0472 | 0.0189 | 0.0255 | 0.0191 | 0.0195 |
| Divorced | 0.120 | 0.171 | 0.183 | 0.114 | 0.0912 | 0.128 | 0.0591 | 0.0546 | 0.106 | 0.162 |
| *Education at t (base: primary or below)* | | | | | | | | | | |
| College+ | 0.395 | 0.367 | 0.478 | 0.538 | 0.389 | 0.333 | 0.565 | 0.238 | 0.378 | 0.194 |
| Upper-secondary | 0.418 | 0.525 | 0.303 | 0.374 | 0.569 | 0.447 | 0.227 | 0.209 | 0.370 | 0.660 |
| Lower-secondary | 0.122 | 0.0841 | 0.176 | 0.0663 | 0.0414 | 0.0870 | 0.188 | 0.279 | 0.159 | 0.106 |
| *Job sector at t (base: self-employed)* | | | | | | | | | | |
| Public | 0.247 | 0.147 | 0.268 | 0.300 | 0.263 | 0.231 | 0.155 | 0.205 | 0.356 | 0.192 |
| Private | 0.519 | 0.658 | 0.599 | 0.514 | 0.506 | 0.496 | 0.468 | 0.538 | 0.403 | 0.571 |
| Missing | 0.115 | 0 | 0 | 0.0983 | 0.126 | 0.175 | 0.286 | 0 | 0.172 | 0.0855 |
| *Job contract at t (base: part-time)* | | | | | | | | | | |
| Full-time | 0.744 | 0.747 | 0.652 | 0.803 | 0.739 | 0.835 | 0.518 | 0.844 | 0.860 | 0.668 |
| *Household finance at t* | | | | | | | | | | |
| Log income | 10.24 | 10.15 | 10.70 | 10.69 | 10.57 | 10.47 | 7.564 | 9.762 | 10.55 | 10.76 |
| | (2.131) | (1.524) | (0.854) | (0.701) | (1.068) | (1.215) | (4.901) | (2.108) | (1.094) | (1.480) |
| Log assets | 10.67 | 10.62 | 11.82 | 11.12 | 10.53 | 11.53 | 7.554 | 11.72 | 11.04 | 9.738 |
| | (4.238) | (3.692) | (2.482) | (3.544) | (3.949) | (2.895) | (6.259) | (2.867) | (3.250) | (5.942) |
| *Other variables at t* | | | | | | | | | | |
| Household size | 2.420 | 2.355 | 2.581 | 2.303 | 2.403 | 2.456 | 2.481 | 2.809 | 2.200 | 2.400 |
| | (1.030) | (1.156) | (1.155) | (0.894) | (0.959) | (1.107) | (1.044) | (1.046) | (0.847) | (1.044) |
| Numeracy | 3.774 | 4.153 | 3.815 | 3.981 | 3.961 | 3.599 | 2.962 | 3.251 | 3.927 | 4.072 |
| | (1.136) | (0.847) | (0.905) | (0.975) | (0.902) | (0.962) | (2.054) | (0.863) | (0.937) | (0.848) |
| Numeracy missing | 0.0283 | 0 | 0 | 0 | 0 | 0 | 0.289 | 0 | 0 | 0 |
| Dutch Mixed | 0.0283 | 0 | 0 | 0 | 0 | 0 | 0.289 | 0 | 0 | 0 |
| Google Trends | 5.258 | 0 | 6.496 | 5.083 | 9.777 | 4.200 | 4.646 | 19.03 | 1.840 | 0.402 |
| | (9.760) | (0) | (9.344) | (13.12) | (10.95) | (3.140) | (11.27) | (9.755) | (4.807) | (1.543) |
| Read | 1.106 | 1.697 | 1.518 | 1.024 | 1.057 | 0.778 | 1.120 | 1.177 | 0.765 | 1.255 |
| | (0.950) | (0.673) | (0.722) | (0.974) | (0.968) | (0.912) | (0.946) | (0.891) | (0.963) | (0.950) |
| Observations | 29,309 | 1,362 | 3,322 | 4,599 | 3,818 | 3,954 | 3,175 | 1,989 | 3,727 | 3,363 |

*Note:* This table presents summary statistics for the selected sample of the SHARE data. Variables are defined in Table 3.10. Standard deviations are in parenthesis. The standard deviations of dummy variables are not reported. AUS stands for Austria, BEL for Belgium, DK for Denmark, DEU for Germany, FRA for France, NL for the Netherlands, ESP for Spain, SWE for Sweden, and CHE for Switzerland. ΔSRA is the difference between the current and pre-reform SRAs.

Table 3.10: Variable descriptions

| **Variable** | **Description** |
|---|---|
| *Panel A. Main variables* | |
| Employed at $t+1$ (or $y_{ij,t+1}$) | =1 if employed and =0 if retired at $t+1$ given that employed at $t$ |
| Anticipation (or $\text{Ant}_{ijt}$) | the reported probability of the government increases pension age before the agent retires |
| SRA | Statutory retirement age |
| *Panel B. Other covariates* | |
| Age | age at the interview date |
| Work sector | |
| -private sector | =1 if works at the private sector |
| -public sector | =1 if works at the public sector |
| -self-employed | =1 if self-employed |
| -missing | =1 if work sector is missing |
| Work contract | |
| - full-time | =1 if works full-time |
| - part-time | =1 if works part-time |
| Self-reported health | |
| -excellent | =1 if the self-reported health is excellent |
| -very good | =1 if the self-reported health is very good |
| -good | =1 if the self-reported health is good |
| -fair | =1 if the self-reported health is fair |
| -poor | =1 if the self-reported health is poor |
| Marital status | |
| -married | =1 if married or partnered |
| -never-married | =1 if never-married |
| -divorced or separated | =1 if divorced or separated |
| -widowed | =1 if widowed |
| Log income[a] | log of the annual household income |
| Log real asset[a] | log of the annual household real asset |
| Education[b] | |
| -College+ | =1 if ISCED$\geq$5: college+ |
| -Upper-secondary | =1 if $4 \geq$ ISCED $\geq 3$: post-secondary, non-tertiary, upper-secondary |
| -Lower-secondary | =1 if ISCED = 2: lower-secondary |
| -Primary or lower | =1 if ISCED $\leq 2$: primary or lower than primary |
| Female | =1 if Female, =0 if Male |
| Citizen | =1 if citizen of the interviewed country |
| Numeracy | Numeracy score (mathematical performance): 1=bad, ..., 5=good |
| Dutch Mixed | Interviews of the Netherlands from waves six and seven |
| Read | =2 if read or watch news daily; =1 if monthly; =0 otherwise |
| *Panel C. Instrumental variables* | |
| Google | Google Trends index with keyword "pension reform" |

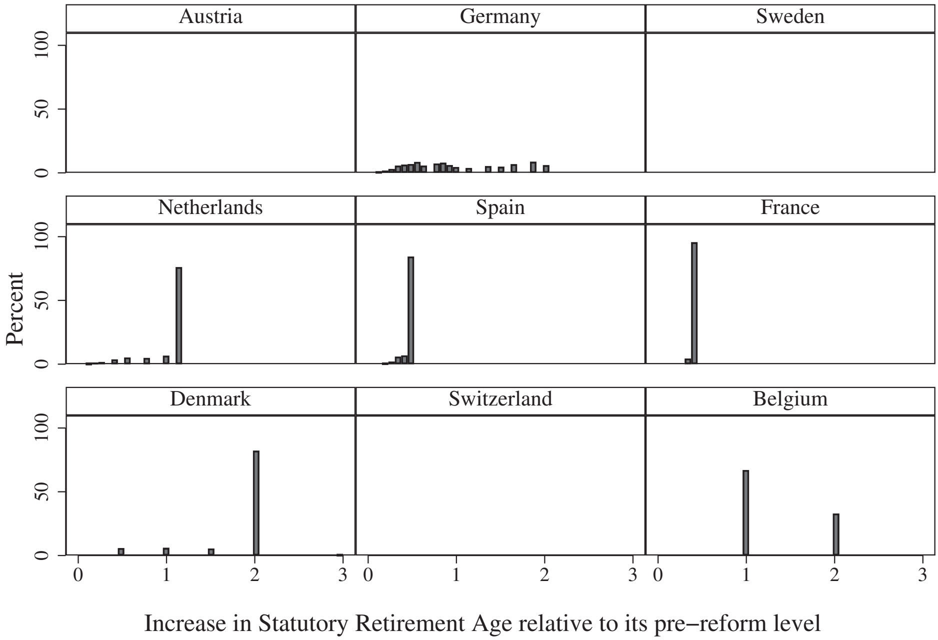
*Notes:*

[a] : We use the imputed version of the household income and real assets available in the imputed version of the SHARE. To make the income and assets comparable across countries, we mutliplied the imputed values of income and assets by the Purchasing Power Index, where Germany 2008 =1, that is available in SHARE. Then we adjusted by the household size by dividing them by $\sqrt{HH}$ where $HH$ is the household size. The household size counts the number of living spouses plus the number of children living together. Finally, the log is defined as $\ln(x+1)$ if $x \geq 0$ and $-\ln(1-x)$ if $x < 0$ where ln is the natural logarithm.

[b] : International Standard Classification of Education (ISCED 97): 0=no education, ..., 6=Ph.D. The measure is defined as the highest obtained education level at given wave.

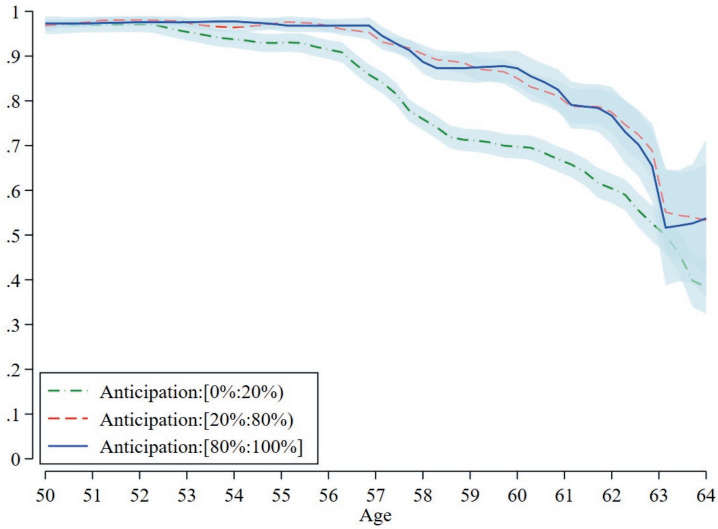
[c] : The SHARE asks from the respondents "what is the (1) day of the month, (2) month, (3) year, and (4) day of the week today?." Depending the number of correct answers, the variable takes values from 0 to 4, where 0=no correct answer, ..., 4=four correct answers.

Figure 3.6: Frequency of the normalized statutory retirement age, by country




*Note:* The figure uses the observations whose normalized SRA is greater than zero. The total number of observations used in this figure is 6,836.

Figure 3.7: Empirical probability of remaining employed at a given age vs. and reported anticipation in the previous survey wave after controlling for observables




*Note:* Figure shows the empirical probability of being remaining employed at given age $a$ conditional on respondents were employed at age $a-2$ after controlling for various observed characteristics. See the note of Figure 3.5.

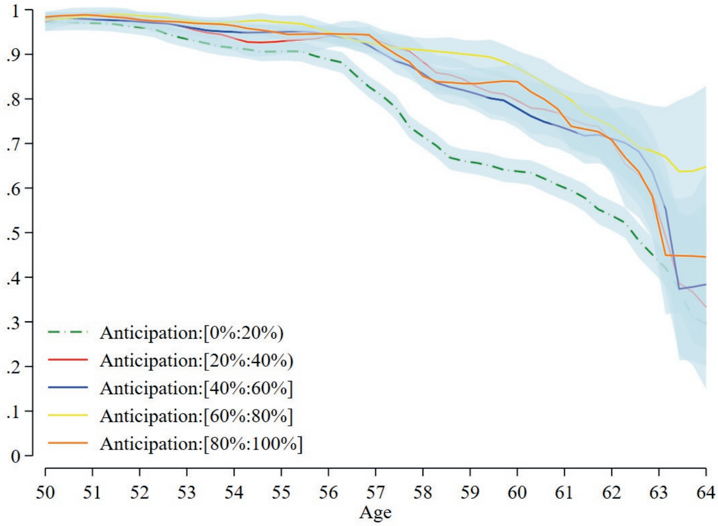
Figure 3.7 shows the empirical probability of remaining employed at age $a$ conditional on being employed at age $a-2$. In this figure, we control for the effect of additional observed characteristics by running the following regression:

$$y_{ijt} = \beta_0 + \mathbf{Z}_{itj}\gamma + \delta_{\mathbf{jt}} + \epsilon_{\mathbf{ijt}}$$

where $y_{ijt}$ is a dummy variable for whether individual $i$ from country $j$ is employed in wave $t$. $\mathbf{Z}_{ijt}$: variety of socio-demographic characteristics: job characteristics in $t-1$, subjective health, marital status interacted with gender, and cognitive skill measures, financial indicators. $\delta_{\mathbf{jt}}$ is a vector of country and year effects. $\beta_0$ is constant and $\epsilon_{ijt}$ is a regression error.

After estimating this linear probability model by OLS, we obtain the regression residuals. In the figure, we we add the estimated effect of dummy of Germany and year 2015 to the residuals to make the scaling similar to that of Figure 3.5.

Figure 3.8: Empirical probability of remaining employed at a given age vs. and reported anticipation in the previous survey wave after controlling for observables




*Note:* Figure shows the empirical probability of being remaining employed at given age $a$ conditional on respondents who were employed at age $a-2$. In the figure, we plot the empirical probabilities of transitioning from employed to retired at a given age conditional on reported anticipation is between [0, 20%); [20, 40%); [40, 60%); [60, 80%); and [80, 100%].

### 3.7.4 IV-probit and Multinomial probit models

#### 3.7.4.1 IV-probit model

The IV-probit assumes that $(u_{iw}, \mathbf{v}_{i,w})$ follows tri-variate normal distribution such that

$$[u_{iw}, \mathbf{v}_{iw}]^T = \begin{pmatrix} u_{iw} \\ \mathbf{v}_{iw} \end{pmatrix} \sim \mathcal{N}\left(0, \begin{pmatrix} \sigma_u & \mathbf{\Sigma}_{uv} \\ \mathbf{\Sigma}_{uv}^T & \mathbf{\Sigma}_v \end{pmatrix}\right) \tag{3.26}$$

where $\sigma_u$ is normalized to one to identify the model.

Let us define that $\mathbf{X}_{iw}$ be vector of endogenous regressors, $\mathbf{W}_{iw}$ be vector of exogenous regressors, and $\mathbf{I}_{iw}$ be the instruments. Following these notations, the latent model can be re-specified as:

$$y_{iw}^* = \mathbf{X}_{iw}\beta + \mathbf{W}_{iw}\gamma + \varepsilon_{iw}. \tag{3.27}$$

and the first-stage regressions are defined as:

$$\mathbf{X}_{iw} = \mathbf{I}_{iw} \cdot \Pi_I + \mathbf{W}_{iw}\Pi_W + \mathbf{v} \tag{3.28}$$

We follow the two-step instruments variables estimator proposed by Rivers and Vuong (1988). Let's stack $(y_{iw}, \mathbf{X}_{iw}, \mathbf{Z}_{iw}, \mathbf{I}_{iw})$ over $i$ and $w$ and denote the corresponding matrices (or vectors) as $(y, \mathbf{X}, \mathbf{W}, \mathbf{I})$. The two-step IV-probit model estimation algorithm proceeds as follows:

1. Regress $\mathbf{X}$ on $[\mathbf{I}, \mathbf{W}]$ using OLS to obtain $[\hat{\Pi}_I, \hat{\Pi}_W]$. The least squares residuals are:

$$\hat{\mathbf{v}} = \mathbf{X} - \mathbf{Z} \cdot \hat{\Pi}_Z - \mathbf{I} \cdot \hat{\Pi}_I \tag{3.29}$$

   and the estimate of $\Sigma_{vv}$ as follows:

$$\hat{\Sigma}_{vv} = \frac{1}{n}\sum_{i=1}^{n} \hat{\mathbf{v}}'\hat{\mathbf{v}}. \tag{3.30}$$

   by replacing $\mathbf{v}$, $\Sigma_{vv}$ and $\Pi$ by their estimates obtained from the previous step. Let the estimate of $g(\mathbf{X}_{iw}|\mathbf{W}_{iw}, \mathbf{I}_{iw}, \Pi_W, \Pi_I, \Sigma_{vv})$ be $\hat{g}_{iw}$

2. Probit analysis of $y$ with $\mathbf{X}, \mathbf{W}$ and $\hat{\mathbf{v}}$ as explanatory variables provides estimates $(\hat{\beta}, \hat{\gamma}, \hat{\lambda})$. Here $\hat{\lambda}$ is the OLS estimator of the parameter of $\hat{\mathbf{v}}$.

Suppose we are interested in predicting the following probability

$$\mathsf{P}(y = 1|\bar{X}, \bar{W}) \tag{3.31}$$

which is the probability of remain employed given values of $[\bar{X}, \bar{W}]$. This probability is is estimated as follows:

$$\hat{\mathsf{P}}(y = 1|\bar{X}, \bar{W}) = \frac{1}{N}\sum_{i=1}^{N}\sum_{w=\underline{w}_i}^{\bar{w}_i} \Phi\Big((\bar{X}\hat{\beta} + \bar{W}\hat{\gamma} + \hat{\mathbf{v}}_{iw}\hat{\lambda})\Big). \tag{3.32}$$

where $N$ is the total number of observations. We specify the first wave-$\underline{w}_i$ and the last-$\bar{w}_i$ as individual-specific because individuals vary in terms of at what waves they participated the survey. $\hat{\mathbf{v}}_{iw}$ is the OLS residual matrix obtained from the first-stage regressions described in Step 1. We estimate the standard errors of $\hat{\mathsf{P}}(y = 1|\bar{X}, \bar{W})$ by bootstrap method. We use block bootstrap method to take into account the dependency among observations from the same individuals. In our analysis, we use random sampling with replacement. This procedure is repeated 200 times to compute the standard errors.

A convenient feature of the two-step IV procedure is that it provides an estimate of $\lambda$ that can be used to construct tests for exogeneity. This test is known as the Wald-exogeneity test and it is similar to the Hausman test for endogeneity for the non-linear model. Under the null of the Wald-exogeneity test, $\lambda = 0$. Not rejecting the null is evidence that the regressors in $X_{iw}$ are exogenous conditional on $W_{iw}$. In that case, we favor the standard probit model specification because it is consistent and more efficient than the IV-probit model. If we reject the null, we favor the IV-probit model specification because the estimates from the probit model is no longer consistent.

#### 3.7.4.2 Multinomial probit model

The latent variables for $J-$alternative model are:

$$y^*_{iwj} = \mathbf{X}_{iw}\beta_j + \mathbf{W}_{iw}\gamma_j + \varepsilon_{iwj} \tag{3.33}$$

for $j = 1, ..., J$, $i = 1, ..., n$, $w = 1, ..\bar{w}$ and $\{\varepsilon_{iw1}, \varepsilon_{iw2}, ...\varepsilon_{iwJ}\} \sim \mathcal{N}(0, 1)$. We observe alternative $k$ for $i$th respondent if

$$\eta_{ik} > \eta_{il} \text{ for } l \neq k \tag{3.34}$$

For $j \neq k$, let

$$\begin{aligned}
\nu_{iwj} &= y^*_{iwj} - y^*_{iwk} && (3.35)\\
&= \mathbf{X}_{iw}(\beta_j - \beta_k) + \mathbf{W}_{iw}(\gamma_j - \gamma_k) + (\varepsilon_{ij} - \varepsilon_{ik}) && (3.36)\\
&= \mathbf{X}_{iw}\tilde{\beta}_{jk} + \mathbf{W}_{iw}\tilde{\gamma}_{jk} + \tilde{\varepsilon}_{iwjk} && (3.37)
\end{aligned}$$

Following the structure impoes on $\varepsilon_{iwj}$, $\forall i, w, j$, the structure of $\tilde{\varepsilon}_{iwjk}$ is $\tilde{\varepsilon}_{iwjk} \sim MVN(\mathbf{0}, \Sigma)$ where

$$\Sigma = \begin{pmatrix} 2 & 1 & ... & 1 \\ 1 & 2 & .... & 1 \\ ... & ... & ... & ... \\ 1 & 1 & ... & 2 \end{pmatrix} \tag{3.38}$$

Let $\alpha_{iwj}$ be:

$$\alpha_{iwj} = \mathbf{X}_{iw}\tilde{\beta}_{jk} + \mathbf{W}_{iw}\tilde{\gamma}_{jk} \tag{3.39}$$

and

$$q_{iw} = [\mathbf{X}_{iw}, \mathbf{W}_{iw}]. \tag{3.40}$$

Following the structure of $\Sigma$, the probability of $i$ chooses outcome $k$ in wave $w$ can be specified as follows:

$$\begin{aligned} \mathsf{P}(y_{iw} = k|\mathbf{X}_{iw}, \mathbf{W}_{iw}) &= \mathsf{P}(\nu_{iw1} \leq 0, ..., \nu_{iw,J-1} \leq 0|\mathbf{X}_{iw}, \mathbf{W}_{iw}) & (3.41) \\ &= \frac{1}{(2\pi)^{(J-1)/2}|\Sigma|^{1/2}} \int_{-\infty}^{-\alpha_{iw1}} ... \int_{-\infty}^{-\alpha_{iw,J-1}} \exp(-\frac{1}{2}\mathbf{q}'\Sigma^{-1}\mathbf{q})\mathbf{dq}. & (3.42) \end{aligned}$$

The estimates of the parameters are obtained by maximizing the following log-likelihood function:

$$\ln L = \sum_{i=1}^{N} \sum_{w} \sum_{j=1}^{J} \ln \mathsf{P}(y_{iw} = j|\mathbf{X}_{iw}, \mathbf{W}_{iw})^{1\{y_{iw}=j\}} \tag{3.43}$$

where $1\{\cdot\}$ is an indicator function which equals to one if the expression inside the bracelet is true. The standard errors are clustered at the household level.

### 3.7.5 More results

Table 3.11: Estimation results of IV-probit

| VARIABLES | (1) IV Linear Strutural eq. | (2) IV Probit Structural eq. | (3) Anticipation First-stage | (4) Anticipation × ΔSRA First-stage |
|---|---|---|---|---|
| *Panel A:* | | | | |
| Anticipation | 0.001 | 0.017* | | |
| | (0.001) | (0.010) | | |
| Anticipation × ΔSRA | -0.001 | -0.023 | | |
| | (0.001) | (0.017) | | |
| ΔSRA | 0.073 | 1.434 | 2.410*** | 63.665*** |
| | (0.085) | (1.055) | (0.744) | (0.545) |
| Pre-reform SRA | 0.016*** | 0.058 | 1.771*** | 0.020 |
| | (0.004) | (0.038) | (0.419) | (0.307) |
| Read | -0.006 | -0.022 | 1.322*** | 1.462*** |
| | (0.004) | (0.033) | (0.509) | (0.373) |
| *Excluded instruments* | | | | |
| Google | | | 0.444*** | 0.193*** |
| | | | (0.060) | (0.044) |
| Google × Read | | | -0.241*** | -0.053* |
| | | | (0.041) | (0.030) |
| Google × ΔSRA | | | -0.263*** | -0.012 |
| | | | (0.088) | (0.064) |
| Google × Read × ΔSRA | | | 0.099** | -0.129*** |
| | | | (0.049) | (0.036) |
| *Panel B: Correlation and sd. of errors of IV Probit* | | | | |
| | | $\varepsilon$ | $u$(Ant) | $u$(Ant × ΔSRA) |
| $\varepsilon$ | | 1 | | |
| $u$(Ant) | | -0.088 | 32.626*** | |
| | | (0.256) | (0.144) | |
| $u$(Ant × ΔSRA) | | 0.257 | 0.519*** | 23.881*** |
| | | (0.311) | (0.005) | (0.334) |

Note: See the footnote of Table 3.1. Panel B shows the estimates of the correlation and standard deviation of the errors from the structural equations ($\varepsilon$) and from the first-stage regressions ($u$(Ant) , $u$(Ant ×SRA$^{\text{norm}}$)). The variance of $\varepsilon$ is normalized to one to identify the model.

Table 3.12: Baseline estimation result without additional covariates

| VARIABLES | M1: Probit (1) | M2: Probit (2) | M3: IV-probit (3) |
|---|---|---|---|
| Anticipation | | 0.006*** | 0.016 |
| | | (0.001) | (0.011) |
| Anticipation × ΔSRA | | -0.005*** | -0.021 |
| | | (0.001) | (0.019) |
| ΔSRA | 0.134** | 0.386*** | 1.399 |
| | (0.056) | (0.092) | (1.160) |
| Pre-reform SRA | 0.113*** | 0.107*** | 0.085** |
| | (0.020) | (0.021) | (0.039) |
| Read | -0.022 | -0.017 | -0.004 |
| | (0.026) | (0.026) | (0.030) |
| log-likelihood | -4,736.4 | -4,647.6 | -162,300.3 |
| Number of parameters | | | |
| -Probit | 32 | 34 | |
| - IV-Probit - structural eq. | | | 34 |
| - first-stage | | | 36×2=72 |
| - (co)variance of error | | | 5 |
| Age dummies | Y | Y | Y |
| Country FE | Y | Y | Y |
| Year-effects | Y | Y | Y |
| Additional controls | N | N | N |
| Under-identification test: | | | |
| : Kleibergen-Paap rk LM (pval.) (pval.) | | | <0.001 |
| Weak inst. test: Cragg-Donald, $F_{5\%,rel} = 11.04$ | | | 13.014 |
| : SW (pval.): Anticipation | | | <0.001 |
| : SW (pval.): Anticipation × ΔSRA | | | <0.001 |
| Wald-exogeneity test (pval.) | | | 0.674 |
| Sargan over-identifying restrictions test (pval.) | | | 0.536 |

Note: *** p<0.01, ** p<0.05, * p<0.1. Standard errors are clustered at a household level and reported in parentheses. The sample consists of $N = 29,710$ observations of 12,245 individuals from 10,402 households. In the IV-Probit model, Anticipation and Anticipation × RA$^{norm}$ are treated as potentially endogenous regressors. All specifications include age dummies, country effects, and year effects. SW stands for Sanderson-Windmeijer multivariate F test of excluded instruments. The Cragg-Donald critical value when at 5% maximal IV relative bias is $F_{5\%,rel} = 11.04$, and at 10% maximal IV relative bias is $F_{10\%,rel} = 7.56$.

Table 3.13: Estimation results of the baseline specification: estimated effects of age groups

| VARIABLES | M1: Probit | M2: Probit | M3: IV-Probit | | |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| | | | St.eq | First-stage regression | |
| | | | | Anticipation | Ant × ΔSRA |
| age: 51 | 0.232* | 0.230* | 0.210 | -0.591 | -0.516 |
| | (0.132) | (0.132) | (0.131) | (1.279) | (1.320) |
| age: 52 | -0.041 | -0.050 | -0.070 | 0.019 | -1.207 |
| | (0.121) | (0.121) | (0.115) | (1.250) | (1.233) |
| age: 53 | -0.187 | -0.168 | -0.145 | -2.782** | -0.848 |
| | (0.116) | (0.116) | (0.116) | (1.303) | (1.201) |
| age: 54 | -0.429*** | -0.392*** | -0.370*** | -5.714*** | -3.284*** |
| | (0.112) | (0.112) | (0.126) | (1.338) | (1.189) |
| age: 55 | -0.408*** | -0.362*** | -0.335** | -8.596*** | -4.445*** |
| | (0.113) | (0.114) | (0.137) | (1.364) | (1.197) |
| age: 56 | -0.520*** | -0.457*** | -0.412** | -12.257*** | -5.842*** |
| | (0.111) | (0.112) | (0.161) | (1.372) | (1.201) |
| age: 57 | -0.748*** | -0.667*** | -0.601*** | -16.109*** | -7.371*** |
| | (0.110) | (0.110) | (0.202) | (1.431) | (1.226) |
| age: 58 | -1.238*** | -1.140*** | -0.991*** | -19.694*** | -6.454*** |
| | (0.107) | (0.107) | (0.299) | (1.432) | (1.165) |
| age: 59 | -1.473*** | -1.328*** | -1.093*** | -27.105*** | -6.179*** |
| | (0.107) | (0.108) | (0.411) | (1.462) | (1.076) |
| age: 60 | -1.556*** | -1.388*** | -1.101** | -30.220*** | -5.180*** |
| | (0.110) | (0.110) | (0.470) | (1.545) | (1.059) |
| age: 61 | -1.827*** | -1.656*** | -1.328** | -31.850*** | -4.775*** |
| | (0.112) | (0.112) | (0.530) | (1.622) | (1.071) |
| age: 62 | -2.011*** | -1.804*** | -1.416** | -37.758*** | -5.081*** |
| | (0.115) | (0.115) | (0.613) | (1.698) | (1.071) |
| age: 63 | -2.584*** | -2.367*** | -1.880** | -41.056*** | -3.388*** |
| | (0.132) | (0.133) | (0.754) | (2.347) | (1.054) |
| age: 64 | -2.990*** | -2.744*** | -2.180** | -47.590*** | -3.904*** |
| | (0.156) | (0.156) | (0.875) | (2.693) | (1.090) |

Note: *** p<0.01, ** p<0.05, * p<0.1. See the notes in Table 3.1. Columns (1) and (2) are based M1: Probit (the model that neglects the anticipation), and M2: Probit (the model that takes into account the anticipation), respectively. Columns (3) to (5) show the estimation results of M3: IV-probit. Column (3) shows the estimations of the structural equation, and Columns (4) and (5) show those of first-stage regressions. In the table, the dummy for age 50 is the baseline.

Table 3.14: Estimation results of the baseline specification: estimated effects of covariates

| VARIABLES | (1) M1: Probit | (2) M2: Probit | (3) M3: IV-Probit | (4) | (5) |
|---|---|---|---|---|---|
| | | | Structural equation | First-stage regression Anticipation | Ant × ΔSRA |
| Health (base: poor) | | | | | |
| excellent | 0.574*** | 0.603*** | 0.565*** | -4.624** | -2.156 |
| | (0.111) | (0.112) | (0.139) | (2.356) | (1.696) |
| very good | 0.547*** | 0.567*** | 0.537*** | -4.276* | -1.730 |
| | (0.108) | (0.109) | (0.130) | (2.316) | (1.654) |
| good | 0.489*** | 0.503*** | 0.468*** | -3.179 | -1.658 |
| | (0.106) | (0.107) | (0.128) | (2.296) | (1.635) |
| fair | 0.331*** | 0.333*** | 0.301** | -1.600 | -1.358 |
| | (0.111) | (0.112) | (0.122) | (2.374) | (1.681) |
| Education (base: primary) | | | | | |
| College+ | 0.221*** | 0.203*** | 0.168** | 3.957*** | 0.919* |
| | (0.062) | (0.062) | (0.086) | (1.254) | (0.539) |
| Upper-secondary | 0.002 | -0.006 | -0.008 | 1.837 | 0.829* |
| | (0.059) | (0.059) | (0.059) | (1.207) | (0.487) |
| Lower-secondary | -0.053 | -0.060 | -0.065 | 2.162 | 0.629 |
| | (0.065) | (0.065) | (0.064) | (1.316) | (0.588) |
| Marital (base: female · never-married) | | | | | |
| male · married | -0.155** | -0.137* | -0.077 | -3.177** | 1.275 |
| | (0.079) | (0.079) | (0.106) | (1.410) | (0.960) |
| male · never-married | -0.093 | -0.085 | -0.021 | -2.444 | 2.067 |
| | (0.111) | (0.112) | (0.130) | (1.896) | (1.424) |
| male · divorced | 0.024 | 0.028 | 0.066 | -0.778 | 1.910 |
| | (0.105) | (0.105) | (0.106) | (1.793) | (1.272) |
| male · widowed | -0.240 | -0.222 | -0.118 | -2.203 | 3.996* |
| | (0.172) | (0.176) | (0.210) | (3.466) | (2.282) |
| female · married | -0.240*** | -0.241*** | -0.188* | -1.534 | 1.262 |
| | (0.077) | (0.077) | (0.103) | (1.381) | (0.951) |
| female · divorced | 0.054 | 0.054 | 0.083 | -0.137 | 1.797* |
| | (0.092) | (0.092) | (0.090) | (1.624) | (1.077) |
| female · widowed | -0.089 | -0.089 | -0.043 | -1.438 | 1.528 |
| | (0.115) | (0.115) | (0.121) | (2.250) | (1.274) |
| Job sector (base: self-employed) | | | | | |
| Public sector | -0.248*** | -0.201*** | -0.169* | -7.016*** | -2.664*** |
| | (0.058) | (0.058) | (0.092) | (1.003) | (0.731) |
| Private sector | -0.134** | -0.097* | -0.056 | -5.725*** | -1.046* |
| | (0.052) | (0.052) | (0.083) | (0.872) | (0.601) |
| Missing | -0.291*** | -0.249** | -0.210 | -6.245*** | -1.999*** |
| | (0.111) | (0.113) | (0.131) | (1.896) | (0.757) |
| Job contract (base: part-time) | | | | | |
| Full-time | 0.230*** | 0.225*** | 0.192*** | 1.520** | -0.172 |
| | (0.037) | (0.038) | (0.064) | (0.667) | (0.499) |
| Other controls | | | | | |
| Log income | 0.018 | 0.020* | 0.021* | -0.296 | -0.072 |
| | (0.012) | (0.012) | (0.012) | (0.181) | (0.104) |
| Log assets | -0.008 | -0.008 | -0.009* | 0.014 | -0.067 |
| | (0.005) | (0.005) | (0.005) | (0.076) | (0.055) |
| Numeracy score | 0.022 | 0.029 | 0.033* | -0.629* | -0.018 |
| | (0.019) | (0.019) | (0.019) | (0.321) | (0.208) |
| Log income | -0.004 | -0.003 | -0.006 | -0.128 | -0.221** |
| | (0.012) | (0.012) | (0.012) | (0.233) | (0.110) |
| Log assets | 0.000 | 0.001 | -0.001 | -0.144* | -0.170*** |
| | (0.004) | (0.004) | (0.005) | (0.077) | (0.060) |
| Numeracy score | 0.020 | 0.022 | 0.024 | -0.187 | 0.053 |
| | (0.017) | (0.017) | (0.017) | (0.315) | (0.218) |
| Numeracy score missing | 0.818*** | 0.821*** | 0.652* | -12.690*** | -13.917*** |
| | (0.271) | (0.271) | (0.365) | (4.709) | (3.369) |

Note: *** p<0.01, ** p<0.05, * p<0.1. See the notes in Table 3.1. Columns (1) and (2) are based M1: Probit (the model that neglects the anticipation), and M2: Probit (the model that takes into account the anticipation), respectively. Columns (3) to (5) show the estimation results of M3: IV-probit. Column (3) shows the estimations of the structural equation, and Columns (4) and (5) show those of first-stage regressions.

Table 3.15: Predicted probabilities of rema

*Panel A:* Predicted probabilities of remaining employed if SRA remains at 65
... and anticipation is 0%, 50% and 100%.

| | Probit model | Linear probability model |
|---|---|---|
| Anticipation: | | |
| 0% | 0.829*** | 0.846*** |
| | (0.036) | (0.022) |
| 50% | 0.898*** | 0.91*** |
| | (0.025) | (0.021) |
| 100% | 0.945*** | 0.964*** |
| | (0.016) | (0.022) |

*Panel B:* Predicted percentage changes in the probabilities of remaining employed if SRA
... increases from 65 to 66 and pre-reform anticipation is 0%, 50% and 100%.

| | Probit model | Linear probability model |
|---|---|---|
| Anticipation: | | |
| 0% | 0.082*** | 0.032*** |
| | (0.023) | (0.007) |
| 50% | 0.027** | -0.007 |
| | (0.012) | (0.005) |
| 100% | -0.006 | -0.004 |
| | (0.008) | (0.006) |

Note: *** p<0.01, ** p<0.05, * p<0.1. Standard errors are clustered at a household level and reported in parentheses. The sample consists of $N = 29,710$ observations of 12,245 individuals from 10,402 households. The probit model results are obtained from Table 3.2 and 3.3. In Panel A, we show the predicted probabilities of 58-year-old average employees remaining employed for the next two years if SRA remains at 65 conditional on anticipation 0%, 50%, and 100%. In Panel B, we show the predicted percentage changes in probabilities of remaining employed if SRA increases from 65 to 66 conditional on anticipation 0%, 50%, and 100%.

Table 3.16: Predicted probabilities of transitioning from $t$ to $t+1$, by work sectors

| | | Transition from state in $t$ | | | |
|---|---|---|---|---|---|
| | | Public | Private | Self | Missing |
| | | (1) | (2) | (3) | (4) |
| Transition to state in $t+1$ | | | | | |
| *Panel A*: Retired | | | | | |
| | $\text{Ant}\vert_{\text{SRA}=65}(\cdot 100)$ | -0.086*** | -0.087*** | -0.087*** | -0.068*** |
| | | (0.007) | (0.009) | (0.009) | (0.011) |
| | $\Delta\text{SRA}\vert_{\text{Ant}=0}$ | -0.056*** | -0.069*** | -0.063*** | -0.037*** |
| | | (0.019) | (0.015) | (0.017) | (0.014) |
| | $\Delta\text{SRA}\vert_{\text{Ant}=100}$ | 0.0002 | 0.004 | -0.002 | -0.001 |
| | | (0.01) | (0.007) | (0.007) | (0.006) |
| *Panel B*: Public sector | | | | | |
| | $\text{Ant}\vert_{\text{SRA}=65}(\cdot 100)$ | 0.013* | 0.004 | 0.004 | 0.048*** |
| | | (0.007) | (0.005) | (0.005) | (0.011) |
| | $\Delta\text{SRA}\vert_{\text{Ant}=0}$ | 0.007 | -0.017*** | -0.008* | 0.007 |
| | | (0.018) | (0.006) | (0.005) | (0.013) |
| | $\Delta\text{SRA}\vert_{\text{Ant}=100}$ | 0.008 | 0.009 | 0.000 | 0.002 |
| | | (0.011) | (0.007) | (0.004) | (0.007) |
| *Panel C*: Private sector | | | | | |
| | $\text{Ant}\vert_{\text{SRA}=65}(\cdot 100)$ | 0.068*** | 0.002 | 0.002 | 0.008*** |
| | | (0.01) | (0.012) | (0.012) | (0.003) |
| | $\Delta\text{SRA}\vert_{\text{Ant}=0}$ | 0.046*** | 0.085*** | 0.029 | 0.019*** |
| | | (0.008) | (0.015) | (0.017) | (0.004) |
| | $\Delta\text{SRA}\vert_{\text{Ant}=100}$ | -0.009 | -0.015 | -0.018 | -0.005** |
| | | (0.006) | (0.01) | (0.012) | (0.003) |
| *Panel D*: Self-employed | | | | | |
| | $\text{Ant}\vert_{\text{SRA}=65}(\cdot 100)$ | 0.005** | 0.082*** | 0.082*** | 0.012** |
| | | (0.002) | (0.021) | (0.021) | (0.005) |
| | $\Delta\text{SRA}\vert_{\text{Ant}=0}$ | 0.002 | 0.001 | 0.043 | 0.011 |
| | | (0.001) | (0.002) | (0.031) | (0.007) |
| | $\Delta\text{SRA}\vert_{\text{Ant}=100}$ | 0.001 | 0.003 | 0.020 | 0.004 |
| | | (0.001) | (0.002) | (0.018) | (0.005) |

Note: *** p<0.01, ** p<0.05, * p<0.1. Note: *** p<0.01, ** p<0.05, * p<0.1. The table shows the estimation results of the multinomial probit model, which extends our baseline model M2: Probit. In wave $t$, individuals are employed in (1) the public sector, (2) in the private sector, (3) as self-employed, (4) or the work sector is missing. In wave $t+1$, they can transition to be (1) retired, (2) employed in the public sector, (3) employed in the private sector, or (4) become self-employed. In wave $t+1$, they can transition to be (1) retired, (2) employed in the public sector, (3) employed in the private sector, or (4) become self-employed. Standard errors are clustered at the household level and reported in parentheses. The log-likelihood at the estimates is -9902.3487.

Table 3.17: Predicted probabilities of transitioning from $t$ to $t+1$, by employed with either full- or part-time contract

| | Transition from state in $t$ | |
|---|---|---|
| | Full-time | Part-time |
| | (1) | (2) |
| Transition to state in $t+1$ | | |
| *Panel A*: Retired | | |
| $\text{Ant}\|_{\text{SRA}=65}(\cdot 100)$ | -0.094*** | -0.101*** |
| | (0.008) | (0.01) |
| $\Delta\text{SRA}\|_{\text{Ant}=0}$ | -0.066*** | -0.077*** |
| | (0.016) | (0.019) |
| $\Delta\text{SRA}\|_{\text{Ant}=100}$ | 0.008 | 0.009 |
| | (0.007) | (0.01) |
| *Panel B*: Full-time | | |
| $\text{Ant}\|_{\text{SRA}=65}(\cdot 100)$ | 0.09*** | 0.071*** |
| | (0.011) | (0.011) |
| $\Delta\text{SRA}\|_{\text{Ant}=0}$ | 0.056*** | 0.037*** |
| | (0.015) | (0.013) |
| $\Delta\text{SRA}\|_{\text{Ant}=100}$ | -0.011 | -0.012 |
| | (0.009) | (0.012) |
| *Panel C*: Part-time | | |
| $\text{Ant}\|_{\text{SRA}=65}(\cdot 100)$ | 0.005 | 0.38*** |
| | (0.007) | (0.014) |
| $\Delta\text{SRA}\|_{\text{Ant}=0}$ | 0.011 | 0.04** |
| | (0.008) | (0.018) |
| $\Delta\text{SRA}\|_{\text{Ant}=100}$ | 0.003 | 0.003 |
| | (0.007) | (0.014) |

Note: *** p<0.01, ** p<0.05, * p<0.1. The table shows the estimation results of the multinomial probit model, which extends our baseline model M2: Probit. In wave $t$, individuals work (1) full-time, or (2) part-time. In wave $t+1$, they can transition to be (1) retired, (2) work full-time or, (3) part-time. Standard errors are clustered at the household level and reported in parentheses. The log-likelihood at the estimates is -8,508.56.

Table 3.18: Heterogeneous effects of anticipation and $\Delta$SRA conditional on gender, numeracy score and marital status

| | Gender | | Numeracy score | | Marital status | | |
|---|---|---|---|---|---|---|---|
| | Female | Male-Female | High | Low-High | Married | Never-married-Married | Div./Sep. - Married |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| Anticipation | 0.006*** | 0.001 | 0.006*** | -0.0001 | 0.006*** | 0.002 | 0.002 |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.002) | (0.002) |
| Ant. $\times$ $\Delta$SRA | -0.004** | -0.002 | -0.005*** | 0.002 | -0.004*** | -0.004 | 0.0001 |
| | (0.001) | (0.002) | (0.001) | (0.002) | (0.001) | (0.005) | (0.006) |
| $\Delta$SRA | 0.319*** | 0.194 | 0.446*** | -0.134 | 0.329*** | 0.634 | 0.662 |
| | (0.124) | (0.178) | (0.115) | (0.187) | (0.096) | (0.472) | (0.423) |
| Pre-reform SRA | 0.064** | 0.067*** | 0.078*** | 0.027 | 0.082*** | 0.018 | -0.051 |
| | (0.029) | (0.025) | (0.024) | (0.060) | (0.025) | (0.080) | (0.067) |
| Read | -0.079* | 0.066 | -0.042 | 0.014 | -0.033 | 0.121 | -0.127 |
| | (0.040) | (0.056) | (0.037) | (0.056) | (0.030) | (0.111) | (0.095) |
| log-Likelihood | -4,376.3 | | -4,430 | | | -4,402.6 | |

Note: *** p<0.01, ** p<0.05, * p<0.1. The table shows the heterogeneous effects of anticipation, $\Delta$SRA, and their interaction across certain socio-economic groups. The estimation results for the heterogeneous effects of the main regressors between males and females are in Columns (1) and (2), between people with high and low numeracy scores are in Columns (3) and (4), and across different marital statuses are in Columns (5), (6) and (7). In Column (7), " Div./Sep." stands for divorced and separated. Standard errors are clustered at the household level and reported in parentheses.

# Chapter 4.

# On the estimation of bequest and precautionary saving motives using self-reported bequest probabilities

## 4.1 Introduction

Retirees in the U.S. are observed, on average, to leave positive wealth upon death, which cannot be rationalized by the standard life-cycle model (Modigliani & Brumberg, 1954). The common explanation of why retirees save so much later in life is because of motivations to leave bequeathable wealth to their heirs once they pass away or to insure themselves from potential risks at advanced ages, such as living longer than expected or encountering high out-of-pocket medical expenses (Yaari, 1965; De Nardi, French, & Jones, 2016b). In the literature, the former is known as the bequest motive and the latter as the precautionary motive.

Establishing the quantitative contribution and relative importance of bequest and precautionary motives is vital for understanding retirees' behavior, intergenerational wealth transfers, and the optimal design of several public policies. For example, if the relative importance of the bequest motive is negligible, most bequests are accidental as it is mainly the precautionary

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motive driving the retirees' savings, thus, changes in estate taxes would not substantially impact retirees' saving decisions (Kopczuk & Lupton, 2007). This also implies that if the government introduces schemes that fully insure retirees' advanced age risks, intergenerational wealth transfer is expected to decrease or become non-existent. On the contrary, if the relative importance of the bequest motive is strong, retirees would save for bequest purposes even if their risks are fully insured. The bequest motive can also explain the empirically observed low annuity demand because, as Lockwood (2012) argued, wealth saved for bequest purposes acts as a self-insurance device at advanced ages; thus, it decreases the annuity demand. In other words, people with a strong bequest motive save more, and if they live longer than expected, they can support themselves by drawing on the wealth they intended to bequeath.

Despite the growing number of empirical works in the past three decades, no consensus has been reached on the quantitative importance of bequest and precautionary motives on retirees' savings. It is known to be challenging to separately identify these motives from the observed savings because both have similar implications, especially at advanced ages. Researchers, therefore, have utilized various types of information from the data beyond savings. In an early study, Hurd (1987) estimated a structural model without medical expense uncertainty. In this analysis, he assumes only people with children have incentives to leave a bequest; thus, he identifies the bequest motive by comparing the age profile of the savings of people with and without any children. Gan et al. (2015) estimated a model similar to Hurd's, but their identification follows the theoretical prediction that, ceteris paribus, people with higher mortality rates have larger incentive to save for a bequest purpose. These studies find that the bequest motive has an economically trivial impact on savings, leading to the conclusion that most bequests are incidental.

Recent studies have examined the risk of encountering high out-of-pocket medical expenses at advanced ages, a crucial factor affecting retirees' saving decisions in the U.S. De Nardi et al. (2010); De Nardi, French, and Jones (2016a) analyze the savings together with heterogenous medical expenses and Medicaid recipiency rates. They found that the marginal utility of a bequest diminishes rapidly with the size of the bequest. In contrast, Lockwood (2018), using additional information on long-term care insurance purchases, finds a slower rate of diminishing marginal utility compared to previous studies and concluded that the bequest motive is an important driver of savings for both middle-income and wealthy retirees. Ameriks et al. (2011) analyze savings together with survey questions about people's state-contingent plans and find that the bequest motive is prevalent and affects the savings of both wealthy and middle-income retirees. However, compared to De Nardi et al. (2010, 2016a) and Lockwood (2012), Ameriks et al. (2011) find that the bequest motive has a smaller quantitative contribution to the savings of the wealthy.

In this paper, we provide new estimates of the relative importance of bequest and precautionary motives on retirees' saving behavior. The novelty of our paper is that we incorporate information on the self-reported probabilities of leaving a bequest, observed in a representative panel - the Health and Retirement Study - into a widely used structural life-cycle model. Self-reported probabilities of surviving to a certain target age provide insights into respondents' varying levels of optimism or pessimism concerning their longevity. Self-reported probabilities of bequeathing are likely to reflect people's long-term savings objective and how they perceive future survival and medical expenses. Thus, once the medical expense and longevity risks are controlled for, these probabilities carry information on what fraction of their wealth people intend to save as a bequest. To understand the intuition, suppose that the government fully insures medical expenses and longevity risks; thus, people's main savings objective is due to a bequest motive as there is no precautionary reason to save. In that case, reporting no chance of leaving any bequest would be evidence of the non-existence of a bequest motive. In contrast, a non-zero probability would support the existence of a bequest motive, and the probability distribution of the amount of bequest informs how strong the motive is.

We estimate the structural life-cycle model by the Method of Simulated Moments, which is in the spirit of Gourinchas and Parker (2002); De Nardi et al. (2010) and Lockwood (2018). Our model takes into account complex relationships between medical expense risk, longevity risk, and savings. The structural approach is compelling in our study because it incorporates liquidity constraints and government transfers, which could not captured adequately via parsimonious reduced-form specifications. It is important to note that to incorporate the information in self-reported bequest probabilities in the model, we do not need to complicate the standard model by adding more control or state variables. Instead, we only need to construct additional moment conditions. Hence, in our case, utilizing the information from elicited self-probabilities is straightforward and does not add substantial computational cost.

Our central findings are as follows. First, using the information in self-reported probabilities to bequeath, together with standard features of the data (for example, wealth, medical expenses, annuity income, etc.), helps to pin down the bequest motive parameters precisely. Compared to the model without self-reported bequest probabilities, the model that utilizes this information suggests that the bequest motive is stronger and more prevalent in the savings decision of wealthy and middle-income retired individuals. This result is relevant to ongoing debates about the existence and extent of the bequest motive.

Next, using the information in self-reported probabilities to bequeath is necessary for the model to be successful in predicting the observed bequeathed wealth by the HRS respondents who passed away between 2002 and 2014. The model without self-reported bequest probabilities tends to over-predict the median bequests, especially among the wealthy. In contrast, the model with self-reported bequest probabilities consistently outperforms the other model in terms of predicting the realized bequests of both the wealthy and the poor.

Thirdly, the precautionary motive to save in anticipation of uncertain medical expenses and the bequest motive both contribute substantially to savings over the life cycle. Based on the estimation that uses self-reported bequest probabilities, a counterfactual analysis shows that the saving behavior of wealthy and middle-income individuals is driven by both motives to save for uncertain medical expenses and for bequest. For example, for individuals aged 60-65 in 1998, if their motive to save in response to medical expenses is shut down, their median wealth would have been around 15% and 40-45% lower at ages 75 and 85, respectively. On the other hand, if the bequest motive is shut down, their median wealth at ages 75 and 85 would have been 8-9% and 25-32% lower, respectively. Shutting down both motives would lead to a drop in median wealth by 16% and 49-50% at ages 75 and 85, respectively. The magnitudes of these drops are slightly larger than those in previous experiments where the medical expenses are turned off. In other words, the majority of the savings of wealthy and middle-income individuals over the life cycle is driven by precautionary motives related to expected medical expenses, as opposed to being driven by the bequest motive.

For relatively poor individuals, savings are not sensitive to expected medical expenses because they rely on government transfers in case of high medical expenses. On average, low-income individuals exhaust their median wealth by age 75. However, if the bequest motive is shut down, they would have exhausted their median wealth by age 73, suggesting that poor individuals with bequest motives de-accumulate their wealth at a slower rate.

Fourthly, we find that, for wealthy and middle-income individuals, their decisions of whether to leave positive bequests are driven primarily by the bequest motive. On the other hand, their decisions of how much wealth would be bequeathed upon death are determined mainly due to their precautionary motive to save in response to medical expenses.

Finally, we use our estimated model to evaluate two hypothetical policy changes. In the first policy, we ask what happens if the U.S. government covers the entire medical expenses of all retirees starting from 1998. We find that this policy substantially decreases the savings of wealthy individuals because they do not have a precautionary motive to save for mitigating uncertain medical expenses. Similarly, the median wealth of middle-income individuals decreases with advancing age. The savings of low-income individuals increase such that the age when they exhaust their median wealth increases from 75 to 79. This is because they have more resources to save and consume in old age when the government fully pays their medical expenses. We also find that the policy decreases the median bequests but increases the fraction of individuals who leave positive bequests.

In the second policy experiment, we examine the impact of increasing the estate tax on savings and bequests. In our counterfactual analysis, we simulate a new estate tax system in which bequeathed wealth below \$20,000 is not taxed and above this amount is taxed at 30%. Consistent with the findings of Cagetti and De Nardi (2009), we find that changing the estate tax does not significantly affect savings. Furthermore, changing the estate tax decreases the median bequests of the top and middle-income groups but does not change the median bequests of the low-income group. This is because the median bequest of the low-income group is too low to be subject to taxation.

Our paper contributes to at least three strands of the literature. Firstly, it contributes to a growing literature on exploring the "retirement saving puzzle" which quantifies various saving motives of the elderly. By incorporating the self-reported bequest probabilities into a structural life-cycle model, we provide a new set of results regarding the relevance and extent of the bequest motive to the existing literature. Our results are similar to those of Lockwood (2012) and Ameriks et al. (2011) in concluding that the bequest motive plays a substantial role in the savings of wealthy and middle-income individuals.

The paper also contributes to the literature focused on identifying unknown parts of a structural model using elicited self-reported probabilities. Van der Klaauw and Wolpin (2008) and Van der Klaauw (2012) show the importance of using elicited self-reported probabilities to identify dynamic discrete choice models. Ameriks et al. (2011, 2020) estimated a life-cycle model using cross-sectional information on people's evaluations of hypothetical scenarios that contain a trade-off between leaving a bequest or having consumption at advanced ages. However, their sample consists of relatively wealthy individuals with internet access.[1] In contrast, by using the information from the representative panel, we demonstrate the feasibility of incorporating existing self-elicited probability data into a structural life-cycle model. We show that our empirical strategy helps researchers to obtain precise estimates of important preference parameters.

In addition, by comparing observed bequests with model-implied counterparts, we validate the predictions within the structural life-cycle model. Specifically, we conduct a comparison involving the median bequests predicted by the model and the median bequests observed that

[1] The sample of Ameriks et al. (2011, 2020) consists of individuals who hold stocks in Vanguard Group. Therefore, their sample more likely consists of wealthier individuals than the average U.S. individuals with the same demographic background.

are not targeted in the estimation. The results demonstrate that the model that incorporates self-reported bequest probabilities consistently performs better than the model that does not incorporate such probabilities.

The remainder of the paper is organized as follows. Section 4.2 develops the economic model. Section 4.3 describes our data for estimation. Section 4.4 describes our strategy to estimate the structural life-cycle model with the self-reported bequest probabilities. Section 4.5 shows the baseline parameter estimates and the model validation. Section 4.6 shows the model implications on disentangling savings motives and two hypothetical policy experiments. The last section concludes.

# 4.2 Life-cycle model of retired elderly singles

Our model is closely related to those of Yaari (1965); Hurd (1987); De Nardi et al. (2010) and Lockwood (2018) in their analysis of savings and bequests. In our model, a single retired agent faces lifespan uncertainty, uncertain medical expenses, and a bequest motive. We assume the agent maximizes her expected utility by choosing how much to save in a risk-free asset.

We use the following notations: $t$ is the agent's age, $h_t$ is the health state at age $t$, $g$ is the gender, and $I$ is the permanent-income.[2] We assume that the health state, $h_t$ $\forall t$, is binary: good ($h_t = 1$) or bad ($h_t = 0$). $g$ equals one if the agent is female; zero otherwise. The agent's maximum potential age to live is $T$.

*Preferences:* In each period, a retired single agent decides how much to consume $c$. The agent's flow of utility from consumption is:

$$u(c) = \frac{c^{1-\gamma} - 1}{1-\gamma}. \tag{4.1}$$

Here $\gamma$ is the relative risk aversion parameter.[3] We assume that the $u(c) = -\infty$ if $c < c_{\min}$ where $c_{\min}$ is the minimum consumption that the agent consumes.

The agent can derive utility from leaving a bequest $w$ to her heirs. Following French (2005)

[2] The definition of permanent-income is in Section 4.3.1.2.

[3] De Nardi et al. (2010) allowed that the utility from consumption also depends on the health state. However, they did not find conclusive evidence that the utility of consumption depends on the health state.

and De Nardi et al. (2010), we assume that the agent's utility from bequests is:

$$\nu(w) = \Big(\frac{\phi}{1-\phi}\Big)^{\gamma} \frac{(\frac{\phi}{1-\phi}k + w)^{1-\gamma}}{1-\gamma}, \quad \text{where } 0 \leq \phi \leq 1 \text{ and } 0 \leq k \tag{4.2}$$

The functional form specification of the utility from a bequest, shown in Eq. 4.2, is used by Lockwood (2018). Here, $\phi$ determines the bequest weight. For example, if $\phi = 0$, the agent does not derive any utility from leaving a bequest. In that case, a realized bequest is purely accidental. The parameter $k \geq 0$ determines the curvature of the utility from the bequest function. The higher the value of $k$, the faster the marginal utility from leaving a bequest decreases. Hence, when $k > 0$, leaving no bequest can be optimal even if the agent has positive wealth.

The specification is also consistent with other interpretations of the bequest motive, such as the strategic (Bernheim, Shleifer, & Summers, 1985) or altruistic motive (Abel & Warshawsky, 1987). It is also flexible enough to accommodate almost all the functional forms used in the literature. When $k = 0$, the utility from bequest follows a standard CRRA type, used by Friedman and Warshawsky (1990). When $\phi = 1$, the utility from bequest is linear, with the constant marginal utility $\nu'(b) = k^{-\gamma}$.[4] The linear utility from bequest form is used by Hurd (1989) and Kopczuk and Lupton (2007). By setting $\tilde{\phi} \equiv \Big(\frac{\phi}{1-\phi}\Big)^{\gamma}$ and $\tilde{k} \equiv \frac{\phi}{1-\phi}k$, one can recover the specification with the bequest motive parameters $(\tilde{\phi}, \tilde{k})$ used by French (2005) and De Nardi et al. (2010).

*Non-asset income:* The agent receives income $y$ from Social Security in each period. We assume that income $y$ is a function of sex $g$ and permanent-income $I$, $y = y(g, I)$.

*Uncertainties:* The agent faces several exogenous risks/uncertainties: (1) health state, (2) out-of-pocket medical expenses (OOPME), and (3) life-span. We treat these risks as exogenous. This can be a reasonable simplification because our research focuses on older retired people who have already shaped their habits, lifestyle, and health. We assume that the uncertainties that the agent encounters have the following distributions:

1. *Health state uncertainty:* $\pi_{t+1|t,h_t,g,I}$ is the probability of health at age $t+1$ being good. It is a function of current health, sex, permanent-income, and age.

2. *Life-span uncertainty:* $s_{t+1|t,h_t,g}$ denotes the probability the agent will survive to age $t+1$

[4] Note that the marginal utility from bequest, when $\phi$ approaches one, is:

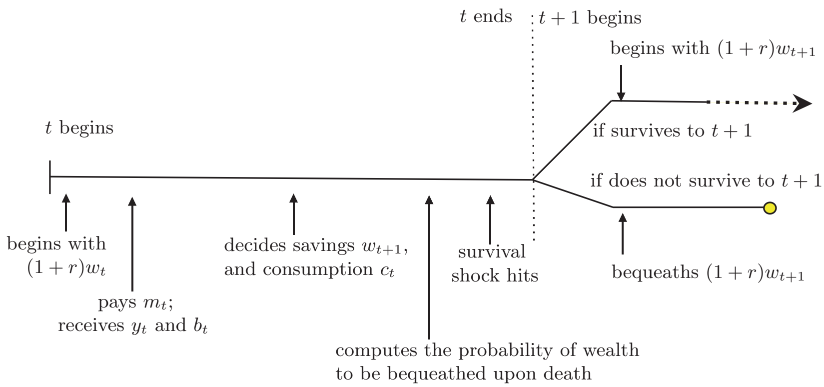
$$\lim_{\phi \to 1} \nu'(b) = \lim_{\phi \to 1} \Big(\frac{\phi}{1-\phi}\Big)^{\gamma} \Big(\frac{\phi}{1-\phi}k + b\Big)^{-\gamma} = \lim_{\phi \to 1} \Big(k + \frac{1-\phi}{\phi}b\Big)^{-\gamma} = k^{-\gamma}. \tag{4.3}$$

conditional on she survived to age $t$, and it is a function of $(t, h_t, g)$. Since the maximum potential age to survive is $T$, the probability of surviving to $T+1$ is zero, i.e., $s_{T+1|T,h_t,g} = 0$. In Section 4.4.1, we discuss our strategy of using the self-reported survival expectations observed in the HRS to estimate survival probabilities.

3. *Medical expense uncertainty:* Let $m_t$ denote the out-of-pocket medical expenses (OOPME). The OOPME depends probabilistically on current health $h_t$, age $t$, sex $g$, and permanent-income $I$. We assume that the log of OOPME follows the normal distribution:

$$\ln m_{t,h_t,g,I} \sim \mathcal{N}(\mu_{t,h_t,g,I}; \sigma^2_{t,h_t,g,I}) \tag{4.4}$$

Figure 4.1: Timing of decision for the agent who survived to age $t$




*Note:* The figure illustrates the decision-making steps of an agent who survived to period $t$ with wealth $(1+r)w_t \geq 0$. In period $t$, the agent receives annuity income $y$ and government transfer $b_t$ and pays OOPME $m_t$. After that, she decides how much to save $w_{t+1}$ and consume $c_t$. Next, the agent forms the distribution of her bequests. Before she enters period $t + 1$, she gets hit by the survival shocks. If she survives to $t + 1$, her problem continues. Otherwise, she passes away and her remaining wealth will be transferred to her heir(s).

*Timing of the model and budget constraint:* Suppose that the agent survived to age $t$ with non-negative accumulated wealth $(1 + r)w_t$. The agent receives income $y$ and encounters uncertain OOPME $m_t$. OOPMEs are not part of consumption.[5]

[5] In our model, OOPME includes long-term care expenses. As Lockwood (2018) noted, the reject rate from applying to purchase long-term care insurance for 65-year-old applicants is between 12 and 23 percent Murtaugh, Kemper, Spillman, and Carlson (1997). Furthermore, many of the largest long-term care insurance companies advise rejecting anyone who is 80 or older regardless of their health status Hendren (2013). Therefore, assuming the long-term care expenses are exogenous is reasonable because we focus on retired elders older than 65. Some may argue that people with and without long-term care insurance experience different medical expense paths; thus, one should model the medical expenses as a function of having long-term care insurance. However, the number of individuals with long-term care insurance is 155, which is around 5% of the sample. Thus, we suspect that modeling long-term care insurance as a state variable would not affect the model estimations substantially.

Following Hubbard, Skinner, and Zeldes (1994, 1995), we assume that there exist government transfers, $b_t$, that guarantee the agent to consume at least $c_{\min}$. The amount of government transfer is defined as follows:

$$b_t = \max\{0, c_{\min} + m_t - [(1+r)w_t + y]\} \tag{4.5}$$

This equation implies that government transfers bridge the gap between the agent's total resources $(1+r)w_t + y - m_t$ and the consumption floor $c_{\min}$. To be consistent with the public insurance program, if the agent receives the government transfer, then $c_t = c_{\min}$ and $w_{t+1} = 0$. If the agent affords to consume more than $c_{\min}$, she is not eligible for government transfers.

Once the agent decides her consumption $c_t$ and savings $w_{t+1}$, she forms her expectation regarding the distribution of her bequest.[6] At the end of period $t$, the survival shock hits the agent. If she passes away, her remaining wealth $w_{t+1}$ will be transferred to her heirs as a bequest at the beginning of period $t+1$; thus, the total value of the bequest is $(1+r)w_{t+1}$. If the agent survives to period $t+1$, the agent enters period $t+1$ with the amount of wealth $(1+r)w_{t+1}$, and her problem continues. The agent cannot die in debt (or leave negative bequests). Therefore, together with survival risk, this restriction implies a no-borrowing constraint.

The timing of the model implies the following wealth accumulation function:

$$w_{t+1} = (1+r)w_t + y + b_t - m_t - c_t, \tag{4.6}$$

where $r$ denotes the risk-free rate of return.

We will represent the model in terms of cash-in-hand $x_t$, such that $x_t$ is the amount of wealth remaining after receiving $y$, $b_t$, and paying $m_t$:

$$x_t = (1+r)w_t + y + b_t - m_t. \tag{4.7}$$

Therefore, the amount of savings at the end of period $t$ equals to:

$$w_{t+1} = x_t - c_t. \tag{4.8}$$

[6] We incorporate the agent's expectation formation regarding her bequest at this step because, in our econometrics model, we fit the theoretically predicted distribution of bequest with their empirical counterparts observed in the Health and Retirement Study.

The motion of the cash-on-hand between periods $t$ and $t+1$ is as follows:

$$
\begin{aligned}
x_{t+1} &= (1+r)w_{t+1} + y + b_{t+1} - m_{t+1} \\
&= (1+r)\Big(\underbrace{(1+r)w_t + y + b_t - m_t}_{=x_t} - c_t\Big) + y + b_{t+1} - m_{t+1} \\
&= (1+r)(x_t - c_t) + y + b_{t+1} - m_{t+1}. \qquad (4.9)
\end{aligned}
$$

The agent cannot die with debt and the consumption floor must be satisfied at every period. To ensure non-borrowing constraints and enforce the consumption floor, the following condition must be satisfied for every period:

$$x_t \geq c_t \geq c_{\min}, \quad \forall t. \qquad (4.10)$$

*The agent's problem:* Let $\beta$ denote the discount factor. The agent is assumed to be an expected discounted utility maximizer. The value function for a single retired individual is given by:

$$
\begin{aligned}
V_t(x_t, h_t, g, I) = \max_{c_t \in [c_{\min}, x_t]} \Big\{ & u(c_t) + \beta s_{t+1|t,h_t,g} \cdot \mathbb{E}_{m_{t+1},h_{t+1}}(V_{t+1}(x_{t+1}, h_{t+1}, g, I)) + ... \\
& \beta(1 - s_{t+1|t,h_t,g}) \cdot \nu\Big((1+r)(x_t - c_t)\Big)\Big\} \qquad (4.11)
\end{aligned}
$$

At period $T+1$, the value function is:

$$V_{T+1}(x_T, h_T, g, I) = \nu\Big((1+r)(x_T - c_T)\Big), \quad \text{and} \quad s_{T+1|T,h_T,g} = 0 \qquad (4.12)$$

subject to the constraints in Eqs. 4.9 and 4.10. $\mathbb{E}_{m_{t+1},h_{t+1}}(\cdot)$ is an expectation over $h_{t+1}$ and $m_{t+1}$ at given $(t, h_t, g, I)$.

As shown in Eq. 4.11, the value function at age $t$ depends on the agent's cash-on-hand $x_t$, health state $h_t$, gender $g$ and permanent-income $I$. The next period's value functions are weighted by $\beta$. They are the functions in case she survives and does not survive to $t+1$ multiplied by their respective probabilities of surviving and not surviving to period $t+1$. If the agent survives to $t+1$, she encounters uncertainties in her health state and medical expenses at $t+1$; thus, she takes an expectation of her value function over these uncertain processes.

Eq. 4.12 shows the terminal condition of the agent's problem. Since the agent does not live beyond age $T+1$, the value function at the terminal periods equals the utility from bequeathing any remaining wealth at the end of period $T$ times $(1+r)$.

# 4.3 Data

## 4.3.1 Sample selection and main variables of interest

Our main variables are from the HRS Core Interviews from survey waves 4 to 12 (years from 1998 to 2012). The HRS samples the non-institutionalized population for each cohort entering the study but continues to track existing respondents even if they became institutionalized. Their wealth, medical expenses, marital status, and vital status were observed through proxy interviews if they could not participate in the survey. Subjective survival expectations were only observed if the respondent could participate in the survey.[7] We selected single retired individuals who were at least 65 years old in 1998 in our analysis because our economic model concerns the behavior of these individuals. If possible, we use the RAND version of the dollar variables, such as individuals' wealth, income, and out-of-pocket medical expenses.

We observe the actual bequests from the HRS-Exit Interview, which is a follow-up survey of the HRS Core Interview after the HRS respondents have passed away. All dollar variables (e.g., financial variables, actual bequests, and medical expenses) are deflated to 1998 dollars using the Consumer Price Index for Urban Wage Earners.

#### 4.3.1.1 Sample selection

We decide not to use the first three waves because of inaccurate wealth data (Rohwedder, Haider, & Hurd, 2006). We restrict our sample to individuals who participated in the fourth wave (i.e., interviews conducted in 1998). We exclude waves after 2012 because the sample becomes too small due to mortality and survey dropouts.

The main sample selection steps are shown in Table 4.1. The initial sample of the HRS from waves four to twelve consists of 21,292 individuals, of which 4,283 individuals were 65 or older in 1998 and retired singles during the period of interest. Following De Nardi et al. (2010) and Lockwood (2018), we consider the respondents as retired if their annual non-asset earnings are less than 3,000 dollars (after adjusting to the dollar value in 1998). Next, we keep the individuals whose wealth is non-negative during the observed waves. We drop the top 5% of the wealth-holders, based on their wealth in 1998, to prevent extreme values and outliers from

[7] For instance, we observe 9,503 numerical responses concerning the subjective probability of bequeathing, representing around 76% of the total observations. Approximately 8% of respondents either replied with "Don't know" or "Refused to Answer." About 15% of the interviews were conducted through proxies, although detailed explanations for proxy usage were unavailable. Roughly 1% of the interviews were skipped due to unknown reasons.

Table 4.1: Sample selection steps

| | Steps | Number of observations (individuals × waves) | Number of individuals |
|---|---|---|---|
| 0 | Initial sample from wave 4 to 12 (from 1998 to 2012) | 131,142 | 21,292 |
| 1 | Keep if age is 65 or older in 1998 | 54,536 | 10,697 |
| 2 | Keep if lived as a single during the observed waves | 18,861 | 4,283 |
| 3 | Keep if retired | 16,143 | 3,857 |
| 4 | Keep if non-housing wealth is non-negative during the observed waves | 13,283 | 3,322 |
| 5 | Drop top 5% of wealthy individuals in 1998 | 12,517 | 3,166 |

biasing our results. Our main sample for the estimation consists of 3,166 individuals who were observed in the survey, on average, for four waves.

In the following subsections, we explain the definitions of the main variables we use for our analysis and their summary statistics.

#### 4.3.1.2 Wealth, OOPME, health status, and other socio-demographic variables

Table 4.2 shows the descriptive statistics of the variables we use in our estimation. Panel A of the table shows the descriptive statistics of the financial variables and medical expenses. Panel B those for respondents' various socio-demographic variables, health state, whether having any children, and age. The definitions of the financial variables, OOPME, and health states are as follows:

*Total and non-housing (net) wealth:* Total wealth is the sum of all assets less mortgages and other debts. The HRS has information on more than ten categories of wealth. For example, the value of housing and real estate, cars, liquid assets, individual retirement accounts, Keoghs, stocks, mutual funds, bonds, and the value of the business.

*Non-asset income and permanent income:* Non-asset income includes the value of Social Security benefits, defined-benefits, annuities, veteran's benefits, and food stamps. Following De Nardi et al. (2010) and Lockwood (2018), we measure permanent income as the individual's average real income over all periods during which the respondent is observed. Because most benefits are a monotonic function of average lifetime labor income, De Nardi et al. (2010) argued that this average income would be a reasonable measure of permanent income.

*Out-of-pocked medical expenses:* The OOPME is the sum of what the respondent has spent

Table 4.2: Descriptive statistics of variables

| VARIABLES | N | mean | sd | min | max |
|---|---|---|---|---|---|
| *Panel A: Financial variables and medical expenses* | | | | | |
| Total wealth / 1000 | 12,517 | 135.0 | 349.7 | 0 | 30,520 |
| Non-housing wealth / 1000 | 12,517 | 88.95 | 365.0 | 0 | 33,312 |
| Non-asset income / 1000 | 12,517 | 13.43 | 29.31 | 0 | 2,405 |
| Permanent income / 1000 | 12,517 | 13.42 | 15.33 | 0 | 624.5 |
| Out-of-pocket medical expenses / 1000 | 12,517 | 2.246 | 7.644 | 0 | 264.9 |
| *Panel B: Time-varying variables: age, health state, and having any kids* | | | | | |
| Age | 12,517 | 81.58 | 6.801 | 65 | 94 |
| Health: good or excellent | 12,517 | 0.573 | 0.495 | 0 | 1 |
| Whether have any kids | 12,517 | 0.830 | 0.375 | 0 | 1 |
| *Panel C: Reported subjective expectations* | | | | | |
| Probability of leaving 0K+ | 6,549 | 63.14 | 46.86 | 0 | 100 |
| Probability of leaving 10K+ | 9,503 | 55.89 | 44.11 | 0 | 100 |
| Probability of leaving 100K+ | 9,311 | 28.61 | 40.97 | 0 | 100 |
| Probability of surviving to a (pre-specified) target age | 5,832 | 35.85 | 33.09 | 0 | 100 |
| *Panel D: Actual bequest related variables* | | | | | |
| Actual bequest / 1000 | 959 | 156.7 | 213.0 | 0 | 998.1 |
| Age of death | 959 | 86.60 | 6.617 | 67 | 100 |
| *Panel E: Time-invariant socio-demographic variables* | | | | | |
| Female | - | 0.781 | 0.414 | 0 | 1 |
| Separated | - | 0.158 | 0.365 | 0 | 1 |
| Widowed | - | 0.779 | 0.415 | 0 | 1 |
| Never-married | - | 0.0632 | 0.243 | 0 | 1 |
| Less than HS | - | 0.473 | 0.499 | 0 | 1 |
| Highest education: HS | - | 0.297 | 0.457 | 0 | 1 |
| Highest education: College | - | 0.145 | 0.352 | 0 | 1 |
| College+ educated | - | 0.0853 | 0.279 | 0 | 1 |
| Caucasian | - | 0.817 | 0.387 | 0 | 1 |
| African-American | - | 0.154 | 0.361 | 0 | 1 |
| Hispanic | - | 0.0111 | 0.105 | 0 | 1 |
| Other ethnicity | - | 0.0179 | 0.133 | 0 | 1 |
| Cohort born after 1924 | - | 0.279 | 0.449 | 0 | 1 |
| Cohort born between 1914 and 1923 | - | 0.476 | 0.500 | 0 | 1 |
| Cohort born before 1913 | - | 0.244 | 0.430 | 0 | 1 |

*Note:* The table presents descriptive statistics of the variables used for estimation. In total, we have observed 12,517 individuals. On average, individuals are observed for approximately four waves. The time-invariant variables are observed for every individual in our sample.

out-of-pocket on insurance premia, drug costs, hospital stays, nursing home care, doctor visits, dental visits, and outpatient care. These medical expenses do not include the expenses covered by insurance, either public or private.

*Health status:* The HRS asks the respondent's self-reported general health status in each wave. The possible answers are (1) Excellent, (2) Very good, (3) Good, (4) Fair, and (5) Poor or bad. Following De Nardi et al. (2010), we define that the health state takes two levels: (1) good if the self-reported health is Excellent, Very good, or Good; and (2) bad if the self-reported health is Fair or Poor or Bad. Following this definition, in our sample, around 57% of respondents had good health, and the rest had bad health.

In our sample, the average wealth is around 135K, annual non-asset income is around 13.4K, and the average annual OOPME is around 2.2K. Around 78% of our sample are females, which can be explained by the fact that most respondents are widowed, and female spouses tend to outlive their partners on average.

Moreover, in Table 4.7 in Appendix 4.8.1, we show the summary statistics of our sample and those of the HRS sample older than 65. The latter sample nests our sample because it includes people who are not-retired and married or partnered. Compared to everyone who was older than 65 in the HRS, our sample consists of individuals who are less educated, poorer, older, and less healthy. The proportions of Caucasians, African-Americans, and Hispanics are similar between the two samples.

#### 4.3.1.3 Self-reported probabilities of bequeathing and surviving

Panel C of Table 4.2 shows the summary statistics of the self-reported bequest probabilities and subjective survival probabilities. The subjective expectations are observed in the HRS Core Interview in every wave during our period of interest, and the definitions of these variables are as follows:

*Self-reported bequest probabilities:* The HRS asks a series of questions about respondents' perceived probabilities of bequeathing (1) any wealth (0K), (2) more than \$10,000 (10K), and (3) more than \$100,000 (100K). From now on, we call these variables "bequest probabilities" or "the probability of bequeathing $tr+$" where $tr$ can be either 0K, 10K, or 100K.[8]

The series of bequest probability questions started with the following question:

[8] For both bequest and subjective survival probabilities, around 6-7% of eligible respondents refused to answer or responded with "Don't Know" to these questions. Since few respondents chose these options, we do not consider the potential sample selection issue and assume that refusing to answer or answering with "Don't Know" are random.

*... Including property and other valuables that you might own, what are the chances that you will leave an inheritance totaling 10K dollars or more? ...*

The respondent can pick an integer between 0 and 100, where 0 means no chance and 100 means absolutely sure. If the response to the probability of bequeathing 10K+ is 0%, then the probability for 0K+ is asked, but that for 100K+ is set to 0%. If the response to the probability of bequeathing 10K+ is 100%, then that probability for 0K+ is set to 100%, but that for 100K+ is asked. Suppose the response to the probability of bequeathing 10K+ is neither 0% nor 100%. In that case, that probability for 0K+ is skipped, but that for 100K+ is asked.[9] We can see the impact of this survey design on the number of non-missing observations for the different probability of bequeathing questions from Table 4.2. For example, the table shows that the number of non-missing observations to the probability for 10K+ is larger than those for 0K+ and 100K+.

*Subjective survival probabilities:* In each wave, the HRS asks the following question:

*... What is the percent chance that you will live to be ta or more? ...*

The respondent can pick an integer between 0 and 100 where 0 means no chance and 100 means absolutely sure.[10] Here *ta* is the target age, linked to the respondent's age. In each survey wave, respondents answered at most two survival expectation questions with different target ages, one with the target age of 75 and another with the age of 85 or older (or 85+). The HRS is designed such that the difference between the target age and the age of respondents is at least ten years, and the target age is always a multiple of 5. Since our main sample consists of relatively old people, most respondents were not eligible to answer the survival expectation question with a target age of 75.

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9 If the respondent had a partner, the question was asked as the chances that you and your husband/wife/partner will leave an inheritance. From wave eight forward, the question is prefaced by the following: ... "Think about an inheritance you (and your (husband/wife/partner) might leave (but not including any inheritance you might leave to each other)" ... We do not expect this additional preface asked since wave eight would affect the respondent's reporting behavior systematically because we only consider single people.

If the reported probability of bequeathing 100K+ is positive, the probability of bequeathing more than 500K dollars is asked. However, we do not use the probabilities of bequeathing 500K+ for two reasons. First, the question of whether to bequeath more than 500K is only asked starting from wave six. Second, in our baseline sample, only 778 individuals ever responded to this question at least once.

10 Besides choosing responses between 0 and 100, respondents can also choose to answer "Don't know" or "Refuse". In our sample, around 12% of the individuals chose the "Don't know" or "Refuse" option.

#### 4.3.1.4 Actual bequests

The last panel of Table 4.2 shows the descriptive statistics for actual bequests and age of death when combining our main sample with the HRS-Exit Interview.

We observe the respondents' realized amount of bequest transferred from them to their heirs from the HRS-Exit Interview, which is a follow-up survey of the HRS after the HRS respondents have passed away. The Exit Interview contains data from the proxy informants (usually the deceased respondents' close family members) who are asked about the deceased respondents' wealth endowment and how it is distributed among their heirs. We use the Exit Interviews from 20002 to 2014 because the questionnaire about the inheritance of Exit interviews in 2000 and earlier years differ substantially from that of the later interviews.

Our main variable of interest is the total value of bequeathed wealth. The total bequest is computed by summing up the market values of (1) primary home, (2) secondary home, (2) liquid assets, and (3) life insurance at the time respondents passed away. Each component of the total bequest is asked in the following order. First, the exact value of the component is asked. If the exact value is not provided, the HRS asks for the lower and upper bounds of the component. In that case, we impute the value of the component by the average of the lower and upper bounds. A similar imputation strategy is used by Hurd and Smith (2002) and Groneck (2017). We set the value as zero if no information about the component is provided but at least one other component's value is provided. The values of bequests from different survey waves are inflation-adjusted to 1998 levels. We observe 153 individuals who bequeathed more than five million. We dropped these observations assuming those were outliers.

Combining the HRS-Exit Interviews with our sample from the HRS Core Interviews, we observe 959 respondents' information on their total realized bequests after they passed away. On average, these respondents pass away at age 87, with a median bequest of around 87K and a mean of 157K in 1998 dollars.

### 4.3.2 On the validity of bequest probabilities

Despite being available for two decades, to our knowledge, few studies have incorporated the information in bequest probabilities from the HRS into their analysis. McGarry (1999) analyze the inter-vivos and bequests between parents and children. In her econometrics analysis, she regresses the probability of bequeathing more than 0K+, 10K+, and 100K+ on children's income and other family characteristics, conditional on parents who have made inter-vivo transfers. She finds that positive and significant impact of children's income on the probability of leaving bequests if families make an inter-vivo transfer; otherwise, there is no significant impact. Hurd and Smith (2002) use the bequest probabilities to construct the aggregate distribution of bequests conditional on parents' age, birth cohort, and wealth. They find parents from younger cohorts and who are wealthier plan to make larger bequests than their counterparts. The ratio between an anticipated bequest and wealth increases as parents' wealth increases. Kopczuk and Lupton (2007) estimate the life-cycle model of the agent with bequest motive by fitting the model-implied consumption profiles to the empirical counterparts. They use the information in bequest probabilities for external validation of their results.

In this section, we show some descriptive facts about the bequest probabilities, for example, whether people's reported probabilities of bequeathing are logical and increasing in their wealth holdings. Next, we will show several reduced-form analyses on whether the bequest probabilities are good predictors of wealth dynamics and actual bequest. Our reduced-form analysis in this section is similar to that of Hurd and Smith (2002), but we use more recent HRS survey waves.

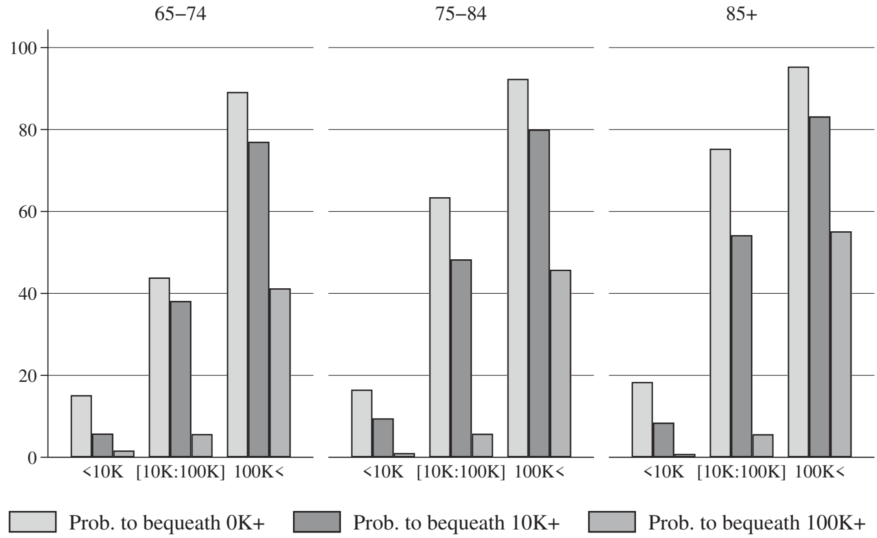
The life-cycle model predicts that, when all else is constant, people with higher wealth are more likely to leave a bequest. To check whether this prediction holds, Figure 4.2 shows the average bequest probabilities conditional on respondents' wealth is less than 10K, between 10K and 100K, and above 100K. It further separates the average probabilities for those aged between 65 and 74, between 75 and 84, and 85 or more. The figure uses the observations from 1998.

We observe from the figure that the average bequest probabilities increase monotonically with wealth. Hence, qualitatively, the descriptive patterns of bequest probabilities predict that wealthy individuals plan to bequeath larger bequests. Furthermore, the figure illustrates that, on average, people report their probabilities logically as the average probability of bequeathing is the largest for 0K+ and the smallest for 100K+.[11]

One interesting finding from Figure 4.2 is that the average probabilities of young and old respondents are not substantially different, especially for those with a wealth of more than 100K. This fact can be explained by two factors that have opposite impacts on the bequest probabilities. On the one hand, compared to younger individuals, older ones are more responsive to their bequest motives because their probability of passing away in the next period is larger. On the other hand, bequest probabilities reflect the uncertain shocks that could decrease wealth, for example, old individuals are more likely to encounter high medical expenses. Hence, on

[11] The positive and monotonic relations between wealth and probabilities exist even after controlling for other facts flexibly. For example, we regress the reported probabilities on ten wealth decile dummies, medical expenses, income, socio-demographic characteristics, health states, etc. We estimate both linear regression and the Fixed-Effects model, with the results summarized in Table 4.9. The main finding from these estimation results is that, even after controlling for other observed factors and individual fixed effects, there still remain statistically significant positive correlations between wealth decile dummies and probabilities.

Figure 4.2: The sample averages of the bequest probabilities in 1998, by wealth and age groups




*Note:* The figure illustrates the sample averages of bequest probabilities from the interview in the year 1998. The sample averages are plotted separately for people who were aged between 65 and 74, 75 and 84, and more than 85, and who had wealth less than 10K (<10K), between 10K and 100K ([10K:100K]), and more than 100K (100K<) in 1998.

average, we observe almost negligible differences between young and old individuals' bequest probabilities.

In the subsequent analysis, we run the following regressions to test whether the bequest probabilities are good predictors of actual wealth and bequests once we control other observed factors:

$$y_{it} = \beta_0 + \beta_1 \mathbb{P}_{it}(\text{Bequest}{>}10\text{K}{+}) + \sum_{d=2}^{10} \beta_d w_{it}^d + \mathbf{X}_{it}\gamma + \alpha_i + \varepsilon_{it} \tag{4.13}$$

Here, the dependent variable $y_{it}$ can be either (1) the logged wealth in the next survey wave (i.e., after two years) or (2) the logged actual bequest. The main explanatory variables are the probability of bequeathing 10K+, $\mathbb{P}_{it}(\text{Bequest}{>}10\text{K}{+})$, and dummies for wealth deciles, $w_t^d$, at period $t$. $\mathbf{X}_{it}$ is a row vector that contains other regressors, for example, logged annuity income, logged OOPME and its squared, age and age squared, and dummies on health state, marital state, highest-obtained education, ethnicity, and birth-cohorts. $\varepsilon_t$ is an error term that is independent of all variables in the right-hand side of Eq. 4.13. A priori, we expect $\beta_1 > 0$ and $\beta_d > 0, \forall d$. The former (resp. latter) implies when all else is constant, individuals with higher probabilities of bequeathing 10K+ (resp. with a larger amount of wealth) hold more wealth after two years and bequeath more, on average.

The first two columns of Table 4.3 show the estimation results of the regression in Eq. 4.13 where the dependent variable is the logged wealth in the next survey wave. The first column excludes the individual fixed effects $\alpha_i$, whereas the second one includes these effects in the regression model. The results show that there is a statistically significant and positive impact on the probability of bequeathing 10K+ on the logged wealth after two years. This result implies that the bequest probabilities carry useful individual-specific information that is not controlled via other regressors yet significantly impacts future wealth dynamics. Therefore, the information in the bequest probabilities can be utilized in the econometric analysis of retired individuals' savings to increase the model's predictive power.

The third column of Table 4.3 shows the estimation results when the dependent variable is the logged actual bequest. Since the dependent variable - the actual bequest - is observed only once in this regression, we cannot run the Fixed Effects model. The results in this column are as expected because we find a positive and significant effect of the probability of bequeathing 10K+ on logged actual bequests. Thus, the bequest probabilities remain good predictors of actual bequests, even after controlling for wealth, various socio-demographic characteristics, health, medical expenses, and other financial variables.[12]

As shown in Table 4.8 in Appendix 4.8.1, when we use the probabilities of bequeathing 0K+ or 100K+ instead of 10K+ as the regressor for the models in Eq. 4.13, the conclusions are qualitatively the same. However, we cannot simultaneously include all the bequest probabilities in the linear regressions because of the HRS survey design explained in Section 4.3.1.3. For instance, if the probabilities of bequeathing \$0K+ and \$10K+ are observed, then \$100K+ is automatically equal to 0%; whereas, if the probabilities of bequeathing \$10K+ and \$100K+ are observed, then \$0K+ is missing.

## 4.4 Estimation strategy

The estimation of the model proceeds in two steps, similar to the strategies used by Gourinchas and Parker (2002), De Nardi et al. (2010) and Lockwood (2018). In the first step, we estimate those parameters that can be identified without explicitly using the life-cycle model. More

[12] When employing log-wealth as an independent variable instead of wealth deciles dummies, the conclusions regarding the relationship between wealth and bequest probabilities remain the same.

Table 4.3: Estimation results: the effect of the probability of bequeathing 10K+ on wealth after two years and actual bequests

| | (1) | (2) | (3) |
|---|---|---|---|
| Dependent variable | Logged wealth after two years | | Logged actual bequest |
| | LS | FE | LS |
| Probability of bequeathing 10K+ | 0.423*** | 0.239** | 0.697*** |
| | (0.0840) | (0.0977) | (0.209) |
| 2nd wealth decile | 1.496*** | -0.647** | 0.227 |
| | (0.243) | (0.291) | (0.512) |
| 3rd wealth decile | 4.262*** | 0.0185 | 1.342*** |
| | (0.243) | (0.349) | (0.516) |
| 4th wealth decile | 5.919*** | 0.659* | 1.894*** |
| | (0.227) | (0.366) | (0.544) |
| 5th wealth decile | 6.802*** | 0.911** | 2.315*** |
| | (0.223) | (0.373) | (0.549) |
| 6th wealth decile | 7.168*** | 0.849** | 2.833*** |
| | (0.225) | (0.382) | (0.557) |
| 7th wealth decile | 7.675*** | 1.023*** | 3.537*** |
| | (0.222) | (0.382) | (0.546) |
| 8th wealth decile | 8.045*** | 1.164*** | 3.787*** |
| | (0.222) | (0.386) | (0.530) |
| 9th wealth decile | 8.449*** | 1.169*** | 4.109*** |
| | (0.222) | (0.390) | (0.529) |
| 10th wealth decile | 8.971*** | 1.301*** | 4.877*** |
| | (0.228) | (0.395) | (0.544) |
| Age | 0.111 | 0.275** | -0.307 |
| | (0.0923) | (0.124) | (0.228) |
| Age squared / 100 | -0.0862 | -0.227*** | 0.198 |
| | (0.0589) | (0.0791) | (0.140) |
| Observations | 7,483 | 7,483 | 3,858 |
| Number of individuals | 2,218 | 2,218 | 1,337 |
| R-squared | 0.680 | 0.086 | 0.236 |

*Note:* Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1. The dependent variables are the logged wealth after two years in Columns (1) and (2) and the logged actual bequest in Column (3). The independent variables are the probability of bequeathing 10K+, the dummies for current wealth deciles, and various financial, medical, sociodemographic, and health variables. The second part of the table is shown in Appendix 4.8.2. The results show that the reported probabilities of bequeathing 10K+ positively and significantly impact wealth after two years and actual bequest when all else is constant, which aligns with the life-cycle model predictions.

specifically, we estimate the parameters of (1) the health transition matrix, (2) the OOPME distribution, (3) the non-asset income profile, and (4) survival probabilities. Let $\chi$ denote the collection of these first-stage parameters.[13]

[13] Kaji, Manresa, and Pouliot (2020) propose a novel technique that employs adversarial training to enhance the estimation process within the economic model by De Nardi et al. (2010). In their approach, the estimator is formulated as the solution to a minimax problem involving two key components: a generator responsible for creating synthetic observations through the structural model and a discriminator tasked with determining the authenticity of observations. The discriminator aims to maximize its classification accuracy, while the generator aims to minimize it. The study demonstrates that when employing a sufficiently robust discriminator, the adversarial estimator achieves parametric efficiency when the model is correctly specified and maintains the parametric rate even under model misspecification.

We model the health transition, OOPME distribution, non-asset income, and survival probabilities as functions of current age $t$, health $h_t$, gender $g$, and permanent income. Instead of using the continuous permanent income, we use the discretized version of this variable to simplify the computation. We ranked the individuals in their position in the permanent income distribution and generated three groups: the top 25%, the second 25%, and the bottom 50% of households. We merge the bottom two quartiles as the two groups show similar age profiles of wealth (see Figure 4.9 in Appendix 4.8.1). Let $I$ denote the indicators of three permanent income group dummies. Appendix 4.8.3 describes a detailed explanation of the first-stage estimation.

In the second stage, we estimate the following parameters using the method of simulated moments (MSM): the coefficient of relative risk aversion $\gamma$, the relative weight to utility from bequest $\phi$, the curvature of bequest utility function $k$, and minimum consumption to be eligible for government transfer $c_{\min}$ (aka. the consumption floor).

In the baseline analysis, we set the time discount factor $\beta = 0.975$, the interest rate $r = 0.03$, and the maximum potential age to live $T = 100$.

### 4.4.1 First-stage estimations and auxiliary statistics

*Health transition matrix:* We assume that the probability of having good health in the next year, $\pi^{good}_{t+1|t,h_t,g,I}$, is a first-order Markov transition process that depends on $(t, h_t, g, I)$. Since the HRS is a biennial survey, we only observe health states every two years. We simulate off-survey year health states using our estimated models and Bayes' rule.

We use the observation of individuals who participated in the HRS for at least two consecutive waves to estimate unknown parameters of the health transition matrix. The estimation results, summarized in Table 4.10 in Appendix 4.8.3, show that currently healthy, rich people and females are more likely to have good health after one year than their counterparts. As people get older, the probability of being in good health in the next year decreases. The current health state has a large and significant impact on the health state of the next year, indicating strong time persistency in the health state.

*Out-of-pocket medical expenses (OOPME):* We assume that the cost of an individual's OOPME, $m_{t,h_t,g,I}$, is log-normally distributed with mean, $\mu_{t,h_t,g,I}$, and variance, $\sigma^2_{t,h_t,g,I}$. We model both mean and variance of logged OOPME as functions of $(t, h_t, g, I)$; thus, our model allows for rich heterogeneity in the medical spending risk facing different people.

Following De Nardi et al. (2010) and Lockwood (2018), we model the mean of logged OOPME as a linear function of a cubic in age, gender, current health, and permanent-income group dummies. We also include interactions between age and gender, age and current health, and age and permanent-income group dummies as additional explanatory variables. We model the variance of logged OOPME as a function of all explanatory variables used to model its mean, except age-cubed.

We estimate the mean and variance of different groups' OOPME using the sample of individuals who had strictly positive OOPME for at least two consecutive waves to use the Fixed Effects (FE) model. The estimation sample consists of 10,410 observations (around 83% of the main sample). The rationale behind using the FE model is to control for the cohort effects because individuals from different cohorts have experienced different levels of medical expenses at the same age due to a secular increase in medical expenses. If we fail to account for the cohort effects, the expected medical expenses of the young cohort when they reach advanced ages would be underestimated. Our method of removing the cohort effects from the OOPME after estimating the FE model is described in Section 4.4.2.2.

Furthermore, the HRS asks for a total OOPME of around two years (duration between previous and current); thus, we divide the OOPME by two to approximate an annual OOPME. The annual OOPME is deflated to the dollar value in 1998.

Table 4.11 in Appendix 4.8.3 shows the estimation results. Due to higher-order polynomials of age and several interaction terms, it is not straightforward to interpret these results. To ease the interpretation, we provide Figure 4.10 that shows the expected medical expenses conditional on $(t, h_t, g, I)$. Our results are as expected. On average, people in worse health spend more than people in better health, women spend more than men, and older people spend more than younger people. Richer people are estimated to spend more than poorer people.

*Non-asset income profiles:* We model the mean of logged non-asset income as a linear function of permanent income group dummies and gender. We estimate the FE model to control for cohort effects. Since the non-asset income is assumed to be time-invariant in real terms, we do not model it as a function of current health and age. Assuming that the non-asset income is time-invariant is reasonable because, for retired people aged 65 and older, their main non-asset income comes from Social Security, which is determined by their work history and is independent of age. The estimation results are summarized in Table 4.12. The results show that, on average, males earn more non-asset income than females. By construction, it is also immediate that people from the higher permanent-income group would earn more non-asset income.

*Subjective survival probabilities:* The HRS asks individuals' perceived probability of reaching certain target age $ta$, as described in Section 4.3.1.3. Following Bissonnette et al. (2017) and De Bresser (2019), we assume that the survival probabilities follow the Gompertz distribution with common proportional baseline hazards. Following this assumption, the agent's perceived probability of surviving to age $ta$ conditional on $t$ being the agent's current age is given by:

$$s_{ta_t|t,h_t,g,I} = \exp\Big(-\frac{\exp(\beta_0^s + \beta_1^s h_t + \beta_2^s g + I\gamma^s)}{\alpha}\Big[\exp\Big(\alpha\frac{ta_t}{100}\Big) - \exp\Big(\alpha\frac{t}{100}\Big)\Big]\Big) \tag{4.14}$$

Here $\alpha$ is the parameter that determines the shape of the baseline hazard (aka. duration dependence parameter). To facilitate the estimation $\alpha$, we divide the target age $ta_t$ and age $t$ by 100. As shown in Eq. 4.14, the variation in survival probability is driven by not only age but also by the current health status, gender, and permanent-income group dummies.

We assume that the reported survival probabilities, $\mathbb{P}_t^{s,rep}$, are observed with an error such that:

$$\mathbb{P}_t^{s,rep} = s_{ta_t|t,h_t,g,I} + \varepsilon_t^s, \qquad \varepsilon_t^s \sim N(0, \sigma^2_{\varepsilon^s}) \tag{4.15}$$

where $\varepsilon_t^s$ is a i.i.d. measurement error which is independent of $(t, h_t, g, I)$ and follows a normal distribution with mean zero and variance $\sigma^2_{\varepsilon^s}$.

We take into account that the reported probabilities are censored between 0% and 100% by defining the density for a reported probability $\mathbb{P}_t^{s,rep}$ conditional $(t, h_t, g, I)$ as follows:

$$f_{t,h_t,g,I} = \begin{cases} 1 - \Phi(\frac{\mathbb{P}_t^{s,rep} - S_{ta_t|t,h_t,g,I}}{\sigma_{\varepsilon^s}}) & \text{if } \mathbb{P}_t^{s,rep} = 100\%, \\ \phi(\frac{\mathbb{P}_t^{s,rep} - S_{ta|t,h_t,g,I}}{\sigma_{\varepsilon^s}}) & \text{if } 0\% < \mathbb{P}_t^{s,rep} < 100\%, \\ \Phi(\frac{\mathbb{P}_t^{s,rep} - S_{ta|t,h_t,g,I}}{\sigma_{\varepsilon^s}}) & \text{if } \mathbb{P}_t^{s,rep} = 0\% \end{cases} \tag{4.16}$$

where $\phi(\cdot)$ and $\Phi(\cdot)$ are the p.d.f and the c.d.f of the standard normal distribution. The likelihood contribution is $f_{\omega_t}$ and $\beta_0^s$, $\beta_1^s$, $\beta_2^s$, $\alpha$, and $\sigma_\varepsilon^s$ are the parameters to estimate.

The estimation of the survival probability model uses the sample of individuals who reported their survival probabilities in the HRS between 1998 and 2012. The estimation sample consists of 5,867 observations, around 47% percent of the main sample. Table 4.13 in Appendix 4.8.3 shows the estimation results, and Figure 4.11 shows the predicted probability of surviving to the next year $t+1$ conditional on $(t, g, h_t, I)$. As shown in the figure, the perceived probability of surviving beyond age $T + 1 = 101$ is zero, following the assumption that individuals plan their life until the end of $T = 100$.

We find that when all else is constant, rich, healthy, young individuals and females have a higher survival probability than their counterparts. However, the majority of the heterogeneity in predicted subjective survival probabilities is due to differences in current health and age. The heterogeneity across genders and permanent-income groups are negligible.[14]

### 4.4.2 Second-stage estimation

In the second stage, we match various empirical and simulated moments of wealth and bequest probabilities. Section 4.4.2.1 explains the simulated wealth and bequest probabilities, and Section 4.4.2.2 explains the construction of moment conditions. Then, we discuss the estimation strategy.

#### 4.4.2.1 Simulation procedure

*Simulated individuals and exogenous shocks:* We start the simulation procedure by simulating the life cycles of each individual ten times; thus, there are $10 \times 3,193$ simulated individuals whose initial state variables are drawn from the joint distribution of state variables in 1998 data (the state variables are: wealth, age, gender, health status, OOPME, permanent-income groups). Moreover, we treat observed wealth in 1998 as individuals' initial endowments.

We generate the simulated series of health states, survival states, and medical expenses for each simulated individual. However, we used individuals' observed health and survival states for the periods when they participated in the HRS. For example, if an individual passed away (resp. alive) in 2004, that individual also passed away (resp. alive) in 2004 in the simulation. If an individual was alive when he or she was last observed in the survey, we simulated that individual's health and "subjective" survival shocks from the age when he or she was last observed until $T$. This procedure eliminates the simulation bias from the model in which individuals' health and survival states do not match with the actual risks individuals faced during the period they observed.

*Model solution and constructing simulated wealth moments:* For each candidate parameter vector of $[\gamma, \phi_\kappa, k, c_{\min}]$, we solve the model separately for men and women, different permanent-income groups, and people with good and bad health states using backward induction. We use the

[14] The lack of a substantial impact of permanent-income on survival probabilities in our study can be attributed to our sample selection. Specifically, we focused on individuals aged 65 or older who are retired and single. As a result, our sample predominantly consists of females and individuals with below-average income levels. For instance, considering the entire HRS sample of individuals aged 65 and above, the average annual income stands at 24K with a standard deviation of 43K. In contrast, within our primary sample, the average income is 13K, with a standard deviation of 29K. This comparatively limited income variation within our sample, when compared to the broader HRS sample, could explain why we found negligible heterogeneity in survival probabilities across different permanent-income groups.

resulting value functions and optimal choice rules to simulate each simulated individual's wealth path from the age observed in 1998 until $T$.

Let $w_{i,y}^{sim}$ be the simulated or model-implied wealth of individual $i$ in year $y$. When constructing simulated wealth moments, we do not include $w_{i,y}^{sim}$ if an individual $i$ passed away in year $y$ at $sim$th simulation.

*Simulated bequest probabilities:* For individual $i$, who is alive at survey year $y$, we generate $s_{i,y}^{dead,sim}$ - $i$'s $sim$th simulated number of years she passes away after $y$. We then compute the simulated bequest of individual $i$ in the following way:

$$bequest_{i,y}^{sim} = (1+r)w_{i,y+\tau}^{sim} \quad \text{where } \tau = s_{i,y}^{dead,sim} \tag{4.17}$$

Here $bequest_{i,y}^{sim}$ is the simulated wealth individual $i$ would bequeath upon his death given that he is alive in year $y$.

As we simulate each individual ten times, individual $i$'s probability of bequeathing more than $threshold_{k,y}$, from the perspective of year $y$, is constructed as follows:

$$P_{i,y,k} = \frac{1}{10}\sum_{sim=1}^{10} 1\{bequest_{i,y}^{sim} > threshold_{k,y}\} \tag{4.18}$$

Here $P_{i,y,k}$ is the model implied probability of individual $i$ bequeaths more than $threshold_{k,y}$ from the perspective of year $y$.

Note that we specify $threshold_{k,y}$ as a function of survey year $y$ to consider the impact of inflation. We assume that when individual $i$ reports his/her probability of bequeathing more than $threshold_{k,y}$, she uses the dollar value in survey year $y$. Thus, we set $threshold_{k,1998}$ equal to {0K, 10K, 100K} for $k = \{1,2,3\}$, and, for $y > 1998$, we deflated $threshold_{k,y}$ by the CPI to express the thresholds in 1998-dollar value.[15]

#### 4.4.2.2 Constructing moment conditions

*Wealth moments:* The wealth moments are constructed for each year $y = \{2000, 2002, ..., 2012\}$ for three cohort groups $c$ and three permanent-income groups $p$. The cohort groups are defined

[15] More specifically, we transform the threshold of $threshold_{k,y}$ as follows:

$$threshold_{k,y} = \frac{threshold_{k,1998}}{\mathrm{CPI}_{y,1998}} \tag{4.19}$$

where $threshold_{k,1998} = \{0; \$10,000\,\$100,000\}$ for $k = \{1,2,3\}$. $\mathrm{CPI}_{y,1998}$ is the consumer price index in year $y$ divided by that in 1998.

based on their birth year and divided into three groups: $c = 1$ if born between 1924 and 1933, $c = 2$ if between 1914 and 1923, and $c = 3$ if before 1913.

For each year-cohort-PI cell $(y, c, p)$, we construct 25th, 50th, or 75th percentile wealth moments. $(q \cdot 25)$th percentile of wealth moment, for $q = \{1, 2, 3\}$, at cell $(y, c, p)$ are defined as follows:

$$m^{m,q}_{y,c,p}(\mathbf{Z}, \Omega, \chi) = \frac{1}{N_{y,c,p}} \sum_{i:i\in(y,c,p)}^{N_{y,c,p}} \Big( 1\{w_{i,y} \leq \bar{w}^{m,q}_{y,c,p}(\mathbf{Z}, \theta)\} \cdot (1 - q \cdot 0.25) ... \\ + 1\{w_{iy} > \bar{w}^{m,q}_{y,c,p}(\mathbf{Z}, \theta)\} \cdot (-q \cdot 0.25) \Big) \tag{4.20}$$

where $w_{i,y}$ is an observed total wealth of individual $i$ from cohort $c$ and permanent-income group $p$ who was alive in year $y$. $\bar{w}^{m,q}_{y,c,p}(\mathbf{Z}, \theta)$ is the $(q \cdot 25)$th percentile of simulated wealth for cell $(y, c, p)$. $1\{w_{i,y} \leq \bar{w}^{m,q}_{t}(\mathbf{Z}, \theta)\}$ equals one if the wealth $w_{i,y}$ is less than or equal to $\bar{w}^{m,q}_{y,c,p}(\mathbf{Z}, \theta)$; zero otherwise. $N_{y,c,p}$ is the number of observations in year $y$, cohort $c$, and permanent-income group $p$.

We require the number of observations to construct each moment to be at least 30 for each $(y, c, p)$ cell, i.e., $N_{y,c,p} \geq 30$; otherwise, we discard the moments with few observations. Discarding the year-cohort-permanent-income cells with fewer than 30 observations eliminates the observations of the second and third cohorts in the final waves. Ultimately, we have 55 year-cohort-permanent income cells. We construct three wealth moments for each cell: (1) 25th, (2) 50th, and (3) 75th percentiles. In total, there are $55 \times 3 = 165$ wealth moments.

*Bequest probability moments:* For each survey year $y = \{1998, 2000, ..., 2012\}$, we match bequest probability moments for three birth-year cohorts $c$ and permanent-income groups $p$. We fit the moments of bequest probabilities of 1998 because the reported probabilities are not used as initial conditions in the model simulation. We construct three moments for each cell $(y, c, p)$: the means of reported probabilities to bequeath (1) 0K+, (2) 10K+, and (3) 100K+. Each moment is constructed by finding the differences between the corresponding empirical and simulated moment.

When constructing the mean of the probability of bequeathing 100K+, we exclude the individuals whose wealth is less than 50,000$ because we think it is (almost) unrealistic for an individual with 50,000$ of wealth would leave a bequest that has a value of more than 100,000$ considering high medical expenses at advanced ages. We also consider simulated bequests that are less than 1,000$ as leaving no bequest.

We discard simulated bequests of individuals who did not report valid probabilities in year $y$. For example, we consider the probabilities of being invalid if (1) the individuals reported either "Don't know" or "Refused to answer," or (2) they did not participate in the survey in year $y$ or passed away before that year, or (3) they are not eligible to answer those probability questions by the HRS design (see Section 4.3.1.3). Therefore, our procedure considers potential attrition and sample selection issues when constructing the bequest probability moments.

Similar to the wealth moments, we also dropped the moments if the number of observations used to construct those moments is less than 30. In total, there are 166 bequest probability moments.

*Removing cohort effects from the target moments:* It is important to control for cohorts' differences because they have been exposed to different economic environments, policy regimes, and asset prices, especially house prices. This implies their wealth holdings at the same age can differ substantially across cohorts. This is also known as the "cohort-age-year" problem.

Following De Nardi et al. (2010), we use FE models to remove cohort effects from the moments targeted in the estimation. We estimate the following linear FE for logged wealth[16]:

$$\ln(wealth_{it} + 1) = \sum_{j=65}^{T} \beta_{age} age_{it} + \alpha_i + \varepsilon_{it}. \tag{4.21}$$

The first batch of regressors on the right-hand side of the equation is the age dummies for ages 65 to 94 (the maximum observed age in our sample is 94). $\alpha_i$ is an individual time-invariant effect and $\varepsilon_{it}$ is an idiosyncratic error independent of the other regressors.

Once we estimate the FE model, we compute the following adjusted logged wealth:

$$\ln(wealth_{it}^{adj} + 1) = \sum_{j=65}^{94} \hat{\beta}_{age} age_{it} + \hat{\alpha}_i + (\hat{\alpha}_{c=3} - \hat{\alpha}_c) + \hat{\varepsilon}_{it} \tag{4.22}$$

where $\hat{\beta}_{age}$, $\hat{\alpha}_i$ and $\hat{\varepsilon}_{it}$ are their corresponding parameters. $\hat{\alpha}_c$ is the average estimated individual fixed effects of cohort $c$, and $\hat{\alpha}_{c=3}$ is that for the oldest cohort. We construct the empirical wealth moments from the predicted adjusted logged wealth from Eq. 4.22. We also follow the same procedure to remove the cohort effects from the medical expenses and non-asset income.

[16] Some individuals have zero wealth. Thus, we add one to all observed wealth before implementing log transformation.

#### 4.4.2.3 Estimating the second-stage parameters

Our Method of Simulated Moments estimation algorithm follows French (2005); De Nardi et al. (2010) and Lockwood (2018) in which the parameter estimates $\hat{\Omega} = [\hat{\gamma}, \hat{\phi}, \hat{k}, \hat{c}_{\min}]$ are the values that minimize the distance, defined by the MSM criterion function, between the simulated and empirical life cycle profiles. The baseline specification is based on the 331 moments conditions: 165 wealth moments and 166 bequest probability moments. We also estimate the model that only used the wealth moments to compare the results with those of the baseline specification.

When defining the MSM criterion function, the optimal weighting matrix is asymptotically efficient; however, it can be biased in small samples. Therefore, we use a baseline weighting matrix that is the inverse of the estimated covariance-variance matrix of the second-stage moments conditions in which some matrix elements are replaced to zero if the number of observations used to estimate those elements are less than ten. Since we do not exactly use the optimal weighting matrix, the second-stage estimates are not efficient but still consistent. We check the robustness of the results using the following alternative weighting matrices: (1) identity matrix, and (2) the inverse of the diagonal of the estimated variance-covariance matrix of the second-stage moments conditions, following Pischke (1995).

Due to the computational challenges involved in determining the optimal weighting matrix, we have chosen not to compute the Hansen-J overidentifying restrictions test.[17] To validate the model, we employed an alternative empirical approach that involved comparing our predicted median bequests with the corresponding actual values. This strategy is valid because the information in actual bequests is not used for the estimation. A comprehensive explanation of this validation method can be found in Section 4.3.2. Similar strategies have been employed in the relevant literature. For example, in their research, Lockwood et al. (2018) compared the predicted and actual percentages of individuals with long-term care insurance, while De Nardi, French, Jones, and McGee (2021) compared the predicted and actual average changes in out-of-pocket medical expenses surrounding the death of a spouse.

We use simulation annealing methods (see, e.g., Goffe, Ferrier, and Rogers (1994)), a non-gradient-based optimization algorithm, to find the set of parameter values that globally minimizes the MSM criterion function. Appendix 4.8.5 explains our MSM estimation procedure and the steps to estimate the standard errors using a non-optimal weighting matrix.

[17] There is a version of the overidentifying restrictions test that does not depend on the optimal weighting matrix but instead utilizes a covariance-variance matrix of moment conditions. However, computing the covariance of certain moment conditions remains challenging due to sample size.

# 4.5 Results

## 4.5.1 Estimation results

*Second-stage parameters' estimates:* Table 4.4 shows the second-stage estimation results. The first column of the table presents the results if we only use the wealth moments, and the second column if we use both wealth and bequest probability moments. The standard errors are in parentheses below their estimates.

Our estimates of $\gamma$, the relative risk aversion parameter, are 3.54 and 2.59 for the model only using wealth moments and for our baseline model, respectively. These values are within the range of the estimates provided by previous studies. For example, the estimates of $\gamma$ are between 3.6 and 3.8 for De Nardi et al. (2010), between 2.0 and 5.0 for Lockwood (2012), and 5.27 for Ameriks et al. (2020).

Table 4.4: Second-stage estimation results

| | Only wealth moments used (1) | Baseline model: all moments used (2) |
|---|---|---|
| *Parameter estimates, $\hat{\Omega}$* | | |
| $\gamma$ : risk aversion | 3.539 | 2.857 |
| | (0.644) | (0.127) |
| $\phi$ : bequest motive weight | 0.352 | 0.586 |
| | (0.728) | (0.081) |
| $k/1000$ : bequest motive curvature | 0.427 | 0.628 |
| | (0.626) | (0.119) |
| $c_{\min}/1000$ : consumption floor | 2.025 | 2.362 |
| | (0.846) | (0.486) |
| Objective function evaluated at the estimates | 2.485 | 1,255 |
| Number of moments | 165 | 331 |

*Note:* Column (1) presents the estimates of the model only using wealth moments. Column (2) presents the estimates of the baseline model - which uses both wealth and bequest probability moments. For both columns, we use the inverse of the variance-covariance matrix of the second-stage moment conditions in which some matrix elements are replaced to zero if the number of observations used to estimate those elements are less than ten. Standard errors are in parentheses. In Appendix 4.8.4, Eq. 4.42 shows the formula for the objective function, and Eq. 4.46 for the standard errors when using a non-optimal weighting matrix.

The estimates of $\phi$ and $k$ together determine the strength of bequest motive. To interpret the implications of the estimated bequest motive parameters, we construct the share of cash-on-hand

$x$ that would be bequeathed if the retired single agent encounters no medical expense uncertainty and knows for sure that he or she will pass away in the next period. Therefore, the decision to save some part of cash-on-hand as a bequest is purely due to the bequest motive. For example, if the agent has no bequest motive, i.e., $\phi = 0$, the agent would consume the entire cash-on-hand, $x$. The derivation of the share of bequest allocation is shown in Appendix 4.8.6.

Figure 4.3 shows the predicted share of cash-on-hand allocated as a bequest $\frac{x-c}{x}$ on the vertical axis, and cash-on-hand in thousands $x$ on the horizontal axis.

The estimates of our baseline model, which uses both wealth and bequest probability moments, predict that the bequest motive kicks into the agents' decision as long as their cash-on-hand exceeds the estimated consumption floor level, which is around 2176 dollars. This result is because the bequest motive curvature parameter $k/1000$ is estimated to be close to zero; hence, our results suggest that not only wealthy but also less wealthy individuals are willing to save part of their wealth as a bequest.

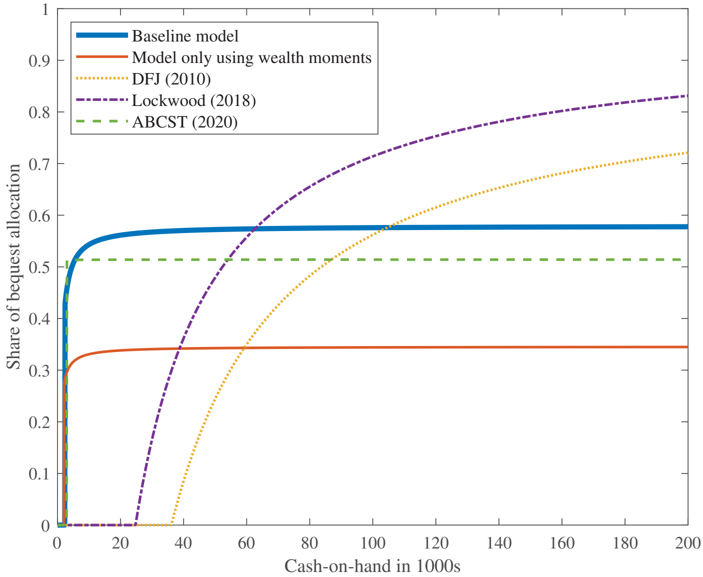
If the cash-on-hand exceeds the consumption floor, the baseline model predicts that around 53% of the cash-on-hand would be allocated as a bequest. In contrast, the model that only uses wealth moments predicts that the share of cash-on-hand allocated to be a bequest is around 31%. The difference between these models is because the bequest motive weight parameter $\phi$ is estimated to be larger in magnitude in our baseline model.

Moreover, compared to the model that only uses wealth moments, the standard errors of the bequest motive parameters are much smaller in our baseline model. For example, the standard error of the estimate of $\phi$ has decreased by a factor of nine, and that of $k/1000$ has decreased by a factor of around six compared to the model only using wealth moments. Therefore, adding bequest probability moments enables us to estimate the bequest motive parameters precisely.

In Figure 4.3, we compare our estimated bequest motive with those from the previous three studies. Our baseline model predictions are close to that of Ameriks et al. (2020), who used the survey questions that elicit people's willingness to save as a bequest or long-term care purpose. Contrary to our baseline finding, De Nardi et al. (2010) and Lockwood (2012) found that people with very low cash-on-hand do not leave any bequest at the terminal period because they both found the estimates of curvature of bequest utility larger than what we found. For example, Lockwood (2012) and De Nardi et al. (2010) found that the share of bequest allocation increases as people's cash-on-hand increases, and the bequest motive kicks in if people's cash-on-hand exceeds around 22K and 38K, respectively.

The estimates of consumption floor $c_{\min}$ are 2.47 and 2.05 for the model that only uses wealth moments and the baseline model, respectively. De Nardi et al. (2010), whose estimates of

Figure 4.3: Estimated bequest motives




*Note:* The figure shows the share of cash-on-hand allocated as a bequest if the agent faces certain death in the next period. There is no medical expenses uncertainty; thus, the share of cash-on-hand allocated as a bequest is purely due to a bequest motive. The figure shows the predicted share allocated to bequests for our baseline model - which uses both wealth and bequest probability moments, and for the model that only uses wealth moments. The figure also plots the share of cash-on-hand allocated as a bequest based on the estimation results of the following three studies: (1) The fourth column of Table 3 from De Nardi et al. (2010), abbreviated in the figure as DFJ(2010), (2) the third column of Table 3 from Lockwood (2018), and (3) Table 3 of Ameriks et al. (2020), abbreviated as ABCST (2020).

the consumption floor are very similar to our point estimates, interpret $c_{\min}$ as an effective consumption floor that accounts for complex determinants of being eligible for government transfer, such as Medicaid usage.

*Model fit:* Our second-stage estimation matches the observed and model-implied 25th, 50th, and 75th percentiles of wealth and means of probabilities of bequeathing 0K+, 10K+, and 100K+, both conditional on age, birth cohort, and permanent-income groups. Figures 4.4 and 4.5 plot the empirical (solid lines) and model-implied (dashed lines) for the model only using wealth moments and the baseline model, respectively. The figures also plot the 95th confidence intervals of the empirical moments. For each figure, Panel A shows the wealth moments, and Panel B shows the bequest probability moments.

As shown in Figure 4.4, the predictions of the model only using wealth moments fit well to the empirical wealth moments, but they do not fit well to the bequest probability moments. More specifically, the average probabilities of bequeathing 100K+ for the youngest cohort in the top and middle permanent-income groups are predicted to be too high compared to their empirical counterparts.

In contrast, our baseline model predictions fit the empirical wealth and bequest probability moments well. This is expected because the baseline model uses the information in the wealth moments and those of the bequest probability. Compared to the model only using wealth moments, our baseline model predicts a slightly lower 75th-percentile of wealth for individuals from the youngest cohort in the top and the middle permanent-income groups. By decreasing the predicted wealth trajectory of these groups, the baseline model improves the fit between the model-implied and empirical means of the probability of bequeathing 100K+. In other words, compared to the model that only uses wealth moments, the baseline model implies that the relatively rich individuals from the youngest cohort would accumulate less wealth over time; thus, their probability of bequeathing 100K+ is smaller.

When using information on bequest probabilities, we find that our estimates of bequest motive parameters are larger. However, the predicted probability of young, wealthy individuals leaving a bequest of 100K+ decreases. This is because our baseline model, compared to one that only uses wealth moments, suggests that individuals have stronger bequest motives but weaker precautionary savings motives. Since the likelihood of young, wealthy individuals passing away in the near future is low, the utility they derive from leaving a bequest in the next few years is also low.[18] As a result, their savings decisions are driven more by precautionary motives than by bequest motives. This means that their probability of leaving a bequest of 100K+ is lower according to our baseline model than it would be according to the other model.

### 4.5.2 Robustness check

Table 4.14 in Appendix 4.9 shows the robustness of the second-stage parameter estimates under different weighting matrices and samples. The first column of the table shows the baseline estimation results (i.e., from Column (2) of Table 4.4). Column (2) shows the baseline model estimates with the identity weighting matrix, and Column (3) with the inverse of the diagonal of the estimated variance-covariance matrix of the second-stage moment conditions as the weighting matrix. With the identity matrix, the results are similar to our baseline model estimates. The diagonal weighting matrix puts more weight on the bequest probability moments, resulting in

[18] For example, according to our subjective survival probability estimates shown in Figure 4.11, for both males and females, their probability of passing away in the next year is less than 10% until age 92 if health is good and 15% if health is bad.

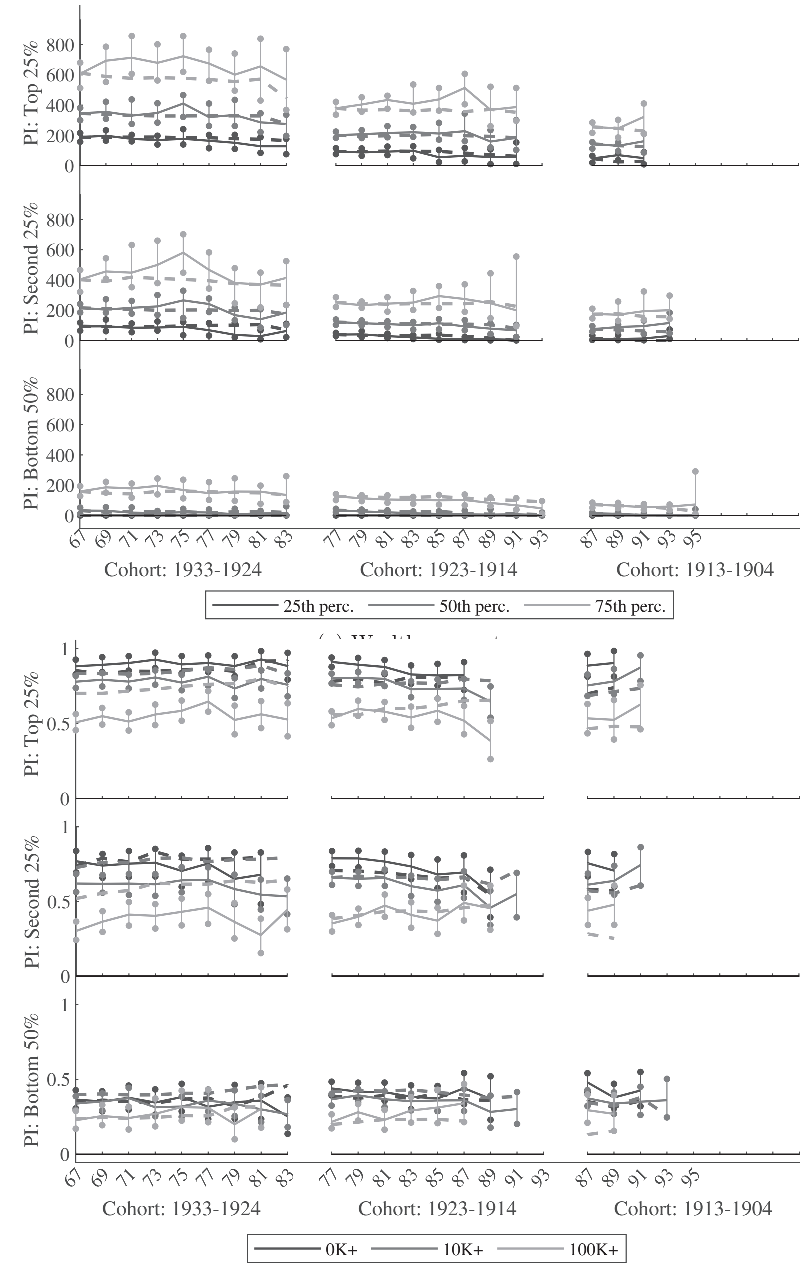
smaller estimates of $\gamma$ and larger estimates of $\phi$. Still, with the diagonal weighting matrix, the estimates of the main preference parameters remain within the range of the estimates provided by previous studies.

Column (4) of the table uses the sample of individuals with children. In our sample, around 83% of the individuals had at least one child, and using this restricted sample reduces the number of moment conditions from 331 to 319. When we restrict the sample, we estimate both the first and second-stage parameters because, for example, the health transition probabilities, life-span uncertainties, and expected medical expenses can differ between people with and without children conditional on health state, age, gender, and permanent income $(h_t, t, g, I)$.

We find that the point estimates of the parameters when using the sample of individuals with children are similar to our baseline estimates. Hence, we conclude that there are no substantial differences in the precautionary and bequest motives of people with and without children. Hurd (1989) and Gan et al. (2015) also found similar results.[19]

[19] One possible explanation of this result stems from the survey question's phrasing, which inquires about the likelihood of leaving bequests to heirs. In this context, "heirs" encompasses not only children but also other individuals such as the respondents' relatives, caregivers, friends, charities, and more. Individuals without children may establish social communities during their later years and intend to allocate their assets to those communities.

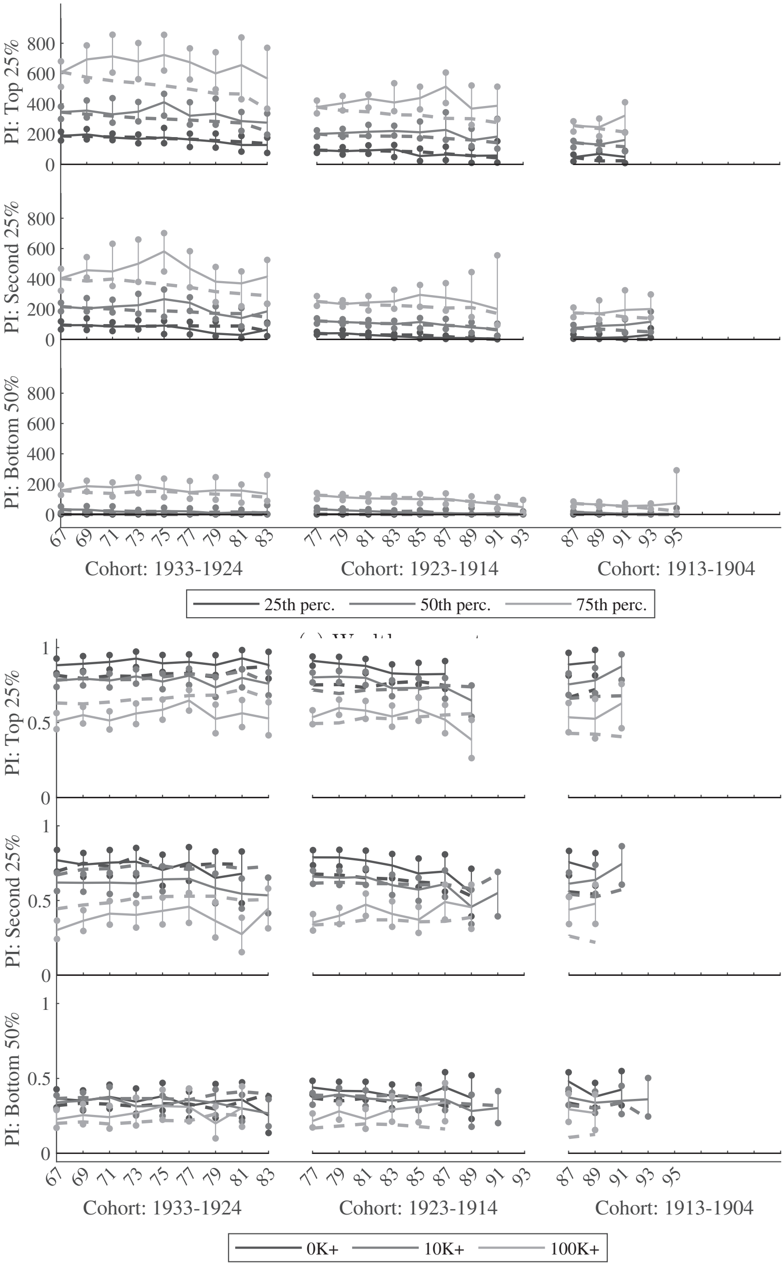
Figure 4.4: Empirical and simulated moments for the model only using the wealth moments




(b) Bequest probability moments

*Note:* The figure shows empirical (solid lines) and simulated moments (dashed lines). Panel A shows those for 25th, 50th, and 75th wealth percentile moments, and Panel B for the average probabilities of bequeathing 0K+, 10K+, and 100K+. The x-axis shows the average age of the surviving members of a given cohort. The y-axis shows the percentiles of wealth and three permanent-income groups. The empirical and simulated wealth moments in 1998 (the left-most points of each set of curves) coincide because the wealth in 1998 was used as initial conditions.

Figure 4.5: Empirical and simulated moments for the baseline model




(b) Bequest probability moments

*Note:* See the footnote of Figure 4.4.

### 4.5.3 Model validation: empirical vs. predicted bequests

In this section, we compare the model-predicted and the observed bequests for the respondents who passed away between 2000 and 2014 and whose family members responded to the HRS-Exit interview. Since we do not use the information on observed bequests in our estimation, comparing the model-implied and observed bequests would help to build additional trust in our model.

Figure 4.6 plots the median empirical and predicted bequests. The figure includes the predictions of the model that only uses wealth moments and the baseline model. We also plot the 95% confidence interval for the median of the empirical bequests.

Panel A of Figure 4.6 plots the median bequests across different permanent-income groups. According to this panel, the model that only used wealth moments and our baseline model perform equally well in predicting the bequests of the lowest permanent-income group. However, for the highest permanent-income group, the model that used only wealth moments overpredicts the median bequest. In contrast, our baseline model predicts the median bequests within the 95% confidence interval of the observed median bequest.

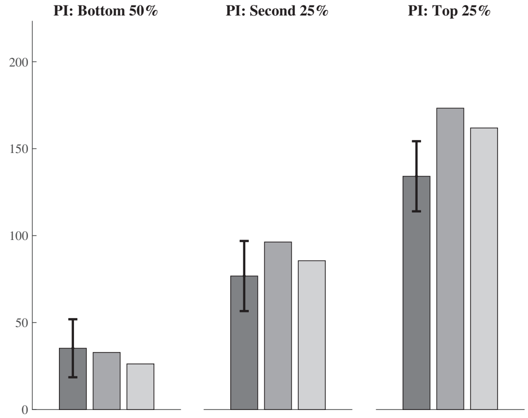
Panel B of the figure plots the median bequests across different wealth quintile groups. Here, we constructed wealth quintiles based on the respondents' wealth in 1998. Similar to the previous panel, the median bequests are well predicted by all models for the lowest two wealth quintiles. For the third quintile, the baseline model predicts the median actual bequest within the 95th confidence interval range; however, the other model overpredicts the median bequest. For the fourth quintiles, both models overpredict the empirical median by more than 80K (which is around 35% of the empirical median); however, the prediction of our baseline model is closer to the empirical median than the other model.

Panel C of the figure shows the median bequests conditional on people's age when they pass away. The first group passed away between ages 65 and 84, the second between 85 and 94, and the last group between ages 95 and 100. Both models predict too large of a median bequest for individuals who passed away between ages 65 and 85; however, the prediction of the baseline model is closer to the actual median. For those who passed away between 85 and 94, the model that only used wealth moments overpedicts the median bequest, whereas the baseline model accurately predicts the median. For the last group, both models predict a smaller median bequest than the actual median, but the baseline model performs relatively worse than the other model.

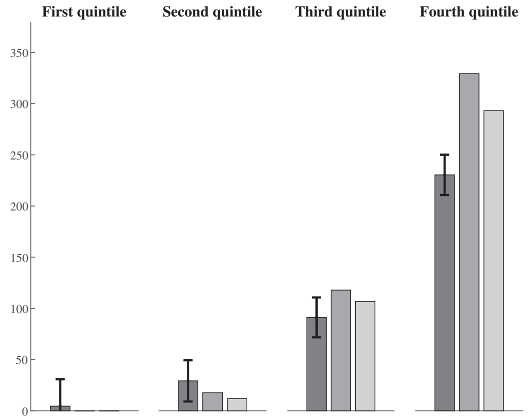
Overall, the baseline model outperforms the model that only used the wealth moments in terms of predicting the actual median bequests of certain groups. Both models accurately predict the observed median bequest of relatively less wealthy individuals. However, our baseline model outperforms in predicting richer individuals' median bequests, whereas the other model predicts too large median bequests. Moreover, for most cases, the baseline model gives the closest predictions to the actual median bequest if we group individuals based on the age they passed away.

Figure 4.6: Median empirical and predicted bequests

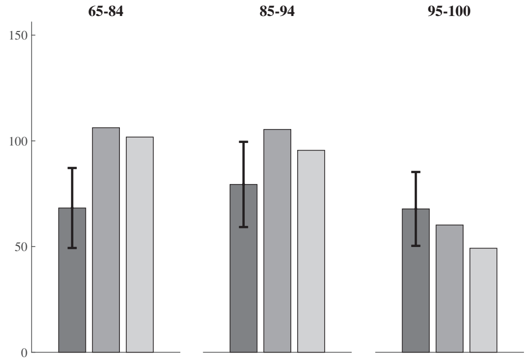
(a) By permanent-income groups




(b) By 1998-wealth quintiles




(c) By age when passed away: between 65-84, 85-94, and 95+




Empirical
Model only using wealth moments
Baseline model

*Note:* The figure plots empirical and simulated median bequests by permanent-income groups, 1998 wealth quintiles, and groups based on the respondent's age when they pass away. The information in empirical bequests is not used for the estimation.

## 4.6 Implications of the results

### 4.6.1 Decomposition of the saving motives

*Implications on life-cycle wealth trajectories:* We perform several counterfactual analyses to quantify the changes in single retirees' wealth if we turn off various savings motives. To perform our decomposition analysis, we fix our model parameters at their estimated values and change one feature of the model at a time. Then, we re-compute the optimal savings decisions assuming the initial endowment of individuals is their wealth in 1998. We compare the resulting wealth dynamics to those generated by our baseline model.

In Figure 4.7, we simulate the median wealth among individuals of the first cohort (aged 65-74 in 1998). If an individual passes away in the simulation, we drop that individual from the analysis; thus, the wealth accumulation profiles embed the mortality bias that is present in the data. The decomposition analysis is conducted for all three permanent-income groups: top 25%, second 25%, and bottom 50%.

In the figure, solid lines track wealth in the baseline model. The dashed lines track wealth if some features of the model are turned off. For example, the dashed lines with "+" markers track the wealth trajectories if the decision to save for the expected medical spending is turned off. More specifically, we turn off the decision rules where individuals take into account the expected medical expenses, but the simulated wealth profiles include medical costs. Therefore, differences in wealth reflect only differences in the behavioral response to expected medical expense shocks, not differences in realized medical expenses. Next, the dashed lines with "×" markers track if we turn off the bequest motives (i.e., setting $\hat{\phi} = 0$) while holding all other preference parameters constant. Thirdly, the dashed lines without markers track the simulated wealth if we turn off both the bequest motive and the decision to save in response to the expected medical expenses.

As shown in the figure, if we only turn off the medical expenses (compare the solid lines with the dashed lines with "+" markers), the individuals in the lowest permanent-income group save almost nothing to cover their medical expenses. This implies that with their little wealth, they rely on government transfers if they encounter high medical expenses. In contrast, middle and top permanent-income groups are sensitive to medical expenses. For example, without having the incentive to save in response to expected medical expenses, the median wealth levels of individuals in the middle and top permanent-income groups fall by nearly 15% at age 75 (i.e., from 171K to 146K for the middle and from 285K to 241K for the top permanent-income group, respectively), and about 40-45% at age 85 (i.e., from 107K to 63K for the middle and from 204K to 112K for the top permanent-income group, respectively).

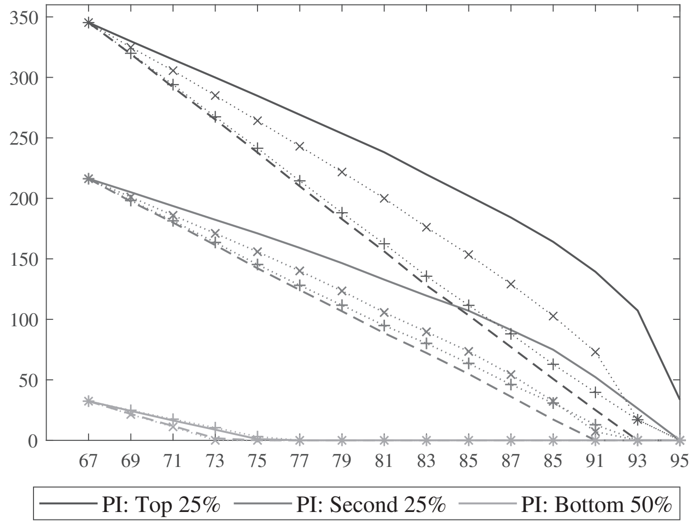
Turning off the bequest motive reduces the median wealth for all permanent-income groups (compare the solid lines with the dashed lines with "×" markers). For example, if the bequest motives are turned off, the median wealth of the middle and top permanent-income groups fall by around 9% (from 171K to 156K) and 8% (from 285K to 263K), respectively, at age 75, and around 32% (from 107K to 73K) and 25% (from 204K to 154K) at age 85. Furthermore, the median wealth of the lowest permanent-income group decreases if the bequest motive is shut down. For example, without a bequest motive, individuals in the lowest permanent-income groups exhaust their median wealth at age 73; however, with a bequest motive, their median wealth is exhausted at age 75.

Next, we turn off both the bequest motive and the decision to save in response to the expected medical expenses (compare the solid lines with the dashed lines without any markers). The counterfactual analysis shows if bequest motive and medical expenses are turned off, the median wealth of the middle permanent-income group drops by 16% and 49% at ages 75 and 85, respectively. For the top permanent-income groups, the median wealth drops by 16% and 50% at ages 75 and 85, respectively. The magnitudes of these drops are slightly larger than those in previous experiments where the medical expenses are turned off. The analysis also shows that middle and top permanent-income groups exhaust their median wealth at ages 91 and 93, respectively. This is because, even after turning off bequest motive and medical expenses, individuals save either to smooth consumption profiles or to insure against living longer than expected, as the survival risk is still present in the model.

Our counterfactual analysis suggests that both bequest motive and medical expenses play an important role in determining the savings of individuals from middle and top permanent-income groups. However, the incentive to save in response to expected medical expenses plays a more important role than bequest motives for these groups. On the other hand, for the lowest permanent-income group, turning off medical expenses does not substantially impact savings, mainly because at a low level of wealth, the individuals rely more on government transfers. However, with the bequest motive, low-income individuals exhaust their median wealth later.

*Implications on bequest distribution:* Table 4.5 documents the relative strength of the different saving motives on the distribution of bequests for the first cohort, who were 65-74 years old in 1998. In each panel of the table, the first row shows bequests under the baseline specification, the second row shows the bequests when there is no saving motive in response to the expected medical expenses, the third row shows when there is a zero utility from leaving a bequest, and

Figure 4.7: Decomposing saving motive: impacts of turning off bequest motive and decision to save in response to the expected medical expenses on the simulated median wealth trajectories




*Note:* The figure shows the simulated median wealth trajectories among individuals of the first cohort (aged 65-69 in 1998) who remain alive for at most 30 years into their simulated future (at which time their average age is 95). The figure depicts the simulated median wealth of individuals from the top 25%, second 25%, and bottom 50% permanent-income groups. The solid line tracks the median wealth in the baseline model. The dashed lines with "×" markers track wealth if the bequest motive is turned off (i.e., setting $\phi = 0$). The dashed lines with "+" markers track wealth if the decision to save for the expected medical expenses is turned off. However, the simulated wealth includes medical expenses; therefore, the differences in solid and dashed lines with "+" markers reflect differences in the decision to save in response to expected medical expenses, not differences in realized medical expenses. The dashed lines without markers are the simulated median wealth trajectories if both bequest motive and medical expenses are turned off.

the fourth row combines these alternatives by showing the scenario when there is no bequest motive and no response to the expected medical expenses. The counterfactual analysis of the distribution of the bequests is conducted separately for each permanent-income group.

Column (1) of Table 4.5 shows the predicted fraction of individuals who would leave positive bequests. If we turn off the decision to save in response to the expected medical expenses, the fraction of people who would leave positive bequests decreases by 16 percentage points for the top (from 75% to 59%), by 13 for the middle (from 62% to 49%), and five for the lowest permanent-income group (from 30% to 25%). On the other hand, if we turn off the bequest motive, these fractions decrease by 31 percentage points for the top, 25 for the middle, and 12 for the lowest permanent-income group. If we turn off both the bequest motive and the motive to save for expected medical expenses, the percentage points drops are slightly larger than those in previous experiments where only the bequest motive is turned off. Hence, the bequest motive determines the main role of determining whether individuals leave positive bequests.

Columns (2) to (5) of the table shows the 25th, 50th, 75th, and 90th percentiles of bequest distributions. The table shows that the 25th percentile of bequests is zero for all permanent-income groups. In the baseline model, the median bequests are 112K, 39K, and zero for the top, middle, and lowest permanent-income groups, respectively. If we turn off the saving for the expected medical expenses, the median bequests drop to 15K for the top permanent-income group but to zero for the other groups. If we turn off the bequest motive, the median bequests are zero for all permanent-income groups. These results imply that the median bequests are very sensitive to medical expenses and bequest motives, and if either one of these is turned off, the median bequests are predicted to be close to zero.

The 75th and 90th percentiles of bequest distributions are also sensitive to bequest motive and expected medical expenses. For example, if the saving response to the expected medical expenses is turned off, the 75th percentile of bequest drops by 62% (from 266K to 102K) for the top and by 58% (from 144K to 60K) for the middle permanent-income group. If the bequest motive is turned off, the respective drops of the 75th percentile of bequests for these groups are 42% (from 266K to 153K) and 47% (from 144K to 76K).[20] These results suggest that less than half of the 75th percentile of bequests are driven by bequest motives and more than half by the precautionary motive of saving in response to expected medical expenses.

If we turn off both the bequest motive and the motive to save for expected medical expenses, the 75th and 90th percentiles of the baseline bequests drop by around 67% and 44-47%, respectively, for both the top and middle permanent-income groups. This suggests that longevity risks and consumption smoothing are significant contributors to the 75th or higher percentiles of bequest distributions but not to the 50th or lower percentiles.

Overall, our results suggest that the bequest motive is a primary factor in determining *whether* individuals leave any bequests upon death. On the other hand, the precautionary motive to save for the expected medical expenses plays a major role in determining *how much* wealth is bequeathed.

### 4.6.2 Policy experiments: impacts of increasing medical expense coverage and estate tax on wealth and bequest

This section simulates two hypothetical policy changes separately for each permanent-income group. The first policy relates to the coverage of medical expenses and the second to the estate tax.

[20] The 90th percentile of the bequest drops by 40-51% if the medical expenses are turned off and by 25-46% if the bequest motive is turned off, depending on the permanent-income group.

Table 4.5: Decomposing savings motives: impacts of turning off bequest motive and decision to save in response to the expected medical expenses on the simulated bequest distribution

| | Fraction of positive bequests | Percentiles 25th | 50th | 75th | 90th |
|---|---|---|---|---|---|
| Panel A: PI: Top 25% | | | | | |
| Baseline | 0.75 | 0 | 112 | 266 | 447 |
| No medical expenses | 0.59 | 0 | 15 | 102 | 250 |
| No bequest motive | 0.44 | 0 | 0 | 153 | 335 |
| No bequest motive and medical expenses | 0.42 | 0 | 0 | 88 | 237 |
| Panel B: PI: Second 25% | | | | | |
| Baseline | 0.62 | 0 | 39 | 144 | 281 |
| No medical expenses | 0.49 | 0 | 0 | 60 | 166 |
| No bequest motive | 0.37 | 0 | 0 | 76 | 211 |
| No bequest motive and medical expenses | 0.36 | 0 | 0 | 48 | 157 |
| Panel C: PI: Bottom 50% | | | | | |
| Baseline | 0.30 | 0 | 0 | 22 | 136 |
| No medical expenses | 0.25 | 0 | 0 | 0 | 66 |
| No bequest motive | 0.18 | 0 | 0 | 0 | 73 |
| No bequest motive and medical expenses | 0.17 | 0 | 0 | 0 | 55 |

*Note:* The table presents percentiles of the simulated bequest distribution in thousands of 1998 dollars among individuals of the first cohort (aged 65-69 in 1998) who remain alive for at most 30 years in the simulated future. "No bequest motive" is the scenario if the bequest motive is turned off. "No medical expenses" is the scenario if the decision to save in response to the expected medical expenses is turned off. "No bequest motive and medical expenses" is if both the bequest motive and decision to save in response to the expected medical expenses are turned off. The simulation of bequest distribution is shown separately for different permanent-income groups.

*What if the government covers the entire medical expenses of retirees starting from 1998?* Our first policy experiment is related to the coverage of medical expenses. The question has a policy relevance because, although the U.S. has means-tested government programs, such as Medicare and Medicaid, to cover certain parts of individuals' medical expenses, the average U.S. retiree pays much more for health care than the average retiree in other developed countries (Papanicolas, Woskie, & Jha, 2018). Medical bills frequently cause financial difficulties and are one of the main causes of households' bankruptcy. This finding was also the main argument that President Obama used to argue for the passage of the Affordable Care Act (Himmelstein, Lawless, Thorne, Foohey, & Woolhandler, 2019).

Based on our estimation results, we ask the following: What if the government covers the entire medical expenses of retirees starting from 1998? This policy affects individuals' decisions in two ways. First, retirees do not save against expected medical expenses. Second, since the government covers the full medical expenses, the medical expense components are removed from individuals' budget constraints.

The simulated median wealth trajectories are shown in Figure 4.8, separately for each permanent-income group. The results show that if the government covers the entire medical expenses since 1998, the age profile of the median wealth decreases for individuals in the top permanent-income group. For the lowest permanent-income group, removing medical expenses increases their wealth such that the age when they exhaust their wealth increases from 75 to 79. The middle permanent-income group's median wealth decreases until age 93 and increases after this age. The reason is that removing medical expenses leaves these individuals with more resources at advanced ages.

Table 4.6 shows the distributions of the bequests. The table shows the predictions for the 50th and 75th percentiles of the bequest distributions and the fraction of positive bequests. Panels A, B, and C show the predictions of the top, middle, and lowest permanent-income groups, respectively. In the first row of each panel, we show the predictions of the baseline model. The second row of each panel shows the predictions if the government covers the entire medical expenses.

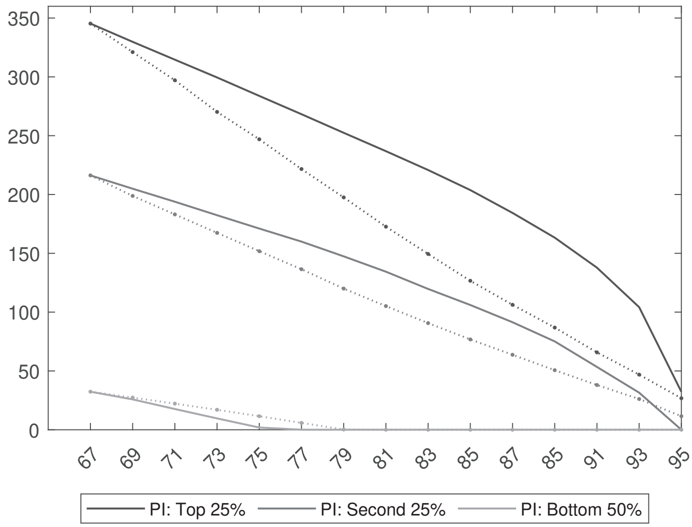
We find that with full medical expense coverage by the government, the fraction of people who would leave positive bequest increases from 75% to 91% for the top, 62% to 80% for the middle, and 30% to 42% for the lowest permanent-income group. Hence, without spending on medical expenses, individuals in all permanent-income groups have more resources to save as a bequest. Moreover, the value of the median bequest decreases by 61% for the top and 38% for the middle, but it increases by 6% for the lowest permanent income group. The median bequest decreases for the top and middle permanent-income groups because their overall savings decrease as they do not have a precautionary motive to save against medical expenses.

*What if the government increases the estate tax starting from 1998?* In the U.S., the estate tax mostly applies to very rich individuals (around only 2 percent of the estates of adult descendants pay any estate taxes), as it applies to estates worth more than $12.06 million in 2022 and $12.92 million in 2023, and many exemptions exist. The federal estate tax rate ranges from 18% to 40%. Some states also have their own estate or inheritance taxes, which vary by location, value, and relationship between a deceased person and his/her heirs (Gale & Slemrod, 2001; IRS, n.d.).

Compared to the other OECD countries, the maximum non-taxable amount of bequeathed wealth in the U.S. is very high. For example, in the Netherlands, as of 2023, the wealth transferred from deceased parents to children is not taxable until 22,918 euros, and the tax rate above this amount is 30-40% (Belastingdienst, n.d.).

Understanding how the changes in estate taxes affect old people's savings has policy relevance because an increase in estate taxes could distort the savings and substantially decrease the

Figure 4.8: Simulated wealth trajectories if the government covers full medical expenses




*Note:* The figure shows the simulated median wealth trajectories among individuals of the first cohort (aged 65-69 in 1998) who remain alive for at most 30 years into their simulated future (at which time their average age is 95). The figure depicts the simulated median wealth of individuals from the top 25%, second 25%, and bottom 50% permanent-income groups. The solid line tracks the median wealth in the baseline model. The dashed lines with "·" markers track wealth under the new policy where the U.S. government covered full medical expenses starting from 1998. To incorporate the impact of the new policy into the model, all medical expense components in the model are removed.

intergenerational wealth transfer. Therefore, we conduct a counterfactual analysis to answer the following: What if the U.S. government set a new estate tax system that resembles the Dutch system starting in 1998? More specifically, we set that in the new estate tax rule, the bequeathed wealth until 20,000 dollars is not taxable, and the tax rate above this amount is 30%. In other words, according to the new estate rule, the bequeathed wealth after tax is:

$$w^{\text{after tax}} = \begin{cases} w & \text{if } w \leq 20,000 \\ (1-\tau)\cdot(w-20,000)+20,000 & \text{if } w > 20,000 \end{cases} \tag{4.23}$$

Here $w$ and $w^{\text{after tax}}$ are the bequeathed wealth before and after the estate taxes, respectively. $\tau = 0.3$ is the tax rate for the bequeathed wealth beyond 20,000 euros.

We incorporate the estate tax into our theoretical model in the following way. First, we assume that before 1998 the estate tax was almost non-existent such that individuals do not consider it in their decisions. This is reasonable since the estate tax is only relevant to very rich individuals in the U.S. Secondly, we assume that agents only care about the bequeathed wealth after tax when they plan their bequest. More specifically, under the new regime, their utility from bequests is as follows:

$$\nu(w) = \left(\frac{\phi}{1-\phi}\right)^{\gamma} \frac{\left(\frac{\phi}{1-\phi}k + w^{\text{after tax}}\right)^{1-\gamma}}{1-\gamma}, \qquad \text{where } 0 \leq \phi \leq 1 \text{ and } 0 \leq k \tag{4.24}$$

Thirdly, to simplify the analysis, we assume the agents do not have any incentive to avoid paying the estate tax; for example, there is no way to transfer wealth (i.e., inter vivos) before the bequeathers pass away.

Our counterfactual analysis shows that increasing the estate tax does not have a substantial impact on the median wealth trajectories of individuals from all permanent-income groups.[21] Therefore, we conclude that increasing the estate tax does not affect the savings of old people. Cagetti and De Nardi (2009) also reached the same conclusion.

In Table 4.6, the third row of each panel shows the impact of introducing new estate taxes on the distribution of the bequests after estate tax. The fractions of positive bequests do not change much when the new estate tax is introduced. However, the value of the median bequests decreases for the middle and top permanent-income groups because a larger portion of the bequeathed wealth is taxed according to the new tax system. For example, the median bequests decrease by 25% for the top and 14% for the middle permanent-income groups. The median bequest does not change for the lowest permanent-income group because their bequeathed median wealth is less than the maximum non-taxable bequeathed wealth amount (which is 20,000 euros).

# 4.7 Conclusion

The precautionary and bequest motives are two potential explanations for the so-called retirement saving puzzle: old individuals, on average, are observed to not spend their savings fast enough compared to what the classic life-cycle model predicts and not exhaust their wealth completely by the time they pass away. Despite a growing body of literature on the retirement saving puzzle, studies have yet to agree on the relative quantitative importance of these two motives in explaining the savings behavior of people at advanced ages.

This paper presents new estimates of the precautionary and bequest motives by incorporating self-reported bequest probabilities into a structural life-cycle model for retired individuals. In this model, retirees face risks related to longevity and medical expenses and derive utility from both consumption and leaving a bequest.

[21] We do not show the results of this analysis because the median wealth trajectories with and without the new estate tax are essentially the same for all permanent-income groups.

Table 4.6: Counterfactuals analysis: impacts of having full medical expense coverage and increasing estate tax on bequest distribution

| Permanent-income group | | Fraction of positive bequests (1) | Percentiles 50th (2) | 75th (3) |
|---|---|---|---|---|
| *Panel A:* | | | | |
| Top 25% | Baseline model prediction | 0.75 | 112.54 | 263.78 |
| | If medical expenses are fully covered | 0.91 | 43.74 [61% ↓] | 119.04 [55% ↓] |
| | If estate tax increases | 0.75 | 84.50 [25% ↓] | 191.02 [28% ↓] |
| *Panel B:* | | | | |
| Second 25% | Baseline model prediction | 0.62 | 38.16 | 142.37 |
| | If medical expenses are fully covered | 0.80 | 23.51 [38% ↓] | 73.13 [49% ↓] |
| | If estate tax increases | 0.62 | 32.73 [14% ↓] | 105.79 [26% ↓] |
| *Panel C:* | | | | |
| Bottom 50% | Baseline model prediction | 0.34 | 0 | 21.16 |
| | If medical expenses are fully covered | 0.45 | 0 - | 20.39 [4% ↓] |
| | If estate tax increases | 0.34 | 0 - | 20.82 [2% ↓] |

*Note:* The table presents the fraction of positive bequests as well as the 50th and 75th percentiles of the simulated bequest distribution in thousands of 1998 dollars among individuals of the first cohort (aged 65-69 in 1998) who remain alive for at most 30 years in the simulated future. Panels A, B, and C show the predictions for the top, middle, and lowest permanent-income groups, respectively. In each panel, the first row shows the predictions of the baseline model. The second and third rows of each panel show the predictions if, starting from 1998, the U.S. government fully covered medical expenses and increased the estate tax, respectively.

We find that incorporating information in self-reported probabilities of bequeathing helps to estimate the bequest motive parameters precisely. Our estimation results suggest that the bequest motive is a prevalent and important factor in understanding the saving decisions of individuals from the top and middle permanent-income groups. Additionally, the model that uses self-reported probabilities accurately predicts the realized bequests of HRS respondents who passed away between 2002 and 2014, while the model that ignores this information tends to overpredict the bequests of relatively wealthy individuals.

Our counterfactual analysis suggests that the savings of middle and top permanent-income groups are sensitive to bequest and precautionary motives to save in response to expected medical expenses. Although both motives explain substantial parts of the savings, the precautionary motive to insure against the expected medical expenses has a dominant role in explaining the savings over the life cycle. The savings of the lowest permanent-income group are less sensitive to bequest motives and almost insensitive to the precautionary motive to save in response to medical expenses, mainly because they can rely on government transfers to pay their medical expenses.

The median bequests are found to be very sensitive to precautionary motives to save for medical expenses and bequest motives. If either motive is removed, median bequests for the top and middle permanent-income groups are predicted to be almost zero. Moreover, these motives account for approximately around 67% of the 75th percentile bequests of the middle and top permanent-income groups. The remaining 75th percentile of bequests is explained by the precautionary savings to insure longevity risks and smooth consumption.

Our analysis of a hypothetical policy that covers all medical expenses for retirees shows that it would significantly decrease the wealth trajectories of relatively wealthy individuals, as they would no longer need to save for expected medical expenses. However, for the lowest permanent-income group, the policy would increase their wealth because they have more resources when the government fully pays their medical expenses. The policy would also decrease median bequests for the top and middle permanent-income groups but increase the proportion of people leaving positive bequests.

The next analysis of a hypothetical policy that taxes 30% of bequeathed wealth beyond $20,000 shows that it does not significantly affect the saving behavior of older individuals. However, it does decrease median bequests for the top and middle permanent-income groups.

Our results demonstrate the benefits of incorporating self-reported probabilities into dynamic structural models. Specifically, we show that researchers can use the information in elicited self-reported probabilities by constructing additional moment conditions without making the benchmark model more complex by adding more control or state variables. Additionally, our results demonstrate that using information from self-reported bequest probabilities provides precise estimates of bequest motive preference parameters. Obtaining precise estimates of bequest motive parameters is essential for accurately quantifying the extent and relevance of the bequest motive in explaining the savings behavior of older individuals.

This paper could be expanded in several ways. Firstly, our focus has been on the saving behavior of single retirees, and it would be interesting to extend the model to understand the behavior of couples, particularly how their wealth changes when one spouse passes away. Secondly, incorporating various strategic motives for bequeathing and inheriting into the life-cycle model could provide insight into why people leave bequests. Thirdly, researchers could use self-reported probabilities other than those related to bequests to estimate the life-cycle model. For example, the HRS contains information on individuals' self-reported probabilities of entering a nursing home or experiencing serious health issues in the near future. These probabilities could be useful in identifying parameters related to precautionary saving motives.

An intriguing direction for future research involves investigating how specific reporting behaviors can impact the estimation of key parameters. Rather than accepting reported bequest probabilities at face value, researchers can consider the influence of systematic non-responses (such as answering either "Don't know" or "Refused to Answer") and epistemic uncertainty by employing the methodologies proposed by De Bresser and Van Soest (2013) and Kleinjans and Van Soest (2014). Additionally, following Giustinelli et al. (2022), researchers can explore the possibility that individuals perceive the future as ambiguous, leading them to report rounded probabilities instead of precise ones for events.

## 4.8 Appendix

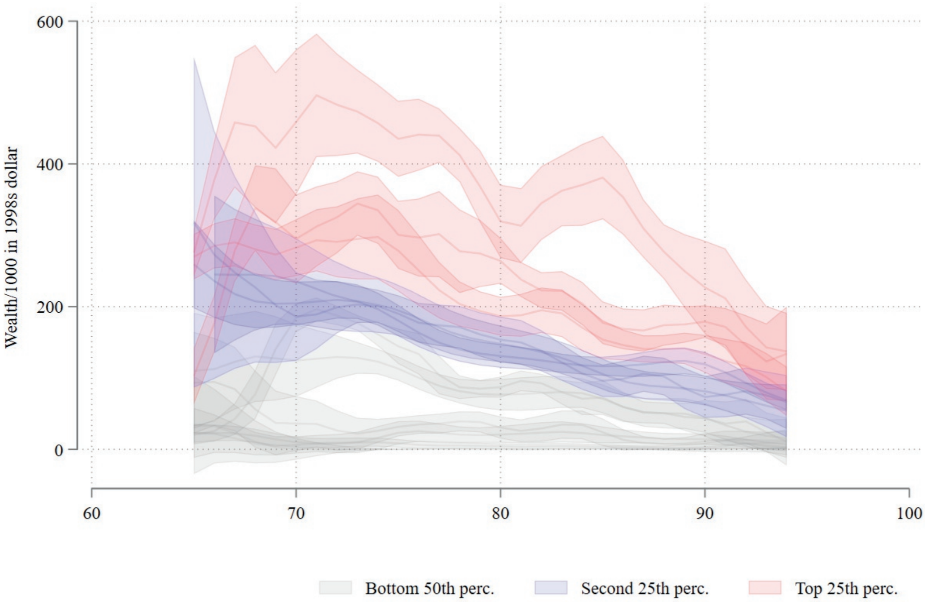
### 4.8.1 Sample description

Table 4.7: Summary statistics: sample of HRS respondents who were 65+ in 1998 vs. our sample

| VARIABLES | (1)<br>Everyone 65+ | (2)<br>Our sample |
|---|---|---|
| *Panel A:* | | |
| Total wealth / 1000 | 345.7 | 135.0 |
| Non-housing wealth / 1000 | 274.9 | 88.95 |
| Non-asset income / 1000 | 24.11 | 13.43 |
| Permanent income / 1000 | 24.09 | 13.42 |
| Out-of-pocket medical expenses / 1000 | 1.837 | 2.246 |
| Age | 78.70 | 81.58 |
| Health: good or excellent | 0.640 | 0.573 |
| Whether have any kids | 0.910 | 0.830 |
| Number of observations | 54,536 | 12,517 |
| *Panel B:* | | |
| Female | 0.575 | 0.781 |
| Separated | 0.0959 | 0.158 |
| Widowed | 0.485 | 0.779 |
| Never-married | 0.0245 | 0.0632 |
| Less than HS | 0.385 | 0.473 |
| Highest education: HS | 0.302 | 0.297 |
| Highest education: College | 0.169 | 0.145 |
| College+ educated | 0.144 | 0.0853 |
| Caucasian | 0.846 | 0.817 |
| African-American | 0.125 | 0.154 |
| Hispanic | 0.0113 | 0.0111 |
| Cohort born after 1924 | 0.536 | 0.279 |
| Cohort born between 1914 and 1923 | 0.350 | 0.476 |
| Cohort born before 1913 | 0.114 | 0.244 |
| Number of individuals | 10,696 | 3,166 |

The table shows the sample averages of the main variables. The first column shows the summary statistics of the sample of people aged 65 and older in the HRS in 1998. The second one shows those of our sample, the subset of the former sample who are single retirees. Compared to the former sample, one average, people in our sample are less educated, poorer, and older.
*Panel A:* Variable are time-varying
*Panel B:* Variables are time-invariant.

Figure 4.9: Median wealth profiles, by age and PI-decile



### 4.8.2 More on the validity of bequest probabilities

Table 4.3 continued.

| Dependent variable | (1)<br>Logged wealth<br>LS | (2)<br>after two years<br>FE | (3)<br>Logged actual<br>bequest, LS |
|---|---|---|---|
| Logged income | 0.111*** | 0.00404 | 0.106* |
| | (0.0290) | (0.0359) | (0.0585) |
| Logged OOPME | 0.134*** | 0.0752 | -0.0372 |
| | (0.0383) | (0.0475) | (0.0849) |
| Logged OOPME squared | -0.0117*** | -0.00659 | 0.0105 |
| | (0.00407) | (0.00498) | (0.00845) |
| Health: good or excellent | 0.227*** | 0.350*** | -0.323** |
| | (0.0623) | (0.0846) | (0.149) |
| Whether have any kids | 0.0391 | 0.348 | 0.405 |
| | (0.102) | (0.352) | (0.419) |
| Separated | -0.253 | | -1.029 |
| | (0.163) | | (0.629) |
| Widowed | -0.0313 | | -0.857 |
| | (0.156) | | (0.593) |
| Female | -0.0313 | | -0.333 |
| | (0.0676) | | (0.231) |
| Less than HS | -0.234** | | -1.112*** |
| | (0.0918) | | (0.298) |
| Highest education: HS | 0.0437 | | -0.540* |
| | (0.0733) | | (0.288) |
| Highest education: College | -0.0660 | | -0.705** |
| | (0.0767) | | (0.292) |
| Caucasian | -0.166 | | 1.829 |
| | (0.206) | | (1.242) |
| African-American | -0.488** | | 3.466*** |
| | (0.227) | | (1.299) |
| Hispanic | -0.988** | | 3.355** |
| | (0.460) | | (1.556) |
| Cohort born after 1935 | -0.105 | | -0.0992 |
| | (0.140) | | (0.407) |
| Cohort born between 1925 and 1934 | -0.0650 | | 0.355 |
| | (0.125) | | (0.314) |
| Permanent income: Bottom 50% | -0.307*** | | 0.603** |
| | (0.0686) | | (0.307) |
| Permanent income: Second 25% 2.0000 | 0.0207 | | 0.277 |
| | (0.0522) | | (0.257) |
| Constant | -0.439 | 1.489 | 18.01* |
| | (3.570) | (4.826) | (9.360) |
| Observations | 7,483 | 7,483 | 3,858 |
| Number of id | | 2,218 | |
| R-squared | 0.680 | 0.086 | 0.226 |

Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table 4.8: Estimation results: the effect of the probability of bequeathing 0K+ and 100K+ on wealth after two years and actual bequests

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | Logged wealth after two years | | Logged actual | Logged wealth after two years | | Logged actual |
| VARIABLES | LS | FE | bequest, LS | LS | FE | bequest, LS |
| Probability of bequeathing 0K+ | 0.633*** | 0.500*** | 0.827*** | | | |
| | (0.118) | (0.170) | (0.247) | | | |
| Probability of bequeathing 100K+ | | | | 0.310*** | 0.167** | 0.648*** |
| | | | | (0.0646) | (0.0782) | (0.165) |
| 2nd wealth decile | 1.587*** | -0.542* | 0.468 | 1.559*** | -0.618** | 0.365 |
| | (0.244) | (0.282) | (0.417) | (0.239) | (0.269) | (0.389) |
| 3rd wealth decile | 4.217*** | -0.283 | 0.641 | 4.272*** | -0.0527 | 0.707* |
| | (0.256) | (0.366) | (0.394) | (0.244) | (0.333) | (0.387) |
| 4th wealth decile | 5.862*** | 0.426 | 1.138*** | 6.044*** | 0.690* | 1.351*** |
| | (0.251) | (0.424) | (0.404) | (0.224) | (0.353) | (0.375) |
| 5th wealth decile | 6.731*** | 0.741* | 1.859*** | 7.014*** | 0.903** | 1.999*** |
| | (0.247) | (0.416) | (0.421) | (0.215) | (0.358) | (0.391) |
| 6th wealth decile | 7.182*** | 0.787* | 2.061*** | 7.360*** | 0.880** | 2.266*** |
| | (0.245) | (0.423) | (0.448) | (0.215) | (0.363) | (0.413) |
| 7th wealth decile | 7.733*** | 1.160*** | 2.628*** | 7.905*** | 1.095*** | 2.824*** |
| | (0.242) | (0.444) | (0.407) | (0.211) | (0.369) | (0.355) |
| 8th wealth decile | 8.056*** | 1.275*** | 2.855*** | 8.196*** | 1.179*** | 3.003*** |
| | (0.241) | (0.452) | (0.411) | (0.212) | (0.372) | (0.360) |
| 9th wealth decile | 8.521*** | 1.363*** | 3.418*** | 8.600*** | 1.224*** | 3.552*** |
| | (0.242) | (0.452) | (0.399) | (0.212) | (0.378) | (0.355) |
| 10th wealth decile | 9.094*** | 1.581*** | 3.916*** | 9.153*** | 1.374*** | 3.936*** |
| | (0.249) | (0.459) | (0.411) | (0.218) | (0.381) | (0.379) |
| Log income | 0.121*** | 0.0312 | -0.107** | 0.111*** | 0.000271 | -0.0131 |
| | (0.0291) | (0.0356) | (0.0435) | (0.0281) | (0.0356) | (0.0573) |
| Log of OOPME | 0.0713 | -0.00146 | 0.0891 | 0.135*** | 0.0675 | 0.0870 |
| | (0.0455) | (0.0614) | (0.0809) | (0.0389) | (0.0483) | (0.0714) |
| Log of OOPME squared | -0.00554 | 0.00405 | -0.00284 | -0.0122*** | -0.00566 | -0.00332 |
| | (0.00496) | (0.00638) | (0.00812) | (0.00415) | (0.00505) | (0.00699) |
| Age | 0.156 | 0.359** | -0.195 | 0.131 | 0.302** | -0.189 |
| | (0.125) | (0.167) | (0.232) | (0.0957) | (0.126) | (0.197) |
| Age squared / 100 | -0.114 | -0.274** | 0.110 | -0.0979 | -0.244*** | 0.105 |
| | (0.0792) | (0.106) | (0.142) | (0.0609) | (0.0803) | (0.121) |
| Health: good or excellent | 0.227*** | 0.319*** | -0.310** | 0.249*** | 0.349*** | -0.242* |
| | (0.0772) | (0.105) | (0.124) | (0.0635) | (0.0862) | (0.136) |
| Whether have any kids | 0.0637 | 0.608 | 0.413 | 0.0118 | 0.280 | 0.732* |
| | (0.126) | (0.501) | (0.316) | (0.105) | (0.341) | (0.420) |
| Separated | -0.313 | | -0.217 | -0.223 | | -0.660 |
| | (0.207) | | (0.461) | (0.164) | | (0.490) |
| Widowed | -0.116 | | -0.321 | -0.0268 | | -0.567 |
| | (0.201) | | (0.463) | (0.159) | | (0.500) |
| Female | 0.0239 | | -0.299* | -0.0415 | | -0.306 |
| | (0.0823) | | (0.173) | (0.0702) | | (0.188) |
| Less than HS | -0.236** | | -0.797*** | -0.287*** | | -0.639*** |
| | (0.113) | | (0.231) | (0.0889) | | (0.235) |
| Highest education: HS | 0.00350 | | -0.640*** | -0.0240 | | -0.681*** |
| | (0.0902) | | (0.191) | (0.0707) | | (0.204) |
| Highest education: College | -0.147 | | -0.562*** | -0.141* | | -0.503** |
| | (0.0982) | | (0.202) | (0.0749) | | (0.196) |
| Caucasian | -0.129 | | 2.067 | -0.151 | | 1.849 |
| | (0.254) | | (1.609) | (0.215) | | (1.557) |
| African-American | -0.563** | | 2.740* | -0.496** | | 2.308 |
| | (0.282) | | (1.626) | (0.235) | | (1.580) |
| Hispanic | -1.172** | | 2.798 | -0.975** | | 2.483 |
| | (0.512) | | (1.735) | (0.472) | | (1.671) |
| Cohort born after 1935 | -0.194 | | -0.773** | -0.105 | | -0.722** |
| | (0.172) | | (0.312) | (0.141) | | (0.308) |
| Cohort born between 1925 and 1934 | -0.0933 | | -0.400 | -0.0413 | | -0.322 |
| | (0.153) | | (0.251) | (0.126) | | (0.253) |
| Permanent income: Bottom 50% | -0.277*** | | -0.277 | -0.323*** | | -0.0706 |
| | (0.0920) | | (0.261) | (0.0700) | | (0.280) |
| Permanent income: Second 25% | 0.0398 | | 0.0672 | 0.0505 | | 0.183 |
| | (0.0699) | | (0.200) | (0.0527) | | (0.222) |
| Constant | -2.522 | -3.206 | 16.46* | -1.310 | 0.495 | 15.74** |
| | (4.852) | (6.508) | (9.485) | (3.714) | (4.911) | (7.994) |
| Observations | 5,094 | 5,094 | 1,887 | 7,338 | 7,338 | 2,610 |
| R-squared | 0.707 | 0.082 | 0.354 | 0.681 | 0.084 | 0.309 |

Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Table 4.9: Estimation results of regressing the reported probabilities of bequeathing more than a certain amount on financial, medical, and socio-demographic characteristics

| VARIABLES | (1)<br>0K+ | (2)<br>0K+ | (3)<br>10K+ | (4)<br>10K+ | (5)<br>100K+ | (6)<br>100K+ |
|---|---|---|---|---|---|---|
| 2nd wealth decile | 1.760 | -1.004 | -0.579 | 0.247 | 0.294 | -0.060 |
| | (1.811) | (2.126) | (1.479) | (1.637) | (0.871) | (0.789) |
| 3rd wealth decile | 13.610*** | 6.290** | 5.141*** | 6.146*** | -1.617 | -0.574 |
| | (2.445) | (2.832) | (1.795) | (2.051) | (1.073) | (1.146) |
| 4th wealth decile | 31.173*** | 17.764*** | 25.312*** | 18.348*** | 0.684 | 1.316 |
| | (2.653) | (3.582) | (2.016) | (2.521) | (1.209) | (1.514) |
| 5th wealth decile | 49.491*** | 26.463*** | 40.653*** | 27.145*** | 4.455*** | 5.831*** |
| | (2.738) | (3.805) | (2.152) | (2.642) | (1.397) | (1.687) |
| 6th wealth decile | 61.149*** | 31.761*** | 49.431*** | 32.349*** | 11.515*** | 6.202*** |
| | (2.470) | (4.012) | (2.095) | (2.764) | (1.643) | (1.938) |
| 7th wealth decile | 63.833*** | 35.779*** | 53.108*** | 33.558*** | 25.648*** | 12.188*** |
| | (2.438) | (4.041) | (2.050) | (2.874) | (1.886) | (2.213) |
| 8th wealth decile | 68.670*** | 39.154*** | 59.526*** | 38.015*** | 42.933*** | 20.196*** |
| | (2.229) | (4.139) | (1.947) | (2.997) | (2.034) | (2.506) |
| 9th wealth decile | 68.528*** | 38.487*** | 61.503*** | 38.930*** | 53.887*** | 20.536*** |
| | (2.354) | (4.270) | (2.040) | (3.095) | (2.082) | (2.705) |
| 10th wealth decile | 72.475*** | 39.589*** | 65.927*** | 40.215*** | 67.763*** | 25.372*** |
| | (2.288) | (4.285) | (2.057) | (3.215) | (2.111) | (3.033) |
| Log income | 0.496* | -0.017 | 0.959*** | 0.530 | 0.269 | 0.468 |
| | (0.274) | (0.373) | (0.259) | (0.391) | (0.215) | (0.325) |
| Log of OOPME | 1.590*** | 1.131* | 1.398*** | 1.211** | 0.158 | 0.439 |
| | (0.558) | (0.577) | (0.479) | (0.489) | (0.429) | (0.426) |
| Log of OOPME - squared | -0.175*** | -0.146** | -0.144*** | -0.144*** | -0.051 | -0.041 |
| | (0.063) | (0.062) | (0.055) | (0.054) | (0.051) | (0.050) |
| Age | 1.310 | 1.344 | 1.446 | 2.359* | 3.399*** | 3.981*** |
| | (1.535) | (1.756) | (1.292) | (1.394) | (1.275) | (1.312) |
| Age squared | -0.008 | -0.010 | -0.009 | -0.017** | -0.020** | -0.026*** |
| | (0.010) | (0.011) | (0.008) | (0.009) | (0.008) | (0.008) |
| Health: good or excellent | 3.787*** | 0.762 | 2.561*** | 1.009 | 0.346 | -1.100 |
| | (0.995) | (1.128) | (0.894) | (0.940) | (0.857) | (0.911) |
| Whether have any kids | -0.357 | -3.551 | 0.434 | -4.461 | 1.283 | 3.236 |
| | (1.541) | (3.028) | (1.567) | (3.834) | (1.581) | (3.543) |
| Separated | 2.775 | | 1.495 | | -2.745 | |
| | (2.518) | | (2.605) | | (2.700) | |
| Widowed | 3.601 | | 2.637 | | -2.551 | |
| | (2.365) | | (2.472) | | (2.614) | |
| Female | -6.384*** | | -8.526*** | | -11.095*** | |
| | (1.148) | | (1.126) | | (1.376) | |
| Less than HS | -5.887*** | | -6.897*** | | -12.326*** | |
| | (1.778) | | (1.834) | | (2.041) | |
| Highest education: HS | -2.673* | | -3.809** | | -7.944*** | |
| | (1.543) | | (1.680) | | (2.011) | |
| Highest education: College | -2.372 | | -2.413 | | -5.340** | |
| | (1.688) | | (1.895) | | (2.229) | |
| Caucasian | 1.640 | | 5.806* | | 8.350*** | |
| | (3.504) | | (3.376) | | (2.909) | |
| African-American | -2.192 | | 2.507 | | 5.992* | |
| | (3.732) | | (3.627) | | (3.062) | |
| Hispanic | -1.322 | | 7.407 | | 12.961*** | |
| | (5.515) | | (5.549) | | (4.640) | |
| Cohort born after 1935 | -10.573*** | | -7.178*** | | -12.269*** | |
| | (2.963) | | (2.418) | | (2.396) | |
| Cohort born between 1925 and 1934 | -7.205*** | | -4.749** | | -5.486*** | |
| | (2.645) | | (2.127) | | (2.086) | |
| Permanent-income: Bottom 50% | -9.183*** | | -9.427*** | | -6.257*** | |
| | (1.599) | | (1.466) | | (1.566) | |
| Permanent-income: Second 25% | -4.145*** | | -5.358*** | | -4.544*** | |
| | (1.464) | | (1.405) | | (1.582) | |
| Constant | -21.070 | 1.830 | -34.733 | -47.239 | -115.725** | -138.615*** |
| | (60.869) | (68.937) | (51.615) | (55.466) | (51.246) | (52.347) |
| Observations | 5,721 | 5,721 | 8,416 | 8,416 | 8,262 | 8,262 |
| Number of individuals | | 1,751 | | 1,845 | | 1,843 |
| R-squared | 0.546 | 0.075 | 0.468 | 0.072 | 0.470 | 0.036 |

Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

### 4.8.3 First-stage estimation results

#### 4.8.3.1 Health state transition

The probability of the health of individual $i$ being good after one year is modeled as follows:

$$\pi^{good}_{it+1|t_i,h_{it},g_i,I_i} = \frac{1}{1+\exp(-[\beta^h_0+\beta^h_1 t_i+\beta^h_2 h_{it}+\beta^h_3 g_i+I_i\gamma^h])}. \tag{4.25}$$

Since the HRS is a biennial survey, we only observe the health after every two years; for example, if $h_{it}$ and $h_{i,t+2}$ observed, then $h_{i,t+1}$ is not observed. Following the health transition probability structure in Eq. 4.25, the probabilities of agent $i$ having good and bad health at age $t_i+2$ conditional on $(t_i, h_{it}, g_i, I_i)$ is given by:

$$\begin{bmatrix} \pi^{good}_{it+2|t_i,h_{it},g_i,I_i} \\ 1-\pi^{good}_{it+2|t_i,h_{it},g_i,I_i} \end{bmatrix} = \begin{bmatrix} \pi^{good}_{it+2|t_i,h_{it}=1,g_i,I_i} & \pi^{good}_{it+2|t_i,h_{it}=0,g_i,I_i} \\ 1-\pi^{good}_{it+2|t_i,h_{it}=1,g_i,I_i} & 1-\pi^{good}_{it+2|t_i,h_{it}=0,g_i,I_i} \end{bmatrix} \begin{bmatrix} \pi^{good}_{it+1|t_i,h_{it},g_i,I_i} \\ 1-\pi^{good}_{it+1|t_i,h_{it},g_i,I_i}. \end{bmatrix} \tag{4.26}$$

The likelihood contribution of agent $i$ with $(t_i, h_{it}, g_i, I_i)$ is given by:

$$\mathscr{L}^{health}_{it+2|t} = 1\{h_{i,t+2}=1\}\cdot \pi^{good}_{it+2|t_i,h_{it},g_i,I_i} + 1\{h_{i,t+2}=0\}\cdot(1-\pi^{good}_{it+2|t_i,h_{it},g_i,I_i}). \tag{4.27}$$

Table 4.10: Estimation results of health transition probability

| VARIABLES | |
|---|---|
| Female | 0.148*** |
| | (0.053) |
| Second PI-tercile | 0.246*** |
| | (0.05) |
| Third PI-tercile | 0.439*** |
| | (0.051) |
| Current health is good | 3.451*** |
| | (0.052) |
| Age | -0.015*** |
| | (0.003) |
| Constant | -0.735*** |
| | (0.267) |
| Observations | 9.689 |
| log-Likelihood | -5345.71 |

Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

We use the observation of individuals who participated in the HRS for at least two consecutive waves to estimate unknown parameters of the health transition matrix. The estimation results are summarized in Table 4.10.

#### 4.8.3.2 Out-of-pocket medical expenses

Let $m_{it}$ be the OOPME of individual $i$ at age $t$. First, we run the following FE model to remove the cohort effects:

$$\ln m_{it} = \sum_{age=65}^{T} \beta'_{age} age_{it} + \alpha'_i + \varepsilon' \tag{4.28}$$

Once we estimate the FE model, the adjusted logged medical expenses is computed as follows:

$$\ln \widetilde{m_{it}} = \sum_{age=65}^{T} \hat{\beta}'_{age} age_{it} + \hat{\alpha}'_i + (\hat{\alpha}_{c:\{1904-1913\}'} - \hat{\alpha}'_c) + \varepsilon'_{it} \tag{4.29}$$

where $\hat{\alpha}'_c$ is the average of $\alpha_i$ of individuals from cohort $c$. In our transformation, the logged medical expenses are adjusted to the level of cohorts who are born between 1904 and 1913.

In the next step, we run the following regression to predict the mean and the variance of the logged medical expenses conditional on $(t, h_t, g, I)$:

$$\begin{aligned}\ln \widetilde{m_{it}} =& \beta_0^m + \beta_1^m t_i + \beta_2^m t_i^2 + \beta_3^m t_i^3 + \beta_4^m h_{it} + \beta_5^m g_i + I_i \gamma^m + ...\\ &+ \beta_8^m (h_{it} \cdot t_i) + \beta_9^m (g_i \cdot t_i) + (I_i \cdot t_i)\gamma^{m'} + \varepsilon_{it}^m \end{aligned} \tag{4.30}$$

and

$$\begin{aligned}(\hat{\varepsilon}_{it}^m)^2 &= (\ln \widetilde{m_{it}} - \widehat{\ln \widetilde{m_{it}}})^2\\ &= \beta_0^\sigma + \beta_1^\sigma t_i + \beta_2^\sigma t_i^2 + \beta_3^\sigma g_i + \beta_4^\sigma h_{it} + I_i \gamma^\sigma + \beta_7^\sigma (g_i \cdot t_i) + \beta_8^\sigma (g_i \cdot t_i) + (I_i \cdot t_i)\gamma^{\sigma'} + \varepsilon_{it}^\sigma \end{aligned} \tag{4.31}$$

where $\widehat{\ln \widetilde{m_{it}}}$ is the predicted logged medical expenses from the regression in Eq. 4.30. $(\hat{\varepsilon}_{it}^m)^2$ is the square of the residual errors.

The estimation results of the regression in Eqs. 4.30 and 4.31 shown in Table 4.11. Based on the results in this table, the means and variance of the logged OOPME conditional on $(t, h_t, g, I)$ are predicted as follows:

$$\widehat{\mu_{t,h_t,g,I}} = \widehat{\ln m}(t, h_t, g, I) \tag{4.32}$$

$$\widehat{\sigma^2_{t,h_t,g,I}} = \widehat{(\hat{\varepsilon}^m)^2}(t, h_t, g, I) \tag{4.33}$$

Table 4.11: First-stage estimation results of out-of-pocket medical expenses

| | (1) | (2) |
|---|---|---|
| Dependent variable | Log OOPME, $\ln \widetilde{w_{it}}$ | Log OOPME squared residuals, $(\hat{\varepsilon}^{m}_{it})^2$ |
| Age | 0.721 | -0.313** |
| | (0.738) | (0.123) |
| Age$^2$/100 | -0.936 | 0.205*** |
| | (0.923) | (0.0757) |
| Age$^3$/10000 | 0.0422 | |
| | (0.0383) | |
| Health good | -0.339 | 2.164** |
| | (0.386) | (0.999) |
| Health good × Age | -0.00213 | -0.0278** |
| | (0.00470) | (0.0122) |
| Female | -0.0377 | -2.826** |
| | (0.475) | (1.171) |
| Female × Age | 0.00245 | 0.0350** |
| | (0.00587) | (0.0145) |
| Second PI-tercile | 0.199 | 0.216 |
| | (0.462) | (1.203) |
| Third PI-tercile | -0.124 | -2.298* |
| | (0.453) | (1.173) |
| Second PI-tercile × Age | 0.00234 | -0.00235 |
| | (0.00562) | (0.0147) |
| Third PI-tercile × Age | 0.00758 | 0.0288** |
| | (0.00554) | (0.0144) |
| Constant | -13.21 | 14.00*** |
| | (19.58) | (5.079) |
| Observations | 10,410 | 8,617 |
| R-squared | 0.073 | 0.008 |

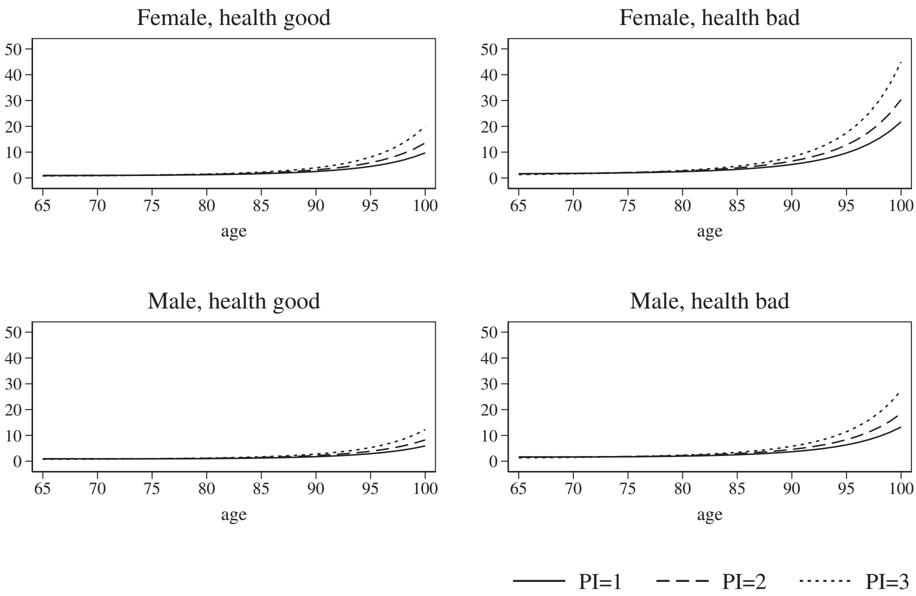
Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Due to higher-order polynomials of age and several interaction terms, it is not straightforward to interpret the estimated parameters in Table 4.11. To ease the interpretation, we provide Figure 4.10 that shows the expected medical expenses conditional on the state variables, $(t, h_t, g, I)$. Following the log-normally distributed assumption, the expected OOPME conditional on $(t, h_t, g, I)$ equals:

$$\mathbb{E}(m_{t,h_t,g,I}) = \exp\left(\widehat{\mu_{t,h_t,g,I}} + \frac{\widehat{\sigma^2_{t,h_t,g,I}}}{2}\right). \tag{4.34}$$

According to Figure 4.10, on average, people in worse health spend more than people in better health, women spend more than men, and older people spend more than younger people. High-income people are estimated to spend more than lower-income people.

Figure 4.10: Expected OOPME/1000, in 1998 dollars conditional on age $t$, current health $h_t$, gender $g$ and permanent-income tercile $I$




#### 4.8.3.3 Non-asset income

Similar to the OOPME prediction, we first run the FE model to remove the cohort effects from the non-asset. After that step, we run the following regression:

$$\ln y_{it} = \beta_0^y + \beta_1^y g_i + \sum_{k=2}^{5} \beta_k^y 1\{I_i = k\} + \sum_{k=2}^{5} \beta_{4+k}^y (1\{I_i = k\} \cdot g_i) + \varepsilon_{it}^y. \tag{4.35}$$

The regression includes only time-invariant states variables, for example, gender and permanent-income tercile dummies, to make the predicted non-asset income consistent with the assumption that the non-asset income is time-invariant.

The estimation results of the regression in Eq. 4.35 is shown in Table 4.12. The results show that richer individuals earn more income than poorer, and males earn more than females, on average, when all else is constant.

#### 4.8.3.4 Subjective survival probability

The estimation results of the subjective survival probability model are shown in Table 4.13.

Table 4.12: First-stage estimation results of non-asset income

| | (1) |
|---|---|
| Dependent variable | Logged income |
| Second PI-tercile | 0.0597*** |
| | (0.00271) |
| Third PI-tercile | 0.104*** |
| | (0.00241) |
| Female | -0.00353* |
| | (0.00193) |
| Second PI-tercile × Female | -0.00156 |
| | (0.00298) |
| Third PI-tercile × Female | 0.000211 |
| | (0.00273) |
| Constant | 2.285*** |
| | (0.00177) |
| Observations | 12,224 |
| R-squared | 0.428 |

Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

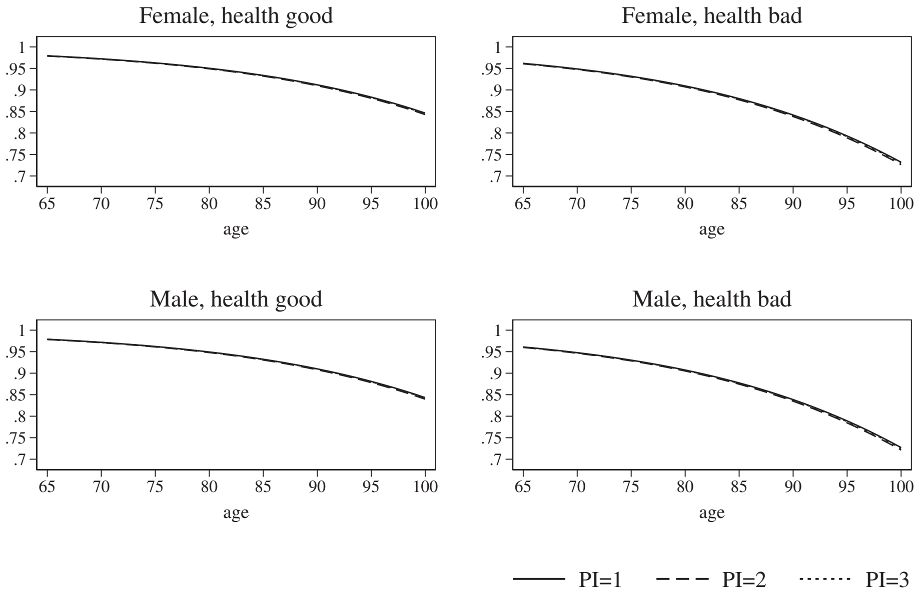
Table 4.13: Estimation results of subjective hazard rates

| VARIABLES | |
|---|---|
| Age/100, $\alpha$ | 6.013*** |
| | (0.348) |
| Health is good | -0.627*** |
| | (0.043) |
| Female | -0.044 |
| | (0.046) |
| Second PI-tercile | -0.0009 |
| | (0.047) |
| Third PI-tercile | -0.028 |
| | (0.043) |
| Standard deviation of reporting error, $\sigma_\varepsilon^s$ | 0.435*** |
| | (0.005) |
| Constant | -2.541*** |
| | (0.295) |
| Observations | 5,867 |
| log-Likelihood | -4,184.1 |

Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Our statistics of interest is the probability of individuals with $(t, h_t, g, I)$ surviving to the next period. Thus, the predicted probabilities of surviving to the next year are illustrated in Figure 4.11. According to Figure 4.11, when all else is constant, richer, healthier, and younger individuals and females have a higher survival probability than poorer, less healthy, and older individuals. Females also have a higher survival probability than males, on average. The majority of the heterogeneity in predicted survival probabilities is due to differences in current health and age. There is a minor heterogeneity across different gender and different permanent-income groups.

Figure 4.11: Predicted subjective probability of surviving to the next year conditional on survived to age $t$ with current health state $h_t$, gender $g$ and permanent-income tercile $I$



### 4.8.4 Model solution: backward induction and forward iteration

Before initiating the second-stage estimation, we set the following. For the baseline specifications, we set the maximum potential age to live as $T = 100$, the annual interest rate of a risk-free asset as $r = 0.03$, and the time discount rate is $\beta = 0.975$.

The cash-on-hand $x_t$ at each period is discretized into 30 points. Let $x_{pt}$ be the $p$th grid point of cash-on-hand at age $t$, $p = 1, ., 30$. For each $t$, $\min\{x_{pt}\} = 1,000$, and $\max\{x_{p,t=65}\}$ is set to two times the observed wealth in the sample. $\max\{x_{pt}\}$ for age $65 < t$ is determined from the hypothetical scenario where an individual never encounters any medical expenses and always consumes $1,000$ amount. Then for each age $t$, the interval $[\min\{x_{pt}\}; \max\{x_{pt}\}]$ is divided into 30 sub-intervals using the log-steps method.

In the second stage, the evaluation of the objective function at given settings and the value for parameters $[\gamma', \phi', k', c'_{\min}]$, proceeded in two steps: (1) backward induction, and (2) the forward iteration.

*The backward induction* is proceeded in the following steps:

*At* $t = T+1$: For $p$th grid-point of cash-on-hand $x_{pt}$, evaluate the value function and let's denote the corresponding value as $V^p_{T+1,h_{T+1},g,I}$. At this period, the value function only depends on the utility from the bequest, which is a function of the remaining wealth to this period.

*From* $t = T$ *to* $65$: For each $p$th grid point $x_{pt}$, states $(h_t, g, I)$, non-asset income $y$, the probability of surviving to the next year $s_{t+1}$, and the probability of health being good in the next period $\pi^{good}_{t+1}$:

1. Generate $m^{sim}_{t+1}$ when health is good and bad:

$$m^{sim}_{t+1,h_{t+1}=j,g,I} = \exp(\eta^{sim} \cdot \sigma_{t+1,h_{t+1}=j,g,I} + \mu_{t+1,h_{t+1}=j,g,I}), \quad j = \{1, 2\} \tag{4.36}$$

   $m^{sim}_{t+1,h_{t+1}=1,g,I}$ and $m^{sim}_{t+1,h_{t+1}=2,g,I}$ are $sim$th simulated next period OOPME if the next period health is good and bad, respectively. For each health state, we simulate `nSim` number of simulated medical expenses of the next period. If $t = T$, then $m^{sim}_{T+1}(h_{T+1} = j) = 0$ $\forall sim, j$ because the agent would pass away at period $T + 1$ with certainty. Here, before the backward induction begins, we generate `nSim`$= 100$ pseudo-random draws from i.i.d standard normal distribution, $\eta^{sim}$. We use Halton draws with base 3 to generate pseudo-random draws to reduce the simulation error.

2. Calculate $V_t^p(x_{pt}, h_t, g, I)$ :

$$V_t^p(x_{pt}, h_t, g, I) = \max_{c_t} \Big( u(c_t) + \beta[s_{t+1}\, \mathbb{E}_t\{V_{t+1}(x_{t+1,h_{t+1},g,I})\} + (1 - s_{t+1})\nu((x_{pt} - c_t))] \Big) \tag{4.37}$$

$$\text{with respect to:} \quad c'_{\min} \le c_t \le x_{pt} \tag{4.38}$$

At given value of $c_t$, $\mathbb{E}_t\{V_{t+1}^{sim}(x_{t+1}, h_{t+1}, g, I)\}$ is computed as follows:

(a) Calculate whether the government transfer is eligible when facing with $m^{sim}_{t+1,h_{t+1}=j,g,I}$, for each $j, sim$:

$$b^{sim}_{t+1,h_{t+1}=j,g,I} = \max\Big\{0,\, c'_{\min} + m^{sim}_{t+1,h_{t+1}=j,g,I} - (1+r)(x_{pt} - c_t) - y\Big\} \tag{4.39}$$

At $t = T$, $y_{T+1} = 0$, $m^{sim}_{T+1,h_{T+1}=j,g,I} = 0$ and $b^{sim}_{T+1,h_{t+1}=j,g,I} = 0$, $\forall j, sim$.

(b) Define $x^{sim}_{t+1,h_{t+1}=j,g,I}$ :

$$x^{sim}_{t+1,h_{t+1}=j,g,I} = (1+r)(x_{pt} - c_t) + b^{sim}_{t+1,h_{t+1}=j,g,I} + y - m^{sim}_{t+1,h_{t+1}=j,g,I}. \tag{4.40}$$

(c) Evaluate $V^{sim}_{t+1}(x_{t+1}, h_{t+1}, g, I)$ at $x^{sim}_{t+1,h_{t+1}=j,g,I}$ when health next period is good $j = 1$, or bad $j = 0$. Here I used the Piece-wise cubic Hermite interpolation method if $x^{sim}_{t+1,h_{t+1}=j,g,I}$ falls off the grid points at $x_{p,t+1}$. The interpolation uses the value functions evaluated at period $t+1$ for each grid point $x_{p,t+1}$: $V^{sim}_{t+1}(x_{p,t+1}, h_{t+1} = j, g, I)$

(d) Then compute $\mathbb{E}_t\{V^{sim}_{t+1}(x_{t+1}, h_{t+1}, g, I)\}$ as follows:

$$\begin{aligned} \mathbb{E}_t\{V^{sim}_{t+1}(x_{t+1}, h_{t+1}, g, I)\} &= \sum_{j=1}^{2} \pi^j_{t+1} \int_0^\infty V_{t+1}(x_{t+1}, h_{t+1} = j, g, I)\, dF(m_{t+1,h_{t+1}=j,g,I}) \\ &\approx \sum_{j=1}^{2} \pi^j_{t+1} \frac{1}{\texttt{nSim}} \sum_{sim=1}^{\texttt{nSim}} V^{sim}_{t+1}(x_{t+1}, h_{t+1} = 1, g, I) \end{aligned} \tag{4.41}$$

Here $\pi^1_{t+1} = \pi^{good}_{t+1}$ and $\pi^2_{t+1} = 1 - \pi^{good}_{t+1}$. As shown in the final line of Eq. 4.41, we use the numerical integration method to approximate the integral of the value function at age $t$ w.r.t. the next period medical expense distribution $m_{t+1}$. The numerical integration gets closer to the true value of the integral as `nSim` increases.

3. Once $\mathbb{E}_t\{V^{sim}_{t+1}(x_{t+1}, h_{t+1}, g, I)\}$ is computed, find the optimal $c_t$ that maximizes $V^p_t(x_{pt}, h_t, g, I)$ at given constraints. The choice of the optimal level of consumption is calculated in each period using `fminbnd`. This is an in-built MATLAB optimizer, a routine combining two methods, 'golden section search' and 'parabolic interpolation.' Moreover, save the optimal wealth to save at the end of period $t$, $w_{t+1}(x_{pt}, t, h_t, g, I)$, for each $x_{pt}$ and states $(t, h_t, g, I)$.

*Forward iteration:* Once the backward induction is complete, we forward-simulate each individual `nSeris`=10 times. More specifically, we simulate `nSeries` series health states for each individual. Then, using the simulated health state paths, we simulate the corresponding `nSeries` series of medical expenses and subjective survival shocks. As an example, Figure 4.12 shows the health states, medical expenses, and subjective survival shocks averaged over `nSeries` series from age from 65 to $T$ for a male who was 65 in 1998 and who started with good health and belonged to the second permanent-income quintile.

Let $m^{series}_t$ and $h^{series}_t$ be the *series*th simulated medical expenses and health states, where $series \in [1,$ `nSeries`$]$ of an individual whose initial conditions in 1998 are $(w_t, t, h_t, g, I)$. For given *series*, we compute the individual's optimal wealth from $s = t$ to $s = T$ as follows:

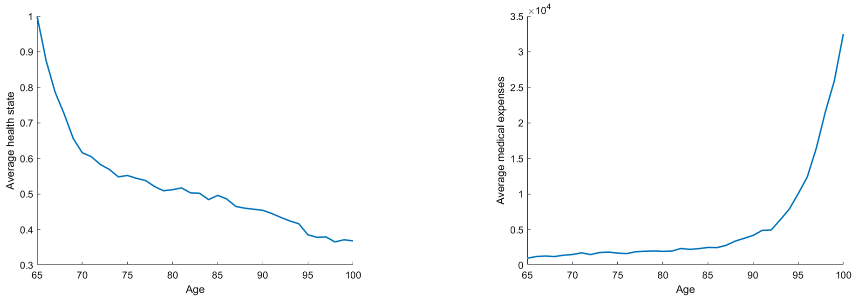
1. Check whether an individual would receive the government transfer at $s : b_s = \max\{0, c'_{\min} + m^{series}_s - (1 + r)w_s - y\}$

2. Calculate the cash-on-hand at age $s$: $x_s = (1 + r)w_s + b_s + y - m^{series}_s$.

3. Find the optimal wealth $(w^{*,series}_{t+1})$ by interpolating from $w_{t+1}(x_{pt}, t, h_t, g, I)$ which is obtained from the backward induction. We use the linear interpolation method at this step.

4. Go to period $s + 1$ and save $(w^{*,series}_{t+1})$.

Figure 4.12: Simulated health states and medical expenses, of a 65-year old man who started with good health in 1998 and belongs to the second permanent-income group, averaged over 10 simulations



### 4.8.5 Criterion function of Method of Simulated Moments

Let the total number of moments be $J$ and the total number of parameters to estimate in the second stage be $K$. Let $\mathbf{m}(\mathbf{Z},\Omega,\chi)$ be $J \times 1$ vector of moments that functions of data $\mathbf{Z}$, the second-step preference parameters $\Omega$ and the first-step parameters $\chi$. The second-stage parameters are estimated by minimizing the MSM objective function, defined as:

$$\hat{\Omega} = \text{argmin}_{\Omega} \frac{1}{1+\frac{N_{ind}}{N_{sim}}} \mathbf{m}(\mathbf{Z},\Omega,\chi)' \widehat{\mathbf{W}}(\mathbf{Z}) \mathbf{m}(\mathbf{Z},\Omega,\chi). \tag{4.42}$$

where $\hat{\Omega}$ is the estimate of the vector of parameters in the second stage. $N_{ind} = 3,166$ is the number of individuals in the sample, and $N_{sim} = N_{ind} \cdot 10$ is the number of simulated individuals. $\widehat{\mathbf{W}}(\mathbf{Z})$ is the positive-definite weighting matrix.

In our baseline analysis, we do not use an optimal weighting matrix because the covariances between moments would be estimated based on little data. Instead, we use construct the weighting matrix $\widehat{\mathbf{W}}(\mathbf{Z})$ as follows:

$$\widehat{\mathbf{W}}(\mathbf{Z}) = \begin{pmatrix} 1/\hat{V}^{m,q=1}_{y=1998,c=1,p=1} & \cdots & \cdots & \cdots & \cdots & \cdots \\ \cdots & \cdots & \cdots & \cdots & \cdots & \cdots \\ \cdots & \cdots & 1/\hat{V}^{b,mean,k=3}_{y=2012,c=3,p=3} & \cdots & \cdots & \cdots \\ \cdots & \cdots & \cdots & \cdots & \cdots & \cdots \\ \cdots & \cdots & \cdots & \cdots & \cdots & 1/\hat{V}^{b,var,k=3}_{y=2012,c=3,p=3} \end{pmatrix} \tag{4.43}$$

Here, for example, $\hat{V}^{m,q}_{1998,1,1}$ is the sample variance for the 25th percentile, $q = 1$, of wealth in 1998 of the first cohort, $c = 1$, and the first permanent-income group, $p = 1$. $\hat{V}^{b,mean,k=3}_{y=2012,c=3,p=3}$ and $\hat{V}^{b,var,k=3}_{y=2012,c=3,p=3}$ are the sample variances of the mean and variance of $k$th=3rd intend bequest probabilities (which is the probability of bequeathing 100K+) for the year 2012, third cohort and third permanent-income group. The off-diagonal elements are the inverse of the corresponding sample covariances. If the number of elements to estimate a certain element of the covariance-variance matrix is less than ten, we replace the value of that element with zero.

The variances of bequests probabilities $\hat{V}^{b,k_y}_{y,c,p}$ are calculated following the standard sample variance formula. The variances of $(q \cdot 25)$th percentile wealth moments are calculated as follows:

$$\hat{V}^{m,q}_{y,c,p} = \frac{1}{N_{y,c,p}} \sum_{i:i\in(y,c,p)}^{N_{y,c,p}} \left( \tilde{w}^{m,q}_{i,y,c,p} - \overline{\tilde{w}^{m,q}_{i,y,c,p}} \right)^2, \text{ for } q \in \{1,2,3\} \tag{4.44}$$

where

$$\tilde{w}^{m,q}_{i,y,c,p} = 1\{w_{i,y} \leq w^{m,q}_{y,c,p}\} \cdot \Big(1 - \frac{q \cdot 25}{100}\Big) + 1\{w_{iy} > w^{m,q}_{y,c,p}\} \cdot \Big(-\frac{q \cdot 25}{100}\Big)\Big), \tag{4.45}$$

Here $w^{m,q}_{y,c,p}$ is $(q \cdot 25)$th percentile of observed wealth in cell $(y, c, p)$. $\overline{\tilde{w}^{m,q}_{i,y,c,p}}$ is the average of $w^{m,q}_{y,c,p}$.

The covariance-variance matrix of $\hat{\Omega}$ is estimated as follows:

$$\widehat{\mathbf{V}}(\hat{\Omega}) = (\mathbf{D}'\widehat{\mathbf{W}}(\mathbf{Z})\mathbf{D})^{-1}(\mathbf{D}'\widehat{\mathbf{W}}(\mathbf{Z})\Big[\hat{\mathbf{Q}}\Big(1 + \frac{N_{ind}}{N_{sim}}\Big)\Big]\widehat{\mathbf{W}}(\mathbf{Z})\mathbf{D})(\mathbf{D}'\widehat{\mathbf{W}}(\mathbf{Z})\mathbf{D})^{-1}. \tag{4.46}$$

Here $\mathbf{D}$ is the gradient matrices of the moment conditions with respect to $\Omega$ and evaluated at $\hat{\Omega}$:

$$\mathbf{D} = \frac{\partial \mathbf{m}(\mathbf{Z}, \Omega, \chi)'}{\partial \Omega}\Bigg|_{\Omega = \hat{\Omega}} \tag{4.47}$$

We approximate the derivates in the gradient matrices $\mathbf{D}$ by numerical differentiation using two points around $\hat{\Omega}$ (Newey & McFadden, 1994).

When calculating $\mathbf{D}$ for the wealth moments, we follow the procedure for analyzing moments conditions of non-smooth functions. For example, the rows of $\mathbf{D}$ for the $q$th percentile of wealth moment conditions for cell $(y, c, p)$ is given by:

$$\Pr(y, c, p) \cdot f(\bar{w}^{m,q}_{y,c,p}(\mathbf{Z}, \theta)|y, c, p) \cdot \frac{\partial \bar{w}^{m,q}_{y,c,p}(\mathbf{Z}, \theta)'}{\partial \Omega}\Bigg|_{\Omega = \hat{\Omega}} \tag{4.48}$$

Here $\Pr(y, c, p)$ is estimated by the number of individuals in cell $(y, c, p)$ divided by the total number of observations. $f(\bar{w}^{m,q}_{y,c,p}(\mathbf{Z}, \theta)|y, c, p)$ is the conditional p.d.f. of wealth of individuals in cell $(y, c, p)$ evaluated at $\bar{w}^{m,q}_{y,c,p}(\mathbf{Z}, \theta)$, which is estimated by a kernel density estimator. The third component is the derivatives of the simulated moments with respect to the second-stage parameters $\Omega$.

The matrix $\hat{\mathbf{Q}}$ is the covariance-variance matrix of the moments evaluated at $\mathbf{m}(\mathbf{Z}, \hat{\Omega}, \chi)$. We approximate $\hat{\mathbf{Q}}$ by using the clustered bootstrap, in which $\mathbf{m}(\mathbf{Z}, \hat{\Omega}, \chi)$ is calculated for 1000 bootstrap sample $b$ of $N_{ind}$ individuals drawn with replacement. The covariance-variance matrix of moments is estimated as follows:

$$\hat{\mathbf{Q}} = \frac{1}{1{,}000 - 1} \sum_{b=1}^{1{,}000} \Big(\mathbf{m}(\mathbf{Z}_b, \hat{\Omega}, \chi) - \overline{\mathbf{m}_{bs}}\Big)\Big(\mathbf{m}(\mathbf{Z}_b, \hat{\Omega}, \chi) - \overline{\mathbf{m}_{bs}}\Big)' \tag{4.49}$$

where $\mathbf{Z}_b$ is the $b$th bootstrap sample, $\mathbf{m}(\mathbf{Z}_b, \hat{\Omega}, \chi)$ is the moments evaluated at sample $\mathbf{Z}_b$, and $\overline{\mathbf{m}_{bs}}$ is the average of those sample moments across the 1,000 bootstrap sample, i.e., $\overline{\mathbf{m}_{bs}} = \frac{1}{1{,}000}\sum_{b=1}^{1{,}000}\mathbf{m}(\mathbf{Z}_b, \hat{\Omega}, \chi)$.

Following De Nardi et al. (2010), we do not correct the estimation uncertainty in $\chi$, the first-step parameters. In other words, we treat the first-stage parameters' estimates $\chi$ as if they were known with certainty. Not correcting for the first-stage parameter estimation uncertainty may cause the estimates of the second-stage parameters to appear more precise than they actually are.

Furthermore, the MSM criterion function in our analysis may have multiple local minima, and some regions can be non-differentiable with respect to the unknown parameters. Therefore, we use the simulated annealing algorithm for numerical optimization, a derivative-free method Goffe et al. (1994). The simulated annealing starts from a single initial parameter vector and achieves robustness by sampling wide parameter space. The algorithm determines the extent of the search by comparing the current point with new points randomly generated within a parameter space. The algorithm accepts all new points that decrease the objective. It also accepts the points that increase the objective probabilistically. By accepting points that increase the objective, the algorithm is less likely to be trapped in local minima, and is able to explore globally for better solutions in its early iterations. Based on the accepted points, it shrinks the parameter search space. The algorithm stops when the search space is sufficiently small. A detailed discussion of simulated annealing can be found on Goffe et al. (1994).

### 4.8.6 Share of bequest allocation at period $T$

Consider an agent survived to $T$ with cash-on-hand $x$. There is no chance that an individual would survive to $T+1$. The agent solves the following:

$$\max_c \frac{c^{1-\gamma}}{1-\gamma} + \beta\Big(\frac{\phi}{1-\phi}\Big)^{\gamma}\frac{\Big((1+r)(x-c)+\frac{\phi}{1-\phi}k\Big)^{1-\gamma}}{1-\gamma} \tag{4.50}$$

$$\text{subject to: } c \geq c_{\min} \tag{4.51}$$

where $c$ denotes the consumption at $T$ and the remaining wealth $(x-c)$ will be bequeathed. The value of the bequest is $(1+r)(x-c)$.

Assuming the optimal consumption exceeds the consumption floor, i.e., $c > c_{\min}$, the first-order condition for an interior solution is:

$$\text{FOC:} \qquad c^{-\gamma} - \beta\Big(\frac{\phi}{1-\phi}\Big)^{\gamma}(1+r)\Big((1+r)(x-c) + \frac{\phi}{1-\phi}k\Big)^{-\gamma} = 0 \tag{4.52}$$

Then, the optimal value of the bequest is:

$$\text{Bequest} = (1+r)(x-c) = \frac{\frac{\phi}{1-\phi}(1+r)}{1+r+\frac{\phi}{1-\phi}(\beta(1+r))^{1/\gamma}}\Big((\beta(1+r))^{1/\gamma}x - k\Big) \tag{4.53}$$

and the optimal bequest is zero if

$$x \leq \max\Big\{\frac{k}{(\beta(1+r))^{1/\gamma}},\, c_{\min}\Big\}. \tag{4.54}$$

## 4.9 Robustness checks

Table 4.14: Model robustness - the baseline model estimations under different weighting matrices and samples

| | Baseline estimates | Under different weighting matrices | | Sample of individuals with kid(s) |
|---|---|---|---|---|
| | | Identity weighting matrix | Diagonal weighting matrix | |
| | (1) | (2) | (3) | (4) |
| $\gamma$ | 2.857 | 3.072 | 1.638 | 2.745 |
| | (0.127) | (0.093) | (0.082) | (0.22) |
| $\phi$ | 0.586 | 0.590 | 0.807 | 0.591 |
| | (0.081) | (0.053) | (0.018) | (0.18) |
| $k/1000$ | 0.628 | 0.54 | 0.12 | 0.555 |
| | (0.119) | (0.103) | (0.062) | (0.257) |
| $c_{\min}/1000$ | 2.362 | 2.721 | 2.125 | 2.206 |
| | (0.486) | (0.136) | (0.119) | (0.297) |
| Number of individuals | 3,166 | 3,166 | 3,166 | 2,607 |
| Number of moments | 331 | 331 | 331 | 319 |

*Note:* The table presents the estimation results of the baseline model under different weighting matrices and samples. Column (1) presents the baseline estimates from Column (2) of Table 4.4. Column (2) presents the baseline estimates if using the identity matrix. Column (3) presents the estimates if using the diagonal weighting matrix, following Pischke (1995). Column (4) uses the sample of individuals with kids. As we use fewer individuals in the last column, the number of moments in those columns is also fewer than in the previous columns. Standard errors are in parentheses. The formula for the standard errors when using a non-optimal weighting matrix is in Eq. 4.46.

# References

Abel, A. B., & Warshawsky, M. (1987). Specification of the joy of giving: insights from altruism. *The Review of Economics and Statistics*, *70*(1), 145–149. pages 123

Acemoglu, D., & Linn, J. (2004). Market size in innovation: Theory and evidence from the pharmaceutical industry. *The Quarterly Journal of Economics*, *119*(3), 1049–1090. pages 75

Ameriks, J., Briggs, J., Caplin, A., Shapiro, M. D., & Tonetti, C. (2020). Long-term-care utility and late-in-life saving. *Journal of Political Economy*, *128*(6), 2375–2451. pages 121, 145, 146, 147

Ameriks, J., Caplin, A., Laufer, S., & Van Nieuwerburgh, S. (2011). The joy of giving or assisted living? using strategic surveys to separate public care aversion from bequest motives. *The Journal of Finance*, *66*(2), 519–561. pages 11, 13, 118, 121

Andrews, I., Stock, J. H., & Sun, L. (2019). Weak instruments in instrumental variables regression: Theory and practice. *Annual Review of Economics*, *11*, 727–753. pages 76

Aquilino, W. S. (1993). Effects of spouse presence during the interview on survey responses concerning marriage. *Public Opinion Quarterly*, *57*(3), 358–376. pages 16

Aquilino, W. S., Wright, D. L., & Supple, A. J. (2000). Response effects due to bystander presence in CASI and paper-and-pencil surveys of drug use and alcohol use. *Substance Use & Misuse*, *35*(6–8), 845–867. pages 16

Armantier, O., Nelson, S., Topa, G., Van der Klaauw, W., & Zafar, B. (2016). The price is right: Updating inflation expectations in a randomized price information experiment. *Review of Economics and Statistics*, *98*(3), 503–523. pages 54

Atav, T., Jongen, E. L., & Rabaté, S. (2019). The effects of the increase in the retirement age in the netherlands. *CPB Discussion Paper*. pages 55, 81, 97

Bartik, T. J. (1991). Who benefits from state and local economic development policies? *W.E. Upjohn Institute*. pages 75

Belastingdienst. (n.d.). *Hoeveel vrijstelling heb ik in 2023 voor de erfbelasting?* Retrieved from

www.belastingdienst.nl/wps/wcm/connect/nl/erfbelasting/content/vrijstelling-erfbelasti
(Accessed: April 20, 2023) pages 160

Bernal, N., & Vermeulen, F. (2014). The impact of an increase in the legal retirement age on the effective retirement age. *De Economist*, *162*(2), 115–145. pages 9, 53, 59, 65

Bernheim, B. D., Shleifer, A., & Summers, L. H. (1985). The strategic bequest motive. *Journal of Political Economy*, *93*(6), 1045–1076. pages 123

Bissonnette, L., Hurd, M. D., & Michaud, P.-C. (2017). Individual survival curves comparing subjective and observed mortality risks. *Health Economics*, *26*(12), 285–303. pages 8, 15, 16, 21, 29, 139

Bozio, A. (2008). Impact evaluation of the 1993 French pension reform on retirement age. *Pensions: An International Journal*, *13*(4), 207–212. pages 53

Browning, M. (2000). The saving behaviour of a two-person household. *Scandinavian Journal of Economics*, *102*(2), 235–251. pages 8, 14

Bruine de Bruin, W., Fischbeck, P. S., Stiber, N. A., & Fischhoff, B. (2002). What number is "fifty-fifty"?: Redistributing excessive 50% responses in elicited probabilities. *Risk Analysis: An International Journal*, *22*(4), 713–723. pages 16, 20, 55, 67, 85

Burgess, E. W., & Wallin, P. (1943). Homogamy in social characteristics. *American Journal of Sociology*, *49*(2), 109–124. pages 15

Burniaux, J.-M., Dang, T.-T., Fore, D., Förster, M. F., Mira D'Ercole, M., & Oxley, H. (1998). Income distribution and poverty in selected OECD countries. *OECD Economics Department Working Papers*, *189*. pages 71

Börsch-Supan, A. (2015). Survey of health, ageing and retirement in europe (share). *Encyclopedia of Geropsychology*, 1–9. doi: 10.1007/978-981-287-080-3_243-1 pages 64

Cagetti, M., & De Nardi, M. (2009). Estate taxation, entrepreneurship, and wealth. *American Economic Review*, *99*(1), 85–111. pages 121, 162

Caliendo, F. N., Gorry, A., & Slavov, S. (2019). The cost of uncertainty about the timing of social security reform. *European Economic Review*, *118*, 101–125. pages 10, 53, 67

Card, D. (2009). Immigration and inequality. *American Economic Review*, *99*(2), 1–21. pages 75

Carone, G., Eckefeldt, P., Giamboni, L., Laine, V., & Pamies, S. (2016). Pension reforms in the European Union since the early 2000's: Achievements and Challenges Ahead. *European Economy Discussion Paper*, *042*. pages 9, 53, 67

Carriere, J. F. (2000). Bivariate survival models for coupled lives. *Scandinavian Actuarial Journal*, *1*, 17–32. pages 26

Ciani, E., Delavande, A., Etheridge, B., & Francesconi, M. (2019). Policy uncertainty and information flows: Evidence from pension reform expectations. *CEPR Discussion Paper No. DP13988*. pages 52, 54, 63, 83, 93, 99

Coibion, O., & Gorodnichenko, Y. (2015). Information rigidity and the expectations formation process: A simple framework and new facts. *American Economic Review*, *105*(8), 2644–78. pages 54

Cragg, J. G., & Donald, S. G. (1993). Testing identifiability and specification in instrumental variable models. *Econometric Theory*, *9*(2), 222–240. doi: 10.1017/S0266466600007519 pages 76

De Bresser, J. (2019). Measuring subjective survival expectations–Do response scales matter? *Journal of Economic Behavior & Organization*, *165*, 136–156. pages 8, 16, 19, 20, 29, 31, 139

De Bresser, J., & Van Soest, A. (2013). Survey response in probabilistic questions and its impact on inference. *Journal of Economic Behavior & Organization*, *96*, 65–84. pages 8, 16, 29, 165

De Nardi, M., French, E., & Jones, J. B. (2009). Life expectancy and old age savings. *American Economic Review*, *99*(2), 110–115. pages 41

De Nardi, M., French, E., & Jones, J. B. (2010). Why do the elderly save? The role of medical expenses. *Journal of Political Economy*, *118*(1), 39–75. pages 11, 118, 119, 122, 123, 127, 128, 130, 135, 136, 137, 143, 144, 145, 146, 147, 182

De Nardi, M., French, E., & Jones, J. B. (2016a). Medicaid insurance in old age. *American Economic Review*, *106*(11), 3480–3520. pages 118

De Nardi, M., French, E., & Jones, J. B. (2016b). Savings after retirement: a survey. *Annual Review of Economics*, *8*, 177–204. pages 117

De Nardi, M., French, E., Jones, J. B., & McGee, R. (2021). *Why do couples and singles save during retirement?* (Tech. Rep.). National Bureau of Economic Research. pages 144

Frees, E. W., Carriere, J., & Valdez, E. (1996). Annuity valuation with dependent mortality. *Journal of Risk and Insurance*, 229–261. pages 26

French, E. (2005). The effects of health, wealth, and wages on labour supply and retirement behaviour. *The Review of Economic Studies*, *72*(2), 395–427. pages 41, 58, 60, 122, 123, 144

French, E., & Jones, J. B. (2011). The effects of health insurance and self-insurance on retirement behavior. *Econometrica*, *79*(3), 693–732. pages 58

Freund, J. E. (1961). A bivariate extension of the exponential distribution. *Journal of the*

*American Statistical Association*, *56*(296), 971–977. pages 15

Friedman, B. M., & Warshawsky, M. J. (1990). The cost of annuities: implications for saving behavior and bequests. *The Quarterly Journal of Economics*, *105*(1), 135–154. pages 123

Gale, W., & Slemrod, J. (2001). Rethinking the estate and gift tax: overview. pages 160

Gan, L., Gong, G., Hurd, M., & McFadden, D. (2015). Subjective mortality risk and bequests. *Journal of Econometrics*, *188*(2), 514–525. pages 11, 15, 118, 149

Giustinelli, P., Manski, C. F., & Molinari, F. (2022). Precise or imprecise probabilities? evidence from survey response related to late-onset dementia. *Journal of the European Economic Association*, *20*(1), 187–221. pages 20, 165

Goffe, W. L., Ferrier, G. D., & Rogers, J. (1994). Global optimization of statistical functions with simulated annealing. *Journal of Econometrics*, *60*(1-2), 65–99. pages 144, 182

Gourieroux, C., & Lu, Y. (2015). Love and death: A Freund model with frailty. *Insurance: Mathematics and Economics*, *63*, 191–203. pages 4, 15, 16, 43, 49

Gourinchas, P.-O., & Parker, J. A. (2002). Consumption over the life cycle. *Econometrica*, *70*(1), 47–89. pages 119, 135

Groneck, M. (2017). Bequests and informal long-term care evidence from HRS-Exit interviews. *Journal of Human Resources*, *52*(2), 531–572. pages 132

Gruber, J., & Wise, D. A. (2002). *Social security programs and retirement around the world: micro estimation.* National Bureau of Economic Research Cambridge, Mass., USA. pages 9, 53

Heimer, R. Z., Myrseth, K. O. R., & Schoenle, R. S. (2019). YOLO: Mortality beliefs and household finance puzzles. *The Journal of Finance*, *74*(6), 2957–2996. pages 8, 15, 43

Hendren, N. (2013). Private information and insurance rejections. *Econometrica*, *81*(5), 1713–1762. pages 124

Himmelstein, D. U., Lawless, R. M., Thorne, D., Foohey, P., & Woolhandler, S. (2019). *Medical bankruptcy: still common despite the affordable care act* (Vol. 109) (No. 3). American Public Health Association. pages 159

Hollingshead, A. B. (1950). Cultural factors in the selection of marriage mates. *American Sociological Review*, *15*(5), 619–627. pages 15, 33

Hubbard, R. G., Skinner, J., & Zeldes, S. P. (1994). Expanding the life-cycle model: precautionary saving and public policy. *American Economic Review*, *84*(2), 174–179. pages 125

Hubbard, R. G., Skinner, J., & Zeldes, S. P. (1995). Precautionary saving and social insurance.

*Journal of Political Economy*, *103*(2), 360–399. pages 125

Hurd, M. D. (1987). Savings of the elderly and desired bequests. *American Economic Review*, 298–312. pages 11, 118, 122

Hurd, M. D. (1989). Mortality risk and bequests. *Econometrica*, *57(4)*, 779-813. pages 8, 14, 123, 149

Hurd, M. D., McFadden, D. L., & Gan, L. (1998). Subjective survival curves and life cycle behavior. In (pp. 259–309). University of Chicago Press. pages 21

Hurd, M. D., & Smith, J. P. (2002). *Expected bequests and their distribution.* National Bureau of Economic Research Cambridge, Mass., USA. pages 132, 133

Iannario, M., & Piccolo, D. (2010). Statistical modelling of subjective survival probabilities. *Genus*, *66*(2), 17–42. pages 15

Immergut, E. M., Anderson, K. M., & Schulze, I. (2007). *The handbook of West European pension politics.* Oxford University Press. pages 9, 52, 63, 93

IRS. (n.d.). *Estate tax.* Retrieved from `https://www.irs.gov/businesses/estate-tax` (Accessed: May 23, 2023) pages 160

Jun, S.-P., Yoo, H. S., & Choi, S. (2018). Ten years of research change using Google Trends: From the perspective of big data utilizations and applications. *Technological Forecasting and Social Change*, *130*, 69–87. pages 74

Kaji, T., Manresa, E., & Pouliot, G. (2020). An adversarial approach to structural estimation. *arXiv preprint arXiv:2007.06169*. pages 136

Karlstrom, A., Palme, M., & Svensson, I. (2004). A dynamic programming approach to model the retirement behaviour of blue-collar workers in sweden. *Journal of Applied Econometrics*, *19*(6), 795–807. pages 65

Kézdi, G., & Willis, R. J. (2011). *Household stock market beliefs and learning* (Tech. Rep.). National Bureau of Economic Research. pages 83

Khwaja, A., Sloan, F., & Chung, S. (2007). The relationship between individual expectations and behaviors: Mortality expectations and smoking decisions. *Journal of Risk and Uncertainty*, *35*(2), 179–201. pages 15

Kleinjans, K. J., & Van Soest, A. (2014). Rounding, focal point answers and nonresponse to subjective probability questions. *Journal of Applied Econometrics*, *29*(4), 567–585. pages 8, 16, 29, 165

Kopczuk, W., & Lupton, J. P. (2007). To leave or not to leave: the distribution of bequest motives. *The Review of Economic Studies*, *74*(1), 207–235. pages 11, 118, 123, 133

Lancaster, T. (1990). *The Econometric Analysis of Transition Data* (Vol. 17). Cambridge

University Press. pages 21, 33

Lillard, L. A., & Willis, R. J. (2001). Cognition and wealth: The importance of probabilistic thinking. *Michigan Retirement Research Center Research Paper No. WP*, *7*. pages 21

Lockwood, L. M. (2012). Bequest motives and the annuity puzzle. *Review of Economic Dynamics*, *15*(2), 226–243. pages 118, 121, 145, 146

Lockwood, L. M. (2018). Incidental bequests and the choice to self-insure late-life risks. *American Economic Review*, *108*(9), 2513–50. pages 11, 118, 119, 122, 123, 124, 127, 128, 135, 137, 144, 147

Luciano, E., Spreeuw, J., & Vigna, E. (2008). Modelling stochastic mortality for dependent lives. *Insurance: Mathematics and Economics*, *43*(2), 234–244. pages 26

Ludwig, A., & Zimper, A. (2013). A parsimonious model of subjective life expectancy. *Theory and Decision*, *75*(4), 519–541. pages 15

Lusardi, A., Michaud, P.-C., & Mitchell, O. S. (2017). Optimal financial knowledge and wealth inequality. *Journal of Political Economy*, *125*(2), 431–477. pages 58

Lüthen, H. (2016). Rates of return and early retirement disincentives: Evidence from a German pension reform. *German Economic Review*, *17*(2), 206–233. pages 53

Malani, A., & Reif, J. (2015). Interpreting pre-trends as anticipation: Impact on estimated treatment effects from tort reform. *Journal of Public Economics*, *124*, 1–17. pages 9, 52

Manski, C. F. (2004). Measuring expectations. *Econometrica*, *72*(5), 1329–1376. pages 7, 16, 192, 194

Manski, C. F., & Molinari, F. (2010). Rounding probabilistic expectations in surveys. *Journal of Business & Economic Statistics*, *28*(2), 219–231. pages 16, 21

McGarry, K. (1999). Inter vivos transfers and intended bequests. *Journal of Public Economics*, *73*(3), 321–351. pages 132

Michaud, P. C., Van Soest, A., & Bissonnette, L. (2020). Understanding joint retirement. *Journal of Economic Behavior & Organization*, *173*, 386–401. pages 14

Modigliani, F., & Brumberg, R. (1954). Utility analysis and the consumption function: An interpretation of cross-section data. *Post-Keynesian Economics*, *1*(1), 388–436. pages 117

Murtaugh, C. M., Kemper, P., Spillman, B. C., & Carlson, B. L. (1997). The amount, distribution, and timing of lifetime nursing home use. *Medical Care*, 204–218. pages 124

Newey, W. K., & McFadden, D. (1994). Large sample estimation and hypothesis testing. *Handbook of econometrics*, *4*, 2111–2245. pages 181

O'Dea, C., & Sturrock, D. (2023). Survival pessimism and the demand for annuities. *The Review of Economics and Statistics*, *105*(2), 442–457. pages 8, 43

OECD. (2017). Pension at a Glance 2017: OECD and G20 Indicators. *Paris: OECD Publishing*. pages 9, 52, 93, 99

Papanicolas, I., Woskie, L. R., & Jha, A. K. (2018). Health care spending in the united states and other high-income countries. *Jama*, *319*(10), 1024–1039. pages 159

Parlevliet, J. (2017). What drives public acceptance of reforms? longitudinal evidence from a dutch pension reform. *Public Choice*, *173*(1-2), 1–23. pages 97

Pfajfar, D., & Žakelj, B. (2014). Experimental evidence on inflation expectation formation. *Journal of Economic Dynamics and Control*, *44*, 147–168. pages 54

Pischke, J.-S. (1995). Measurement error and earnings dynamics: Some estimates from the PSID validation study. *Journal of Business & Economic Statistics*, *13*(3), 305–314. pages 144, 183

Rabaté, S., & Rochut, J. (2020). Employment and substitution effects of raising the statutory retirement age in france. *Journal of Pension Economics & Finance*, *19*(3), 293–308. pages 81

Rivers, D., & Vuong, Q. H. (1988). Limited information estimators and exogeneity tests for simultaneous probit models. *Journal of Econometrics*, *39*(3), 347–366. pages 78, 106

Rohwedder, S., Haider, S. J., & Hurd, M. D. (2006). Increases in wealth among the elderly in the early 1990s: how much is due to survey design? *Review of Income and Wealth*, *52*(4), 509–524. pages 127

Rust, J., & Phelan, C. (1997). How social security and medicare affect retirement behavior in a world of incomplete markets. *Econometrica: Journal of the Econometric Society*, 781–831. pages 59, 65

Salm, M. (2010). Subjective mortality expectations and consumption and saving behaviours among the elderly. *Canadian Journal of Economics/Revue Canadienne d'Économique*, *43*(3), 1040–1057. pages 15

Sanders, L., & Melenberg, B. (2016). Estimating the joint survival probabilities of married individuals. *Insurance: Mathematics and Economics*, *67*, 88–106. pages 15

Sanderson, E., & Windmeijer, F. (2016). A weak instrument F-test in linear IV models with multiple endogenous variables. *Journal of Econometrics*, *190*(2), 212–221. pages 76

Scharn, M., Sewdas, R., Boot, C. R., Huisman, M., Lindeboom, M., & Van Der Beek, A. J. (2018). Domains and determinants of retirement timing: A systematic review of longitudinal studies. *BMC Public Health*, *18*(1), 1–14. pages 9, 53

Smith, V. K., Taylor, D. H., & Sloan, F. A. (2001). Longevity expectations and death: Can people predict their own demise? *American Economic Review*, *91*(4), 1126–1134. pages

14, 33, 40

Spreeuw, J., & Owadally, I. (2013). Investigating the broken-heart effect: a model for short-term dependence between the remaining lifetimes of joint lives. *Annals of Actuarial Science*, *7*(2), 236–257. pages 15, 18, 35

Train, K. E. (2009). *Discrete choice methods with simulation*. Cambridge University Press. pages 34, 49

Van den Berg, G. J., Lindeboom, M., & Portrait, F. (2011). Conjugal bereavement effects on health and mortality at advanced ages. *Journal of Health Economics*, *30*(4), 774–794. pages 15, 35

Van der Klaauw, W. (2012). On the use of expectations data in estimating structural dynamic choice models. *Journal of Labor Economics*, *30*(3), 521–554. pages 13, 121

Van der Klaauw, W., & Wolpin, K. I. (2008). Social security and the retirement and savings behavior of low-income households. *Journal of Econometrics*, *145*(1–2), 21–42. pages 8, 12, 13, 14, 15, 121

Wang, Y. (2014). Dynamic implications of subjective expectations: Evidence from adult smokers. *American Economic Journal: Applied Economics*, *6*(1), 1–37. pages 15

Williams Jr, J. R. (2005). Depression as a mediator between spousal bereavement and mortality from cardiovascular disease: Appreciating and managing the adverse health consequences of depression in an elderly surviving spouse. *Southern Medical Journal*, *98*(1), 90–96. pages 15

Wooldridge, J. M. (2015). Control function methods in applied econometrics. *Journal of Human Resources*, *50*(2), 420–445. pages 78

Yaari, M. E. (1965). Uncertain lifetime, life insurance, and the theory of the consumer. *The Review of Economic Studies*, *32*(2), 137–150. pages 117, 122

# Academic summary

This thesis explores the role of subjective expectations in shaping economic decisions, with a focus on the elderly population. Over the past three decades, economists have increasingly sought to understand these probabilistic expectations (Manski, 2004). Subjective expectations have become a crucial tool for relaxing and validating critical assumptions in economic analysis. The thesis comprises three chapters, each contributing to our understanding of economic decisions in the context of the elderly.

In the first study, chapter two, we investigate the complex relationship between actual and perceived survival probabilities among married couples, a factor influencing savings, retirement timing, bequests, and insurance choices (Hurd, 1989; Browning, 2000; Van Soest, 2008). Empirical evidence challenges the assumption that couples' perceptions align with actuarial survival probabilities (Bissonnette et al., 2017; Heimer et al., 2019). We develop an econometric model that considers both actual and perceived survival probabilities among married couples, addressing the interdependence of their lifetimes and the influence of common-lifestyle and bereavement effects. Additionally, we examine the practice of rounding perceived probabilities. Results indicate a positive correlation between actual and perceived remaining lifetimes, with perceived lifetimes showing a stronger dependence, especially among older couples. The bereavement effect emerges as a dominant factor, while there is significant dispersion in both actual and perceived survival curves across individuals. Demographic factors, such as ethnicity, education level, birth cohort, income, and health, contribute to this dispersion. Notably, Hispanics, college-educated individuals, and those with high cognitive abilities provide more precise answers, while African-American males and individuals born before 1945 are more likely to provide rounded responses.

The second study, chapter three, delves into the impact of pension reforms that raise the statutory retirement age (SRA) on labor supply, focusing on individuals close to retirement. These reforms have been introduced in response to the financial instability of pension systems due to aging populations (OECD, 2017). A unique feature of pension reforms is the anticipation preceding their implementation, driven by political debates and media coverage (Immergut, 2007). This anticipatory behavior poses a challenge in estimating the causal effects of the reforms. We develop a life-cycle model to explore how anticipation of pension reforms affects individuals' employment status and how the reform's impact varies based on anticipation levels. Using data from the Survey of Health, Ageing, and Retirement in Europe (SHARE) and Google Trends data as an instrumental variable, we find that individuals who strongly anticipate being affected by future pension reforms are more likely to remain employed. The study also explores potential alternative pathways to early retirement and finds no evidence supporting such strategies.

The final study, chapter four, focuses on the bequest and precautionary saving motives among retirees. These motives have been challenging to distinguish in prior research due to their similar implications (Hurd, 1987; Gan et al., 2015). This chapter introduces a novel approach by incorporating self-reported probabilities of leaving a bequest into a structural life-cycle model. The self-reported probabilities reflect individuals' perceptions of their longevity and future survival, providing insights into the strength and existence of the bequest motive. By considering the relationships between medical expense risk, longevity risk, and savings, the study aims to shed light on the relative importance of these motives. The inclusion of self-reported bequest probabilities reveals a stronger influence of the bequest motive on retirees' savings decisions, significantly improving predictions of realized bequests. Counterfactual analyses demonstrate the impact of policy changes, such as government coverage of medical expenses and changes in the estate tax, on savings behavior.

In summary, this thesis leverages subjective expectations to enhance economic analysis, offering valuable insights into survival probabilities, labor supply responses to pension reforms, and the identification of saving motives among the elderly population. These findings have practical implications for policymakers, particularly in the areas of pension reform, life insurance, and health care coverage.

# Academische samenvatting

Deze scriptie onderzoekt de rol van subjectieve verwachtingen bij het vormgeven van economische beslissingen, met een focus op de oudere bevolking. In de afgelopen drie decennia hebben economen steeds verder geprobeerd om deze probabilistische verwachtingen te begrijpen (Manski, 2004). Subjectieve verwachtingen zijn een cruciaal instrument geworden om belangrijke aannames in economische analyses te verzachten en te valideren. De scriptie bestaat uit drie hoofdstukken, elk draagt bij aan ons begrip van economische beslissingen in de context van ouderen.

In het eerste onderzoek, hoofdstuk twee, onderzoeken we de complexe relatie tussen daadwerkelijke en verwachte overlevingskansen bij gehuwde stellen, een factor die van invloed is op spaargeld, timing van pensionering, erfenissen en verzekeringskeuzes (Hurd, 1989; Browning, 2000; Van Soest, 2008). Empirisch bewijs betwist de veronderstelling dat de percepties van stellen overeenkomen met actuariële overlevingskansen (Bissonnette et al., 2017; Heimer et al., 2019). We ontwikkelen een econometrisch model dat zowel daadwerkelijke als verwachte overlevingskansen bij gehuwde stellen overweegt, waarbij de onderlinge afhankelijkheid van hun levensduur en de invloed van gemeenschappelijke levensstijl en rouweffecten worden aangepakt. Daarnaast onderzoeken we de praktijk van het afronden van verwachte waarschijnlijkheden. De resultaten laten een positieve correlatie zien tussen daadwerkelijke en verwachte resterende levensduur, waarbij verwachte levensduur een sterkere afhankelijkheid vertoont, vooral bij oudere stellen. Het rouweffect blijkt de dominante factor te zijn, terwijl er aanzienlijke spreiding is in zowel daadwerkelijke als verwachte overlevingscurves over individuen. Demografische factoren zoals etniciteit, opleidingsniveau, geboortecohorte, inkomen en gezondheid dragen bij aan deze spreiding. Opmerkelijk is dat Hispanics, universitair opgeleide personen en degenen met hoge cognitieve vermogens nauwkeurigere antwoorden geven, terwijl Afro-Amerikaanse mannen en personen geboren voor 1945 eerder geneigd zijn afgeronde antwoorden te geven.

Het tweede onderzoek, hoofdstuk drie, gaat in op de impact van pensioenhervormingen die de wettelijke pensioengerechtigde leeftijd verhogen op de arbeidsaanbod, met de nadruk op personen die dicht bij pensionering staan. Deze hervormingen zijn ingevoerd als reactie op de financiële instabiliteit van pensioensystemen als gevolg van vergrijzende bevolkingen (OECD, 2017). Een uniek kenmerk van pensioenhervormingen is de verwachting voorafgaand aan hun implementatie, gedreven door politieke debatten en media-aandacht (Immergut, 2007). Dit anticiperende gedrag vormt een uitdaging bij het schatten van de causale effecten van de hervormingen. We ontwikkelen een levenscyclusmodel om te verkennen hoe verwachting van pensioenhervormingen van invloed is op de arbeidsstatus van individuen en hoe het effect van de hervorming varieert op basis van anticipatieniveaus. Met behulp van gegevens uit de Survey of Health, Ageing, and Retirement in Europe (SHARE) en Google Trends-gegevens als instrumentele variabele (Malani et al., 2015), ontdekken we dat personen die sterk anticiperen op toekomstige pensioenhervormingen eerder geneigd zijn om te blijven werken. De studie onderzoekt ook mogelijke alternatieve paden naar vervroegd pensioen en vindt geen bewijs ter ondersteuning van dergelijke strategieën.

Het laatste onderzoek, hoofdstuk vier, richt zich op de motieven voor erfenissen en voorzorgsspaargedrag onder gepensioneerden. Deze motieven waren moeilijk te onderscheiden in eerder onderzoek vanwege hun vergelijkbare implicaties (Hurd, 1987; Gan et al., 2015). Dit hoofdstuk introduceert een nieuwe benadering door zelfgerapporteerde waarschijnlijkheden van het nalaten van een erfenis op te nemen in een structureel levenscyclusmodel. De zelfgerapporteerde waarschijnlijkheden weerspiegelen de percepties van individuen over hun levensverwachting en toekomstige overlevingskansen, waardoor inzicht wordt geboden in de mate en het bestaan van het erfenismotief. Door rekening te houden met de relaties tussen medische kostenrisico, levensduurrisico en spaargedrag, heeft de studie tot doel meer inzicht te bieden in het relatieve belang van deze motieven. De opname van zelfgerapporteerde erfeniswaarschijnlijkheden onthult een sterkere invloed van het erfenismotief op de spaarbeslissingen van gepensioneerden, wat de voorspelling van gerealiseerde erfenissen aanzienlijk verbetert. Onze analyses tonen de impact van beleidswijzigingen, zoals overheidsdekking van medische kosten en veranderingen in de successierechten, op spaargedrag.

Samengevat maakt deze scriptie gebruik van subjectieve verwachtingen om economische analyses te versterken en waardevolle inzichten te bieden in overlevingskansen, arbeidsaanbodreacties op pensioenhervormingen en de identificatie van spaarmotieven onder de oudere bevolking. Deze bevindingen hebben praktische implicaties voor beleidsmakers, met name op het gebied van pensioenhervorming, levensverzekeringen en ziektekostenverzekering.

# Summary for non-experts

This thesis explores how people's perceptions of their future and uncertain events, often referred to as subjective expectations, impact their economic decisions, with a particular focus on the elderly population. Economists have increasingly recognized the importance of understanding these subjective expectations in economic analysis. The growing availability of subjective expectations data enables researchers to validate crucial assumptions in economic analysis.

In the first chapter, we investigate the relationship between actual and perceived survival probabilities among married couples, which influence their savings, retirement choices, bequests, and insurance decisions. Our study challenges the assumption that couples' perceptions align with actuarial survival probabilities and presents an econometric model to address this. The results reveal a positive connection between actual and perceived lifespans, with demographic factors contributing to response variations.

The second chapter delves into the impact of pension reforms that increase the retirement age on people's decisions to continue working. What makes our study unique is its consideration of people's anticipation of imminent pension reforms affecting their retirement age. We find that those who strongly anticipate being affected by these reforms are more likely to remain employed.

The third chapter concentrates on bequest and precautionary saving motives among retirees, which can be challenging to differentiate from observed data on people's savings. Our research introduces self-reported probabilities of leaving a bequest into a life-cycle model, offering insights into the strength and presence of the bequest motive. The study sheds light on the relative importance of these motives and demonstrates how policy changes can impact savings behavior.

In summary, this thesis uses subjective expectations to enhance economic analysis, providing insights into survival probabilities, responses to pension reforms, and saving motives among the elderly. These findings have practical implications for policymakers, especially in the areas of pension reform, life insurance, and healthcare coverage.

# Samenvatting voor niet-deskundigen

Deze scriptie onderzoekt hoe de percepties van mensen over hun toekomst en onzekere gebeurtenissen, vaak aangeduid als subjectieve verwachtingen, van invloed zijn op hun economische beslissingen, met een specifieke focus op de oudere bevolking. Economen herkennen steeds meer het belang van het begrijpen van deze subjectieve verwachtingen in economische analyses. De toenemende beschikbaarheid van gegevens over subjectieve verwachtingen stelt onderzoekers in staat cruciale aannames in economische analyses te valideren.

In het eerste hoofdstuk onderzoeken we de relatie tussen daadwerkelijke en waargenomen overlevingskansen bij gehuwde stellen, die van invloed zijn op hun spaargedrag, pensioenkeuzes, erfenissen en verzekeringsbeslissingen. Ons onderzoek betwist de veronderstelling dat de percepties van stellen overeenkomen met actuariële overlevingskansen en presenteert een econometrisch model om dit aan te pakken. De resultaten onthullen een positieve relatie tussen daadwerkelijke en waargenomen levensduur, waarbij demografische factoren bijdragen aan waargenomen variaties.

Het tweede hoofdstuk gaat in op de impact van pensioenhervormingen die de pensioengerechtigde leeftijd verhogen op de beslissingen van mensen om te blijven werken. Wat ons onderzoek uniek maakt, is de overweging van de verwachting van mensen op aanstaande pensioenhervormingen die van invloed zijn op hun pensioengerechtigde leeftijd. Wij ontdekken dat degenen die sterk anticiperen op de gevolgen van deze hervormingen, eerder geneigd zijn om in dienst te blijven.

Het derde hoofdstuk richt zich op motieven voor erfenissen en voorzorgsspaargedrag onder gepensioneerden, die moeilijk te onderscheiden zijn van waargenomen gegevens over de spaaractiviteiten van mensen. Ons onderzoek introduceert zelfgerapporteerde waarschijnlijkheden van het nalaten van een erfenis in een levenscyclusmodel en biedt inzicht in de kracht en aanwezigheid van het erfenismotief. De studie werpt licht op het relatieve belang van deze motieven en toont aan hoe beleidswijzigingen het spaargedrag kunnen beïnvloeden.

Samenvattend maakt deze scriptie gebruik van subjectieve verwachtingen om economische analyses te verbeteren en inzicht te bieden in overlevingskansen, reacties op pensioenhervormingen en spaarmotieven onder ouderen. Deze bevindingen hebben praktische implicaties voor beleidsmakers, met name op het gebied van pensioenhervorming, levensverzekeringen en ziektekostenverzekeringen.

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In the four essays collected in this PhD thesis, we explore the use of subjective expectations in understanding various economic decisions of the elderly population. The theme of these chapters is the proposal of various modeling and estimation strategies that leverage self-elicited probabilities to enhance existing empirical methods. In the first paper, we construct an econometric model to analyze both actual and perceived survival probabilities among married couples. The second paper introduces the possibility of controlling for people's anticipatory behavior using self-elicited probabilities. We illustrate this approach in the context of estimating the impact of pension reforms that raise the statutory retirement age on individuals' employment when the reform could have been anticipated prior to implementation. Finally, our last paper employs self-elicited probabilities related to bequeathing wealth to estimate specific preference parameters within a life-cycle model. These parameters, related to precautionary and bequest motives, are traditionally challenging to estimate precisely, but we demonstrate that by incorporating additional information from self-reported probabilities of bequeathing, we can estimate them with reasonable precision.

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