How Accurate are Retirees' Assessments of Their Retirement Risk?:

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HOW ACCURATE ARE RETIREES' ASSESSMENTS OF THEIR RETIREMENT RISK?

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Abstract

Retirees with limited financial resources face numerous risks, including out-living their money (longevity risk), investment losses (market risk), unexpected health expenses (health risk), the unforeseen needs of family members (family risk), and even retirement benefit cuts (policy risk). This study systematically values and ranks the financial impacts of these risks from both the objective and subjective perspectives and then compares them to show the gaps between retirees' actual risks and their perceptions of the risks in a unified framework. It finds that 1) under the empirical analysis, the greatest risk is longevity risk, followed by health risk; 2) under the subjective analysis, retirees perceive market risk as the highest-ranking risk due to their exaggeration of market volatility; and 3) the longevity risk and health risk are valued less in the subjective ranking than in the objective ranking, because retirees underestimate their life spans and their health costs in late life.

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INTRODUCTION

Managing resources in retirement has always been challenging, particularly for retirees with limited financial resources, because they face numerous risks. Moreover, fundamental changes that have occurred in recent decades have made it increasingly difficult for individuals to plan and manage their retirement resources effectively (GAO, 2017). For example: 1) the increase in longevity raises the risk of outliving retirement savings; 2) a marked shift by employers away from traditional defined benefit pension plans to defined contribution plans, such as 401(k)s and Individual Retirement Accounts (IRAs), has increased the risks and responsibilities in planning and managing retirement spending; 3) the high and rapidly rising cost of health care, especially long-term care in later life, further complicates retirement planning; and 4) Social Security benefits – the primary retirement income source for the majority of retirees – would be reduced by about 25 percent under current law if Congress takes no action before 2035 when the trust fund reserves are projected to be exhausted (SSA, 2019). Therefore, it is valuable to identify and quantify the retirement risks to better understand the challenges facing retirees.

The empirical literature has separately addressed the various sources of retirement risk and their impacts on retirement security, including out-living one's money (longevity risk), investment losses (market risk), unexpected health expenses (health risk), the unforeseen needs of family members (family risk), and even retirement benefit cuts (policy risk). Because these sources of risk are distributed along multiple dimensions, including a retiree's time horizon (longevity risk), savings levels (market risk), benefit receipt (policy risk), and money paid out of pocket for expenses (health risk and family risk), it is necessary to quantify and rank these risks using appropriate measures under a unified framework.

In addition to the objective risks, retirees must make decisions based on their beliefs about future events, which are represented by subjective risk distributions. These beliefs often deviate from the distributions in the empirical data, and they are central to understanding retirees' choices and outcomes (Manski 2004). Therefore, a comparison of the subjective and objective risks is crucial, because: 1) a complete overview of both types of risk can inform public policies that improve retirement security; and 2) the gaps between the perceived and actual risks shed light on the ways to improve private financial products.

To fill the gap in the literature, this study measures various sources of retirement risk from both the objective and subjective perspectives and will attempt to answer the following two questions: 1) what is the ranking of each of the various retirement risks for a typical household, based on the empirical data? and 2) do people perceive their risks accurately? In other words, do retirees' expectations of their future risks follow the same rank order as the empirical ranking of risk? To compare the objective and subjective risks, this study systematically values and ranks the financial impact of retirement risks using the method of utility-equivalent wealth (i.e., the wealth compensation for a certain risk). This analysis has three steps.

The first step is to build a life-cycle optimization model that includes all the sources of risk, using the empirical distributions as inputs. A typical retired household holds limited resources, such as retirement savings and housing wealth, both of which are measured by the survey data. The household in this model faces five categories or risk: 1) mortality or longevity risk, meaning that the retiree may either die young without consuming all of the wealth or live longer than expected after exhausting all the money; 2) market risk, such as bad stock returns or a decline in housing values; 3) health risk, defined as unexpected medical expenses and long-term care needs; 4) family risk, including the death of a spouse or the unforeseen needs of family members, such as providing financial aid to adult children; and 5) policy risk, mainly a Social Security benefit cut. Building a life cycle model results in an optimized function indicating how much a typical retired household can consume and invest over the life cycle to optimize resource use and an expected lifetime utility associated with the household's optimized profile. The lifetime utility serves as the benchmark in the objective model to compare with the alternative in the next step.

The second step is to quantify each source of objective risk by solving the optimization model repeatedly by removing one risk source at a time. After each risk source is removed and estimated, it is returned to the optimization model, and the procedure is repeated for the next risk. For example, the health risk is removed by fixing the medical expenditures at the average level in place of a random shock every year. The result of removing one objective risk is that a risk-averse retiree would need less initial retirement wealth to reach the same lifetime utility level as in the objective benchmark. This wealth decrease represents the financial impact and thus quantifies the economic value of the risk. A similar procedure is used for all the other risks. In this way, each objective risk is properly valued and ranked under their respective risk distributions.

Given the discrepancy between the empirical risk distribution and the subjective risk expectation due to limited financial literacy or personal biases, the last step of this study is to repeat the exercise above using the subjective risk distributions calibrated from the survey data instead of empirical data. As a result, this study produces two sets of rankings that can be compared: objective and subjective. When the objective risk levels are ranked, the result shows that longevity risk ranks at the top of the list, followed by health risk and market risk. Policy risk is last because Social Security reform is unlikely to have a significant impact on people who have already retired. However, market risk is first in the subjective ranking because retirees exaggerate financial market volatility. Longevity risk and health risk are valued as less important in the subjective ranking than in objective ranking, due to the retiree's underestimation of their longevity – "survival pessimism" – and the underestimation of health expenditures late in life.

The remainder of this dissertation is structured as follows. Chapter 1 reviews the literature on the various sources of retirement risk and describes the gaps between empirical studies and subjective perceptions. Chapter 2 describes the data with summary statistics. Chapter 3 introduces the life cycle structural model and details how these sources of risk fit in. Chapter 4 shows the results, from both the objective and subjective perspectives. Chapter 5 concludes and discusses future research in this area.

1 LITERATURE

The literature on retirement risk so far has consisted of two lines of research. The first is the overall retirement risk level, i.e., whether retirees are adequately prepared to meet the costs of retirement life. For example, the most recent National Retirement Risk Index shows that half of today's working households in the United States will not be able to maintain their standard of living in the retirement (Munnell, Hou, and Sanzenbacher 2018), a finding that is consistent with many studies (Vernon 2018).[1] In this line of research, the standard measurement is the so-called replacement rate, which is the ratio of post-retirement income to pre-retirement income for each household. Whether a household is at risk is normally determined by comparing the replacement rate with a target replacement rate that is deemed to be adequate for retirees to meet their basic needs.[2] This measurement is intuitive and easily understood by a general audience and straightforward to apply in practice. However, it has two flaws: 1) as a static index, it normally projects the future with expected means and thus ignores the variance, i.e., future uncertainties such as health shocks and market volatility; and 2) it cannot be broken down by various sources of risk.[3]

[1] Vernon (2018) finds that various studies show roughly half of all older American workers not having adequate retirement savings for retirement.
[2] The income data in the calculation typically come from surveys, administrative records, or model projections.
[3] The SOA (2018) discusses various replacement rate models in the literature, and lists other problems such as no universal way to measure both the numerator and denominator, and no agreed-upon definition of what constitutes an "adequate".

The second line of research takes a closer look at retirement risk through two channels: 1) identifying various sources of the risk; and 2) exploring their magnitudes and how to manage them. The risks are often identified through qualitative surveys. For example, the 2017 Risks and Process of Retirement Survey by the Society of Actuaries (SOA) evaluates Americans' retirement preparedness and highlights the leading concerns, such as health care affordability, nursing home or long-term care expenditures, and whether savings keeps up with inflation. In other studies, uncertainties such as major downturns in the stock market and changes to the Social Security program are frequently addressed.[4] The qualitative studies contribute to the literature by sketching the contours of the risk facing retirees. In order to answer the questions of how big the risks are and how they can be managed, a quantitative model is often required that uses risk distributions from the empirical data. However, most studies are limited to one or two sources of risk. Furthermore, due to the limited financial knowledge or personal biases, it is not easy for people to accurately understand their retirement risks.[5] Thanks to improvements in survey data, recent research pays more attention to the deviation of subjective risk expectations from the empirical risk distributions and its consequences to retirement planning and retirement security. The rest of this section summarizes five major risk sources that have been identified in the literature.

[4] For example, see 2018 Prudential Retirement Preparedness Survey and 2018 MassMutual Retirement Savings Risk Study.

[5] In fact, Munnell, Hou, and Sanzenbacher (2017) show that only half of people correctly understanding whether they have enough resources for their retirement.

1.1 Longevity Risk

Longevity risk is possibly one of the largest and least understood retirement risks (Crawford, Haan, and Runchey 2008). It was studied as early as Yaari (1965) who introduced the concept of the unsolved annuity puzzle.[6] Later research, in recognition of the enormous impact of longevity risk, often includes it as a fundamental element in quantitative models (e.g., Cocco and Gomes, 2012). Those studies often focus on solving the annuity puzzle (e.g., Davidoff, Brown, and Diamond 2005) or evaluating retirement income strategies (e.g, Sun and Webb 2012). In terms of putting an economic value on longevity risk, a seminal paper by Mitchell et al. (1999) finds that a typical retiree would accept a wealth reduction of more than 30 percent if the longevity risk could be hedged by annuities.[7] A recent paper by Milevsky and Young (2018) studies the value of longevity risk pooling and finds a similar result. These studies either use empirical mortality data such as life tables for the general population or annuitants or estimate parametric mortality models based on demographics. However, recent literature argues that a subjective survival probability is more appropriate in the context of a rational agent making decisions, because it influences behavior and welfare outcomes (e.g., Griffin, Hesketh, and Loh 2012; van Solinge and Henkens 2010). For example, O'Dea and Sturrock (2018) find significant "survival pessimism," on average, and Bissonnette et al. (2017) calculate a 7-percent welfare loss if a subjective survival probability is used in the decision-making process.[8]

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[6] A well-known prediction of the standard life-cycle model is that in the presence of lifespan uncertainty, people should invest in nothing but annuities.
[7] Their model assumes no shocks other than longevity risk.
[8] There are two other research lines of longevity risk 1) systematic risk, which results from incorrect assumptions about the base mortality rate and level of mortality improvement; and 2) stochastic mortality,

1.2 Market Risk

Another significant risk comes from the U.S. retirement system shifting from defined benefit (DB) to defined contribution (DC) plans in recent decades. Instead of being covered by pension benefits in retirement, individuals increasingly are taking responsibility for saving and investing, which used to be the responsibility of financial professionals. With this shift, retirees face considerable risk of market volatility (Poterba et al. 2005). They also face risk in the drawdown phase after retirement, because the literature suggests that retirees neither annuitize the plan assets nor make meaningful withdrawals other than following Required Minimum Distributions (RMD) unless they experience a financial or health shock.[9] Therefore, retirement savings are exposed to large market risks such as the 2008 or 2020 market crash, and older workers may have very little time to recoup their losses.[10] The same argument can be applied to the housing market as well, because few people are downsizing after retirement until they face a shock late in life.[11] Interestingly, the literature suggests a significant gap between the subjective perceptions of market returns and actual returns. For example, individuals have substantially lower expectations of stock market gains than historical averages would justify but higher expectations of volatility, a robust finding across various data sources and countries.[12] This gap is consistent with low stock market participation,

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or aggregate mortality risk, meaning that future mortality rates are uncertain and agents update them by the drivers that are also stochastic. They are beyond the scope of this paper.

[9] For example, see Poterba et al. (2011) and Brown (2009).

[10] See Butrica, Smith, and Toder (2010).

[11] Munnell et al. (2019) shows that almost 70% of homeowners stay in their home after retirement until they die.

[12] For example, HRS data by Dominitz and Manski (2007) and Hurd (2009) "Subjective Probabilities in Household Surveys", Michigan Survey of Consumer Confidence by Dominitz and Manski (2005), and the

which suggests a welfare loss compared to investing under rational expectations (Angrisani, Hurd, and Meijer 2012).

1.3 Health Risk

Health costs in retirement have increased substantially over the past few decades.[13] In the empirical data, out-of-pocket medical expenses rise quickly with age, and the potential liquidity shortages caused by health costs is a crucial driver of saving for retirement (De Nardi, French, and Jones 2010), especially for long-term care (Kopecky and Koreshova 2009). A recent study finds that 70 percent of adults who survive to age 65 develop severe long-term services and supports (LTSS) needs before they die and 48 percent receive some paid care over their lifetime (Johnson 2019). Most will receive informal help from family and friends, but increasing numbers of older Americans will receive home care from paid helpers and many will end up in nursing homes (Johnson, Toohey, and Weiner 2007). Although predictors such as permanent income, initial health, and initial marital status have large effects on LTSS spending, much of the dispersion in such spending is due to events that occur later in life (Jones et al. 2018), which makes it difficult to predict. Thus, the prospect of becoming disabled and needing care is perhaps the most significant risk facing older Americans. Not surprisingly, more affluent individuals said in a recent survey that they were more worried about rising health care costs than about any other financial issue (Merrill Lynch Wealth

data from De Nederlandsche Bank Households Survey for Dutch households by Hurd, Van Rooij, and Winter (2011).

[13] For example, see 2019 Fidelity Retiree Health Care Cost Estimate.

Management, 2012). However, very few people take actions such as buying long-term care insurance, probably because those products are expensive, and low-income people have access to LTSS coverage through Medicaid (Brown and Finkelstein, 2008; Kopecky and Koreshkova, 2014; Friedberg et al. 2015).[14]

1.4 Family Risk

One type of risk that recently has increasingly gained attention in the literature is family risk, such as getting a divorce, family emergency, children needing help because of being ill or unemployed.[15] This type of risk might be harder to manage than the longevity, market, and health risks because 1) it is difficult to predict and could have an affect over a long period of time (Rappaport, 2019); and 2) very few people have prepared financially for potential family events and challenges, but the empirical data suggests that this risk is not negligible. For example, a survey conducted by Merrill Lynch investigated the link between retirement and family issues. It found that 88 percent of respondents age 50+ have not budgeted or prepared for providing financial support to others; however, 62 percent of them have actually provided an average $14,900 in financial assistance to family members in the last five years.[16] More recent studies on family transfers confirm the empirical findings that many older adults provide financial help to younger family members rather than vice versa. For example, the Employee

[14] Many but not all initial stays in nursing homes qualify for Medicare.
[15] Sellars and Cutler (2019).
[16] Among respondents age 50+ who provided money to family members in the last five years, most of the recipients (68%) are adult children (age 21+), following by grandchildren (26%). See Merrill Lynch, "Family & Retirement: The Elephant in the Room," study in partnership with Age Wave, 2016.

Benefit Research Institute (EBRI) reports that 28-51 percent of older households make cash transfers to young family members that average between $14,000 and $17,000 (the amounts vary by age group), while only 5 percent of older households receive transfers from younger family members.[17] Not surprisingly, retirees would be willing to make sacrifices to financially support family members, especially their children and grandchildren even if they could not really afford it. However, other family risks are not that "enjoyable". For example, gray divorce – divorce among older adults – increased from 2 percent in 1960 to 14 percent in 2010 (Merrill Lynch, 2016), costing about $15,000 per person (Thumbtack, 2020).[18]

1.5 Policy Risk

Last but not least, policy risk such as Social Security reform or pension plan benefit reduction has a dramatic impact on retirement security as well. Social Security is the primary income source for most retirees, and the trust fund reserves are projected to become exhausted in 2035. After that, payroll taxes are expected to be enough to pay about 75 percent of scheduled benefits under current law.[19] Therefore, without any changes from the Congress, there would be a 25 percent benefit reduction to everybody. However, it is unlikely to happen for the following three reasons. First, the current trust fund shortfall – $35.2 trillion closed group unfunded liabilities as of 2019 (Nickerson and

[17] Banerjee (2015).
[18] For more discussion about the impact of divorce on retirement security in general, see Munnell, Hou, and Sanzenbacher (2018)
[19] SSA (2019a).

Burkhalter, 2019) – is conceptually related to the positive lifetime net transfers received by the earliest generations of program participants, sometimes called Legacy Debt or the Missing Trust Fund that built up during the early years of the Social Security program (Leimer 2016). This fact suggests that taxing society more widely, such as through an income tax increase, might be a better approach than benefit reduction (Munnell, Hou, and Sanzenbacher, 2017).[20] Second, although benefit changes have played a significant role in restoring Social Security solvency historically, it has not been the only way. For example, Diamond (2018) shows that, in the 1983 legislative reforms, 39 percent of the solution to Social Security's shortfalls comes from beneficiaries, which is smaller than the 44 percent contributed from the taxpayers.[21] Third, even benefit changes rarely take the form of direct benefit cuts; rather are carried out through actions such as delay the cost-of-living adjustment (COLA) and raise the normal retirement age from the 1983 reform. Aubry and Crawford (2017) document and compare the reform patterns for over 200 major state and local pension plans after the financial crisis, and they confirm that the changes in employee contributions and COLAs the most prevalent reforms. Furthermore, benefit cuts tend to be phased in, and therefore impose little of their burden on the people already receiving benefits. However, on the subjective side, people seem too pessimistic about their future benefits from Social Security. According to a recent survey from Pew in 2019, only 23 percent of workers approaching to retirement expect to receive benefits

[20] The fact that the unfunded obligation comes from the legacy debt is likely not enter the calculus of the congress. One reason why congress is unlikely to cut the benefits is that they see considerable support for the program among their constituents.

[21] For the rest of the solution, 16 percent from coverage extensions, and 1 percent from others.

at the current level; 48 percent say benefits will be provided but will be reduced; and 28 percent expect to receive no benefit at their retirement.[22]

To sum up, the literature shows that retirees with limited financial resources face the following risks: out-living one's money (longevity risk), investment losses (market risk), unexpected health expenses (health risk), unforeseen family needs (family risk), and retirement benefit cuts (policy risk). Due to the financial literacy and personal bias, retirees often have beliefs of those risks deviating from the risk distributions shown in the empirical data. No study to date has 1) systematically and simultaneously valued and ranked the financial impacts of these risks within a unified framework; and 2) measured various sources of retirement risk from both the *objective* and *subjective* perspectives.

[22] Pew Research Center, March 2019, "Looking to the Future, Public Sees an America in Decline on Many Fronts"

2 DATA

This paper mainly uses the data from the *Health and Retirement Study* (HRS), a biennial longitudinal survey of a representative sample of Americans over age 50. The survey interviews approximately 20,000 respondents every two years on subjects like health care, housing, assets, pensions, employment, and disability. It is the most comprehensive survey of older Americans, and the economic measures captured by the survey data are regarded as being of very high quality.[23]

2.1 Retirement Wealth

The HRS wealth and income data have been widely used in the retirement research field. This paper looks at retirement wealth for households around age 65 in the HRS 2016 survey.[24] Wealth includes 1) housing wealth, which is the net value of the primary residence, calculated as the gross value of the primary residence less any relevant mortgages and home loans; 2) retirement savings calculated as the total balances of all accounts from 401(k)s, 403(b)s, and other DC plans, and IRA accounts if any exists; and 3) other financial wealth, which is calculated as the sum of the value of stocks, bonds, mutual funds, and the value of checking, savings, and money market accounts,

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[23] French and McCauley (2017).

[24] The HRS 2018 survey data is published by the time of this paper, however, the analytical weights data has not been available yet. Hence, this paper uses HRS 2016 survey data for the analysis.

certificates of deposit, and government savings bonds – minus debts and holdings of all DC and IRA assets .[25]

Table 1. *Median Retirement Wealth for Households at Age 65.*

Panel A: Single men

	P50	P75	P90	P95	Mean
Housing wealth	$95,869	$217,302	$396,789	$1,065,206	$176,578
Retirement saving	140,607	269,497	575,212	710,919	221,752
Other financial wealth	53,260	181,085	514,495	3,216,924	292,923
Total retirement wealth	323,823	742,005	1,335,567	4,388,651	691,253

Panel B: Single women

	P50	P75	P90	P95	Mean
Housing wealth	138,477	255,650	532,603	605,037	194,501
Retirement saving	117,173	276,954	585,864	795,397	273,341
Other financial wealth	15,978	85,217	388,800	826,600	159,413
Total retirement wealth	378,148	634,330	1,250,552	1,596,432	627,255

Panel C: Married couples

	P50	P75	P90	P95	Mean
Housing wealth	191,737	362,170	568,820	852,165	287,360
Retirement saving	289,736	693,449	1,246,292	1,790,612	517,085
Other financial wealth	47,934	213,041	670,015	1,576,506	357,276
Total retirement wealth	645,515	1,308,997	2,402,041	4,170,283	1,161,721

Source: Hou and Sanzenbacher (2020), and HRS 2016.
Note: In 2020 dollars. The sample restricts to households having defined contribution wealth and housing wealth.

Table 1 shows the median household wealth for single men, single women, and married couples calculated in Hou and Sanzenbacher (2020). To map the traditional concept of net worth, total household wealth here excludes Social Security and private sector

[25] For households where debt exceeds wealth, the measure of non-DC financial wealth is allowed to be negative. Similarly, for households where debt exceeds equity, housing wealth is allowed to be negative.

defined benefit wealth, which is already in the form of income flows and doesn't require taking withdrawals.[26] This paper applies the Social Security benefit data documented in Clingman, Burkhalter, and Chaplain (2019), which is $20,355 for a typical worker with median earnings and retired at 65.[27]

2.2 MEDICAL EXPENDITURES

Medical expenditures are defined as the sum of what the individual spends out of pocket on insurance premiums, drug costs, hospital stays, nursing home care, doctor visits, dental visits, and outpatient care, excluding expenses covered by public or private insurance. The HRS collects this data through both the regular interviews in the core surveys and through the exit surveys, which cover the medical costs in the last years of life. French et al (2017) compare the medical expenditure data from the HRS, the Medicare Current Beneficiary Survey (MCBS), and the Medical Expenditure Panel Survey (MEPS). They find that the HRS data is more comprehensive and that it matches up well with the data from other datasets.

Table 2 shows the summary statistics for medical expenditures by gender and age groups using HRS 2016. It illustrates the fat tail of the medical spending distribution found in the literature (e.g., French et al, 2017; Jones et al, 2018).

[26] Since DB plans are not common any more, they are not included in the analysis, but they are well documented in Hou and Sanzenbacher (2020).
[27] See the appendix Table A1 for more detail.

Table 2. *Out-of-Pocket Medical Expenditures over Two-year Period, by Age and Gender.*

Panel A: Men

Age	Mean	Std	P50	P90	P95
65-69	$2,674	$4,783	$1,096	$6,471	$10,099
70-74	3,310	5,398	1,612	7,535	12,464
75-79	3,721	7,607	1,677	8,491	13,113
80-84	4,849	16,592	1,683	8,771	14,833
85+	8,437	20,231	2,021	16,768	37,813
Total	3,866	10,119	1,505	8,115	13,221

Panel B: Women

Age	Mean	Std	P50	P90	P95
65-69	$3,216	$5,593	$1,489	$7,984	$12,361
70-74	3,747	6,674	1,797	8,706	13,973
75-79	3,576	6,579	1,505	8,685	13,113
80-84	5,144	14,208	1,694	10,190	16,123
85+	12,083	36,146	1,806	22,496	73,469
Total	4,968	16,075	1,612	9,781	15,693

Source: HRS 2016.
Note: In 2020 dollars.

2.3 FAMILY TRANSFERS

Family transfers are defined as financial help, such as giving money, helping pay bills, or covering specific costs for medical care, insurance, schooling, a home down payment, rent, etc. The HRS survey collects the amount of given and received by children, parents, other relatives, and friends. This paper calculates the net transfer as the sum of total money transferred out of the retired household less the total amount received. Table 3 shows that roughly one-third of households age 65+ making family transfers over a two-year period, mainly in the form of giving money to children.[28] Among the households making transfers, the median amount is $3,300 over the two years, but the mean is highly skewed at $11,000.

Table 3. *Net Family Transfers over Two-Year Period by Age.*

Age	Share of households making transfer	Among households making transfer				
		Mean	Std	P50	P90	P95
65-74	42.8%	$10,439	$38,661	$3,269	$24,683	$41,409
75-84	34.0	12,732	91,254	3,051	27,242	54,485
85+	28.3	10,092	30,076	2,179	36,505	64,005
Total	38.6	11,024	57,200	3,269	26,153	43,588

Source: HRS 2014 (the latest available data for HRS RAND family files).
Note: In 2020 dollars.

2.4 SUBJECTIVE EXPECTATIONS

The HRS has asked respondents to assess the probability of various outcomes. The respondents give a number from 0 to 100 where 0 means absolutely no chance and 100 means absolutely sure to happen.[29] The rest of this section discusses the questions for each retirement risk source in this analysis.

[28] The statistics by types of transfers are shown in the appendix Table A2.
[29] The exact wording of the questions in the HRS is summarized in the appendix Table A3.

2.4.1 Survival Probabilities

The survival probability question is asked based on the respondent's current age. If the age is less than 65, the question is asked for the chance of living to age 75; if the age is 65-69, the target age asked is age 80, and so on.[30] Due to the high frequency of focal point responses, the HRS has introduced a control question since 2006 to respondents who answer 50 percent to understand whether the respondent's answer expresses epistemic uncertainty. This paper exploits that question by recoding the answers as missing unless they are confirmed as equally likely.[31]

Table 4. *Probability of Living to Age 80 for Age 65-69 in 2016.*

	Average expectation	Expectation implied by life table	
		At age 65	At age 69
Men	58.3%	66.0%	69.7%
Women	64.0	75.0	77.7

Source: HRS 2016 and author's calculation.

Table 4 shows the average subjective probability of 65- to 69-year-olds living to age 80 answered, compared with the empirical life table probabilities.[32] It is clear that

[30] No such questions asked for age 90+.
[31] The control question asks "Do you think that it is about equally likely that you will die before age X as it is that you will live to age X or beyond, or are you just unsure about the chances, or do you think no one can know these things?" The missing is recoded for the answers of "unsure", "can't know", "don't know", and "refused to answer".
[32] The calculation is based on unpublished cohort life tables used for 2019 SSA trustees report by the Social Security's Office of the Chief Actuary. It is available upon request.

individuals are pessimistic about their survival probabilities.[33] For example, the probability for a woman at ages 65 to 69 living to age 80 is 75 percent to 78 percent, but women of this age in the survey have an average expectation of only 64 percent, which is much lower than the lower bound of the range.

2.4.2 Stock Performance

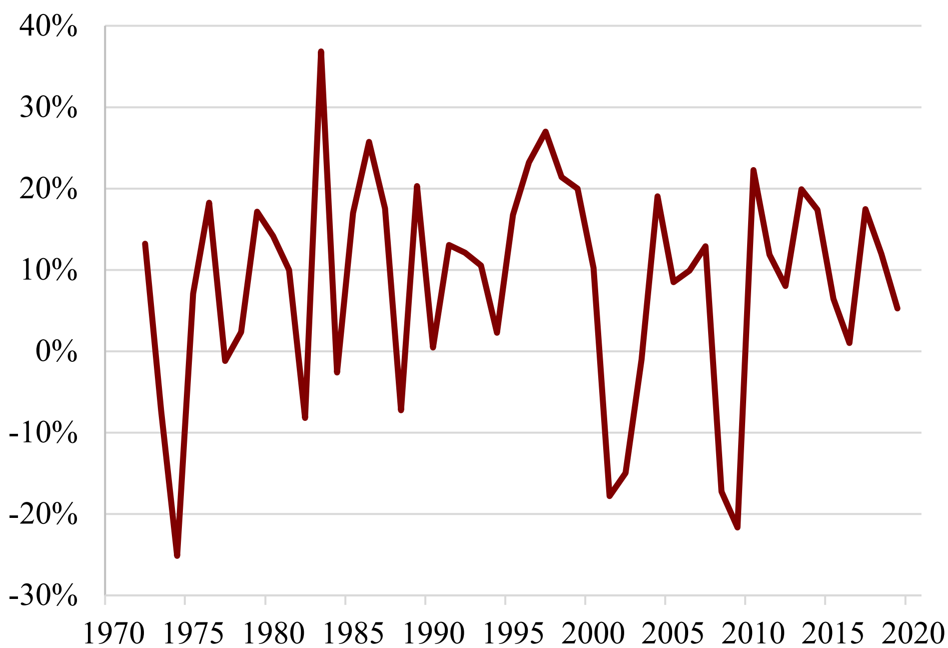
The HRS has elicited respondents' beliefs about the stock returns since 2002 by asking the probability that stocks will be worth more next year than they are today.[34] Similar to the survival probability questions, a control question was added in 2006 for respondents who answer 50 percent.[35] Moreover, since 2010 respondents have been asked two more questions to provide additional data points: the chance of gaining 20 percent or more over the next year and the chance of losing 20 percent or more .

To review the performance of all U.S. equity securities, Figure 1 shows the historical price change for the Wilshire 5000 Price Index, which is widely accepted as the definitive benchmark for the U.S. equity market.[36] The return bounces between the plus- and minus-20 percent range but stays positive most of the time. On the contrary, Table 5 shows that individuals on average have very pessimistic and larger volatility expectations

[33] The subjective expectations are higher than the range implied by life table in late life, which shows the optimism and survival bias (O'Dea and Sturrock 2018). However, for the analysis of the life cycle model in this paper, the subjective survival probabilities at age 65-69 are more relevant.
[34] As a proxy of stock market, the question asks the mutual fund shares invested in blue chip stocks like those in the Dow Jones Industrial Average.
[35] In HRS 2008 only, this follow-up question is added to respondents who answer 0% and 100% as well. In 2002, a question for 10 percent or more was added in the survey. In 2008, one of the eight questions, market gains/losses 10/20/30/40 percent or more, was randomly assigned to respondents. Since those questions are only appear in one year of the survey, this paper doesn't use them in the analysis.
[36] The empirical analysis also uses Wilshire 5000 to calculate the stock return volatility.

than the empirical data indicate, and the pattern is stable by gender, age, and survey years. For example, the chance that stock prices will be higher next year is consistently less than half, and the chance that prices will gain or lose 20 percent more next year are both always about one-quarter. One might blame this negative emotion on the aftereffects of the global financial crisis. However, Heiss et al. (2019) find a similar result through another panel dataset covering the periods before and after the financial crisis.[37]

Figure 1. *Historical Nominal Price Change from Wilshire 5000 Price Index,1972-2019.*



Source: Wilshire 5000 Price Index,1972-2019

Table 5. *Expectation of the Stock Market Performance in the Next Year.*

[37] See Figure 2 in Heiss et al. (2019). The expectation of market gain is never above 50% from 2004 to 2016.

	Lose 20% more	Worth more	Gain 20% more
All	24.0%	42.6%	23.0%
By gender:			
Men	22.5	45.8	22.0
Women	25.6	39.5	24.1
By year:			
2010	22.1	41.9	23.8
2012	25.2	41.9	23.0
2014	24.4	42.8	23.2
2016	24.4	43.9	22.3
By age:			
65-69	25.7	45.1	23.7
70-74	25.0	43.5	23.2
75-79	22.6	40.5	22.6
80-84	21.7	39.9	22.8
85+	19.3	37.1	20.7

Source: HRS 2010-2016.

2.4.3 Housing Price

Similar questions for respondents' expectations of their home value have been asked since 2010 HRS. Rather than asking everyone whether prices will be 20 percent higher and 20 percent lower, the HRS randomly assigned to respondents one of eight future values, gain/fall more than 10, 20, 30 and 40 percent compared to what it is worth today.

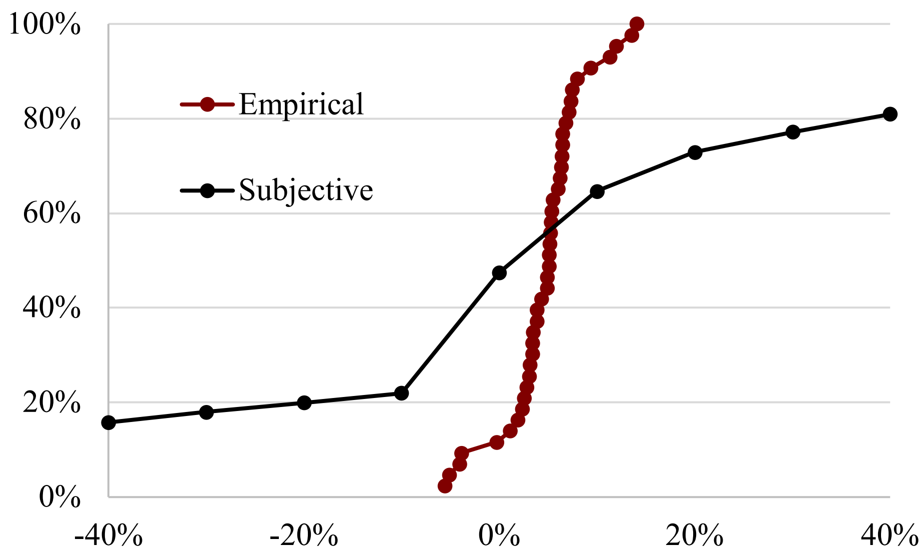
Table 6. *Expectation of the Housing Price Change in the Next Year.*

Performance	Loss 40% more	Loss 30% more	Loss 20% more	Loss 10% more	Worth more	Gain 10% more	Gain 20% more	Gain 30% more	Gain 40% more
Expectation	15.8%	18.0%	20.0%	22.0%	52.6%	35.4%	27.1%	22.8%	19.1%

Source: HRS 2010-2016

Table 6 shows the average answers of these questions. Among the respondents who have been asked the chance of their home value being worth more by this time next year, their average expectation is 53 percent. Among the answers of falling more than 40 percent and gaining more than 40 percent, the average chances are 16 percent and 19 percent.

Figure 2. *CDF of Housing Price Change, Subjective Distribution vs. Empirical Data.*



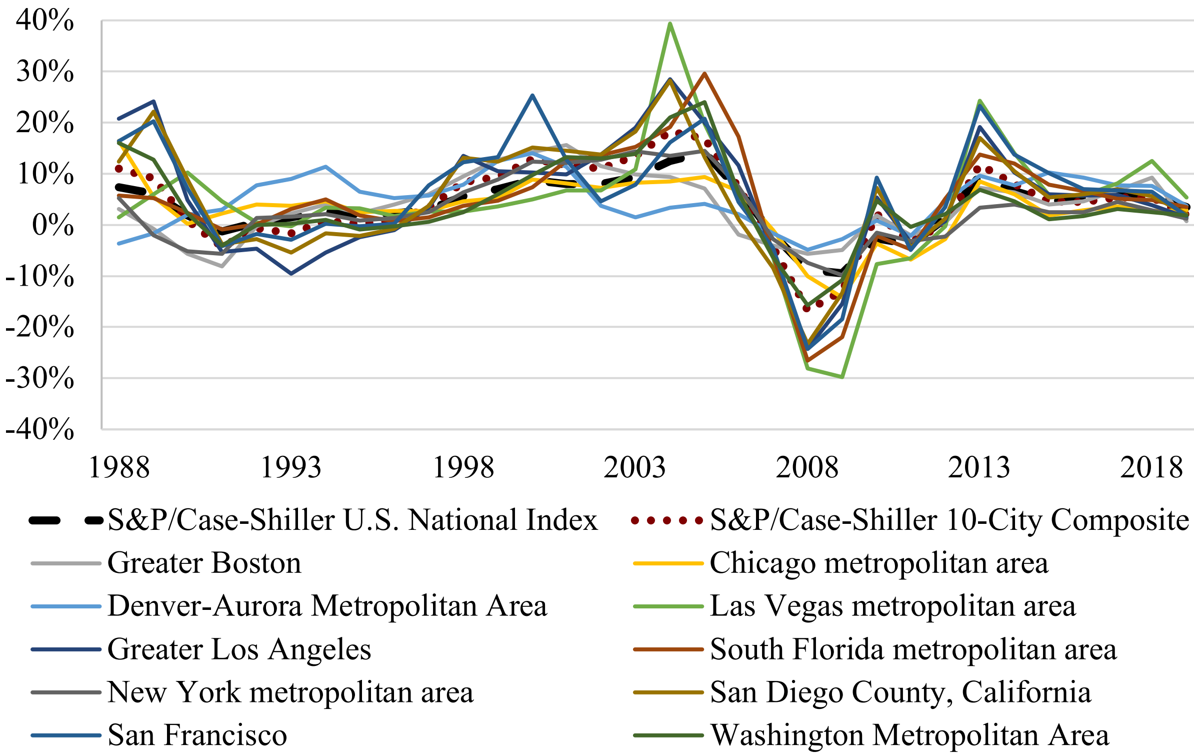
Source: HRS 2010-2016 and All-Transactions House Price Index for the U.S. 1975-2019.

To be intuitive, Figure 2 converts the average answers to those questions to a subjective probability distribution and plots its cumulative distribution function (CDF) to compare with the historical housing market data.[38] Similar to the stock market responses, the

[38] Similar to the answers for stock market, there is no significant difference among demographic groups at average level in the subjective expectation of the housing price. See Appendix Table A4 for statistics by demographics.

house price responses show a significant overestimation of market volatility.[39] The change in housing prices, when calculated based on All-Transactions House Price Index for the U.S., never goes out of the range of plus- and minus- 20 percent in the period of 1975-2019, but people clearly have a much larger range in mind. One might argue that the regional housing price data is a better reference than national average, because HRS asks the change of their own housing price, and diversification is impractical for most of the households.

Figure 3. *S&P/Case-Shiller Home Price Index Change, 1988-2019.*



Source: S&P Dow Jones Indices LLC, S&P/Case-Shiller Home Price Index, 1988-2019.

[39] Although we can't rule out the impact of housing bubble burst because of the data only from 2010 onwards, this finding is consistent with earlier literature. For example, Capozza and Seguin (1996) provide evidence that participants tend to overreact to the housing market.

Figure 3 shows the indexes of 10 major Metropolitan Statistical areas in the U.S. that are used to create the S&P/Case-Shiller 10-City Composite Home Price Index. Similar to the stock price pattern in Figure 1, the housing returns bounce between the plus- and minus-20-percent range for most of the time, and never go 40 percent above or 30 percent below.

2.4.4 Medical Spending

Since 2010, the HRS has also asked for respondents' expectations of their medical expenditures, defined as out-of-pocket medical spending such as doctor and dentist expenses, hospitals, nursing homes, prescription drugs and any others, excluding what is covered by insurance. To begin with, the respondents are asked to estimate the probability of spending $1,500 or more in the coming year. Depending on the answer to this question, they are then asked about other thresholds such as $500, $3,000 and $8,000. For example, if the respondent feels having zero chance of spending $3,000, then the question about $8,000 in spending won't be asked.

Table 7. *Subjective Expectation of Medical Spending in the Next Year.*

Panel A: Men

Age	Spend $1500+	Spend $3000+	Spend $8000+
65-69	44.2%	25.7%	11.7%
70-74	45.1	25.9	12.3
75-79	43.1	24.6	11.8
80-84	42.9	25.5	12.4
85+	41.6	26.1	13.7

Panel B: Women			
Age	Spend $1500+	Spend $3000+	Spend $8000+
65-69	44.0%	26.1%	13.0%
70-74	44.5	26.9	13.9
75-79	40.5	24.6	12.8
80-84	39.0	23.9	12.6
85+	36.7	22.9	13.3

Source: HRS 2010-2016.

Table 7 shows the average subjective expectations for various spending thresholds by age group.[40] It is surprising to see that the expectations barely change as age increases. Given the patterns in Table 2 for the empirical data, older people seem to underestimate medical spending, and younger people seem overestimate.

2.4.5 Family Transfers

Similar to the medical spending questions, the first HRS question about family transfers is to estimate the chances of giving/receiving financial help of $5,000 or more in *the next 10 years*. In 2004 and 2006, other thresholds such as $1,000, $10,000 and $20,000 or more were asked based on the answers to previous questions.[41] Unfortunately, the transfer expectation was removed in the 2008 and later surveys. Based on 2006 data, the average expectation of the chance that HRS households age 65+ will provide financial help of $5,000 or more is 34.8 percent; the expectation of receiving $5,000 is 9.2

[40] Statistics by gender and survey years are similar. See the appendix Table A5 for detail.
[41] For example, if the respondent answers less than 30 percent chance to the question of $5,000 or more, then the question of $1,000 will be asked; if the answer is greater than 30 percent, the follow up question is $10,000. Because those questions are asked only under certain conditions, this analysis doesn't include them.

percent.[42] These subjective estimates for the next ten years are actually less than what Table 3 would show if converted to annual numbers. It means that individuals underestimate the possibility of the family transfer, consistent with Merrill Lynch (2016).

2.4.6 Social Security Benefit

For the subjective expectation of a Social Security benefit reduction, the HRS questions are slightly different depending on whether the respondent is receiving a benefit now or will receive one in the future. For modeling purpose, this paper focuses on the first question, which asks respondents for their expectation that the benefit they receive from Social Security will be cut at some point over the next 10 years. The average answer is about 40 percent chance in HRS 2016, which is somewhat lower than other surveys, such as Walker et al. (2014) and Parker et al (2019).[43]

[42] The variation by demographics such as gender and age group are fairly small. See the Appendix Table A6 for detail.
[43] See the Appendix Table A7 for the variation by subgroups.

3 MODEL

This paper constructs a lifecycle optimization model for a retired household with a constant relative risk aversion (CRRA) utility function $U_t = \frac{{C_t}^{1-\gamma}}{1-\gamma}$. This model has been widely used in the literature (e.g., Ameriks et al. 2011; Brown and Warshawsky 2013; Horneff et al. 2020).[44] At the age of 65, the household holds housing wealth H_{65}, retirement savings K_{65}, and other financial wealth (liquid assets) L_{65}, calibrated using the HRS household wealth data as shown in Table 1.[45] At the beginning of each age t, the retiree needs to decide: 1) the withdrawal amount D_t from retirement accounts, with a restriction of the RMD rule; 2) consumption C_t of liquid assets; and 3) the share of assets invested in stocks and bonds. During each year, the retiree faces five sources of risk as discussed below.

3.1 LONGEVITY RISK

At age t, the retiree faces an age-specific mortality rate q_t and a survival probability to next year $p_t = 1 - q_t$. If the retiree dies, the bequest amount would be the total wealth

[44] Another frequently used utility form is Epstein-Zin-Weil-type preferences (e.g., Cocco et al 2005, Pang and Warshawsky 2010), which could be treated as a generalized form of CRRA.
[45] The literature acknowledges the importance of retirement timing decisions. For example, see Hou et al. (2018). Despite the increasing Full Retirement Age (FRA) to 67 for the young cohorts, many still retire early. This paper focuses on quantifying the retirement risk instead of optimizing retirement decision. Thus, it assumes that the retirement begins at age 65, an average retirement age for men in the U.S. (CRR Frequently Requested Data, 2018).

at this time $B_t = L_t + K_t + H_t$.[46] The objective mortality data come from the gender-specific cohort life tables used in the *2019 Social Security Trustees Report*, and this paper uses the cohort whose age 65 in 2020 (see Appendix Table A8).[47] The subjective survival probability is estimated using the Gompertz model commonly used in the literature (e.g., Brown, 2002; Bissonnette et al. 2017; de Bresser, 2019; Colchero and Kiyakoglu, 2020).[48] The baseline hazard rate is homogenous, given by:

$$\mathcal{H}_t = e^{\beta x} e^{\lambda t} \tag{1}$$

where $\mathcal{H}_t$ is the mortality force at age t, the rate of aging $\lambda > 0$, and $e^{\beta x} > 0$ is the initial level mortality determined by characteristics x (including gender, race and ethnicity, education attainment, etc.) and their coefficients β. To capture the heterogeneity, this paper introduces the idiosyncratic component using a frailty term that multiplies to the above homogenous hazard rate. Following Bissonnette et al. (2017), this term is assumed to follow a gamma distribution with variance of $1/\varsigma$. Hence, the survival probability from age t_0 to t_1, given by:

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[46] The literature acknowledges the importance of the bequest motive. For example, see Lockwood (2012), (2018).

[47] One would argue that the mortality rate is highly related to the health status. To avoid tracking how the transition of health status affect the mortality, this paper focuses on the situation where general illness and treatments do not impose a correlation between morbidity and assumed mortality. The implicit assumption is that health spending is only undertaken if it is expected to result in support of longevity, at least at population average levels.

[48] Bissonnette et al (2017) shows that the Gompertz specification yields the best result using likelihood estimation. They also test other forms, such as Weibull hazard, and the result is similar.

$$\mathcal{S}(t_1|t_0) = \left(\frac{\varsigma + \frac{1}{\lambda} e^{\beta x}(e^{\lambda t_0} - 1)}{\varsigma + \frac{1}{\lambda} e^{\beta x}(e^{\lambda t_1} - 1)} \right)^{\varsigma} \tag{2}$$

can be estimated using the self-reported probability of living to certain ages in the HRS data.[49]

As documented in the literature, self-reported probabilities are subject to focal answers (0 percent, 50 percent, and 100 percent) and rounding errors.[50] One way to improve the accuracy of the estimate is to assume each respondent has a latent variable that indicates the standard for rounding the response values, for example, to multiples of 5, 10, 25, 25, and 100. If Bayes' theorem were applied here, a given answer by a respondent could be interpreted as some probability that the true subjective expectation lies in an interval according to the rounding standard. Then, the probability of the rounding standard for each respondent could be joined with the survival probability function form above to perform the maximum likelihood estimation (e.g., Kleinjans and van Soest, 2014; Bissonnette and de Bresser, 2018). However, this approach is not appropriate in this study for two reasons: 1) the estimated rounding standard for the same respondent might be inconsistent across the various subjective survey questions, such as for longevity risk, market risk, health risk, etc.; and 2) to estimate a universal rounding standard, one have

[49] This paper applies the coefficient in Bissonnette et al (2017) which are estimated using the same HRS data. See the coefficient estimate in the appendix Table A9.
[50] Rounding is the familiar practice of reporting one value whenever a real number lies in an interval (Manski and Molinari, 2010).

to multiply all of the density functions together, which is computationally infeasible.[51] In fact, O'Dea and Sturrock (2019) examine the rounding standard and find that individuals who answer 50 percent in survival questions almost always give a range of answers to other probability questions, and are no more likely to answer 50 percent to other questions than are the rest of the sample.[52] Moreover, to estimate the rounding standard and construct upper and lower bounds on subjective expectations using the survey data alone is not sufficiently informative for making inferences either (Bissonnette and de Bresser 2018). Since there is no clear evidence of consistently rounding up or rounding down in the data, this paper doesn't consider the rounding standard in the estimation.

3.2 MARKET RISK

The market risk in the models comes from two sources: uncertain equity returns R^e and uncertain housing returns R^h, assuming no correlation for simplicity. In the empirical model, the equity price and housing prices are assumed to follow the log-normal distribution with parameters matching the historical mean and variance of the market data.[53] Of course, many observers believe that equity returns will be lower in a low

[51] Manski and Molinari (2010) examine the HRS expectation module as a whole and find that a small fraction of respondents uses only focal answers throughout. Most of respondents make full use of the 0%-100% chance scale.
[52] They find that, of the 16,345 individuals who answered one or more survival questions, only 41 individuals (0.2%) answered "50%" to all survival questions in all waves.
[53] It is arguable that whether housing price should be modeled as stationary process or not. For example, Zhang, Jong and Haurin (2013) argues that the logarithm of real house price is not a unit root process. Shao, Chen and Sherris (2019) show that an ARMA(2,4) - GARCH(1,1) model is the optimal among the models they consider.

interest rate environment.[54] To incorporate this, the analysis adjusts real equity returns from Ibbotson Large Cap Index and Wilshire 5000 based on the methods outlined in Burtless et al. (2016) updated with current returns data.[55] This provides a real return to equity of 4.5 percent annually, which lines up with the latest market forecast for large-cap U.S. equities, such as State Street (2019). For simplicity, bonds are assumed to earn a risk-free return R_f equal to 1 percent in real term.[56] Furthermore, the housing data comes from S&P/Case-Shiller Home Price Index. As discussed in Figure 3, the regional housing price data might be a batter reference than the national average, because the diversification is impractical for most of the retired households. Table 8 shows the historical standard deviation of home price index changes at national level and ten major metropolitan areas. The standard deviation at national level is 5.4 percent, while the numbers at the city level vary from 5.0 to 12.5 percent. Thus, this project applies the

[54] Many industry and academic experts believe future equity returns will be lower than historical returns, mainly due to a decline in the risk-free rate. For industry examples of future expected returns, see BlackRock (2019) and Bogle and Nolan (2015). For an academic discussion of why the risk-free rate may be lower going forward, see Summers (2014, 2015). Summers suggest six factors. First, the market may have experienced a reduction in demand for capital due to a lower capital intensity of modern firms (e.g., WhatsApp has a greater valuation than Sony with virtually no capital required to generate that value). Second, declining population growth leads to lower interest rates as the growth of the labor force slows. Third, increasing inequality in income and an increasing capital share of income would both increase the propensity to save. Fourth, a decline in the price of capital goods would depress interest rates. Fifth, lower inflation serves to lower the after-tax real return on capital. Finally, globally an increasing share of assets is invested in safe assets such as Treasury bonds, lowering average returns.

[55] Burtless et al. (2016) examines three approaches to determine what future equity returns might be. The first is to look at the inverse of the price/earnings (P/E) ratio. This ratio was 19.4 as of December 2018, which suggests a real return of 5.2 percent. Short-term earnings yields, however, can be misleading. Campbell and Shiller (1998) argue that the 10-year earnings yield is a much better predictor of the returns on stocks. The current cyclically adjusted PE (CAPE) ratio is 28.3, suggesting future long-run real returns of 3.5 percent (Shiller 2019). The third approach is based on the Gordon growth model, which establishes a steady state relationship between market value, stock returns, and GDP. Assuming a dividend yield of roughly 2.1 percent (Shiller 2019) and a projected GDP growth of 2.2 percent (Social Security Administration 2019b), the stock return implied by the Gordon equation is 4.3 percent. The results of these three simple exercises suggest future real equity returns ranging from 3.5 percent to 5.2 percent. Therefore, this project anchors the average simulated equity returns to 4.5 percent, the middle of this range.

[56] This assumption is consistent with most recent academic research and projections from the industry. For example, see Horneff et al. (2020) and Morningstar (2018).

average of the standard deviation from these ten major Metropolitan Statistical areas that are used to create the S&P/Case-Shiller 10-City Composite Home Price Index. Finally, Inflation risk is also worth considering over the long term; however, the literature suggests a small welfare impact from calibrating to low inflation variance in recent years.[57] Therefore, this project models investment returns in real terms without taking into account inflation uncertainty. Table 9 summarizes the market assumptions in the objective model.

Table 8. *Standard Deviation of Home Price Change from 1988 to 2019, by Regions.*

S&P/Case-Shiller U.S. National Index	5.4%
S&P/Case-Shiller 10-City Composite	7.8%
Greater Boston	6.1%
Chicago metropolitan area	5.9%
Denver-Aurora Metropolitan Area	5.0%
Las Vegas metropolitan area	12.5%
Greater Los Angeles	11.6%
South Florida metropolitan area	10.5%
New York metropolitan area	6.5%
San Diego County, California	10.7%
San Francisco	10.9%
Washington Metropolitan Area	8.3%
Average of 10 Metropolitan Statistical areas	8.8%

Source: S&P Dow Jones Indices LLC, S&P/Case-Shiller Home Price Index, 1988-2019.

Table 9. *Market Return Assumptions from Empirical data, in Real Term.*

Asset class	Housing	Equity	Bond
Mean	1.0%	4.5%	1.0%
Standard deviation	8.8%	15.7%	0.0%

Source: Ibbotson Large Cap Index, Wilshire 5000, and S&P/Case-Shiller Home Price Index for U.S.

[57] Munnell, Wettstein, and Hou (2019) consider stochastic inflation calibrated to the distribution from historical data after 2000, and they find the result changes in the welfare analysis are negligible.

For the estimation of the subjective market returns, this paper takes an approach that is simpler than the approach used in the subjective longevity analysis.[58] Keep in mind that the purpose of this study is to quantify the objective and the subjective retirement risks from various sources and compare them; the purpose is not to discover the determinants of subjective expectations and how they interact with realized return.[59] To that end, this paper estimates the typical retiree's expectation of market returns by applying the sample average of the subjective probabilities as the data points, and then applies the same distribution type used in the empirical settings to estimate the underlying risk parameters.[60] To avoid an over-identification issue when there are more data points than there are parameters to be estimated, a minimum distance estimation procedure is applied to obtain each risk distribution.[61] There are two caveats under this approach. First, by taking the averages of the cross-sectional data in the HRS survey, the study doesn't make full use of the longitudinal feature of the HRS dataset.[62] This seems problematic, since it is reasonable to believe that the market returns experienced by the respondents are likely to influence their subjective expectation for the future. However, Heiss et al. (2019) study the subjective expectations elicited from a panel dataset covering the 2008 financial market crisis, and they find that most of respondents report return expectations that align

[58] As mentioned above, it is not appropriate in this study to estimate the rounding type for all sources of subjective expectations.
[59] Indeed, substantial heterogeneity of subjective expectations has been documented at the individual level. For example, see Heiss et al (2019) for how individuals' expectations predict their stock-market decisions.
[60] One might argue that the rounding errors are somewhat mitigated by taking the averages.
[61] Hurd and Rohwedder (2011) take a different approach to calculate the mean and standard deviation from subjective risk distribution. Given the subjective questions, they separate the entire real line by mutually exclusive intervals and express the expectation answers using conditional expectation from historical distribution. Angrisani et al. (2013) experiment both approaches and show similar results.
[62] For example, the questions of 20% more or less for stock market expectation only introduced since 2010.

with random-walk process rather than mean reversion or persistence updating.[63] To some extent, their finding mitigates this issue; nevertheless, little is known about how individuals form and adjust their expectations. Second, assuming the same distribution type for the subjective analysis as is used in the empirical study is a common procedure in the literature (Manski, 2018); however, a different type of distribution might better fit to the subjective data (Smithson and Blakey, 2018). As an example, this paper examines over 60 continuous distribution types that are commonly used to estimate the subjective distribution of housing returns, and certainly some distributions fit the data better, as shown in the Appendix Table A10 and Figure A2. However, it is well beyond the scope of this study to identify the best distribution type used in the estimation of each risk source. Hence, this paper leaves this question for future work.

3.3 HEALTH RISK

This model assumes that medical expenses are exogenous and are not used in the calculation of utility. This assumption implies that the household makes medical expenditure only if it supports the average longevity of the population.[64] The objective analysis follows the common settings in the literature (e.g., De Nardi et al 2010), and the dynamic of the stochastic out-of-pocket health expenses M_t at age t is given by:

[63] They use the CentER Panel data of about 2,000 Dutch households over a 12-year period, including the 2008 financial market crisis.

[64] The literature varies in treating the costs of health care in the utility function. For example, Yogo (2009) develops a model where retirees choose the level of health expenditure and the allocation of wealth between bonds, stocks, and housing. In his setting, the medical expenditures are endogenous. See Pang and Warshawsky (2010) for more discussion.

$$Ln\, M_t = m(t) + \sigma(t) * \psi_t \tag{3}$$

where $m(t)$ and $\sigma(t)$ are the mean and variance of the log of medical expenses that depend on demographics such as age and gender. The idiosyncratic component ψ_t is decomposed to two parts, a transitory shock ε_t^{tran} and a permanent shock P_t, which is assumed to follow an AR(1) process with innovation ε_t^{perm}.[65]

$$\psi_t = P_t + \varepsilon_t^{tran} \tag{4}$$

$$P_t = P_{t-1} * \eta + \varepsilon_t^{perm} \tag{5}$$

The distributions and dynamics are calibrated using out-of-pocket medical expenses in the HRS as described in the data section.[66] Similar to the settings for the objective risk distribution, the subjective medical expenses over the next year are assumed to follow the log-normal distribution with age-specific parameters $m(t)$ and $\sigma(t)$ estimated for five age subgroups, 65-69, 70-74, 75-79, 80-84, and 85+.[67]

[65] French and Jones (2004) show that medical spending shocks are well described by the sum of a persistent AR (1) process and a white noise shock. Feenberg and Skinner (1994) find a similar result. See also Hirth et al. (2015).

[66] This paper applies the coefficients estimated in De Nardi et al. (2010). See the Appendix Table A11.

[67] As for the subjective market expectations, this paper assumes a random-walk setting rather than AR (1) process to avoid over-assumptions restricted by data limitation. Another way to see this is that, for an agent at average health status to make decisions at the beginning of the retirement, the best approach to make assumptions of future medical expenditure without experiencing the realized expenses is to use the average expectation from the older counterparties.

3.4 FAMILY RISK

For married couples, the main source of uncertainty is from the spouse, such as the spousal medical expenditures and mortality. To reflect this spousal risk, two steps are required to upgrade the model from singles to married couples: 1) similar to the head of the household, the spouse is also exposed to longevity risk through an uncertain life span; health risk through uncertain medical expenditures; and policy risk through Social Security reform;[68] and 2) to represent married couples in the analysis, the utility function for singles $U_t = \frac{C_t{}^{1-\gamma}}{1-\gamma}$ changes to $U_t = \tau\,(\omega^h \frac{C_t^h{}^{1-\gamma}}{1-\gamma} + \omega^s \frac{C_t^s{}^{1-\gamma}}{1-\gamma})$, where C_t^h and C_t^s are consumption for the head and the spouse at period t, assuming equally divided, equal Pareto weights $\omega^h = \omega^s = 0.5$, and an equivalence scale of consumption for couples $\tau = 1.52$ taken from Browning et al. (2013). In addition to the spouse, a second source of family risk is the unforeseen transfer of financial help provided to children, parents, relatives or friends.[69]

For the objective analysis, the transfer is simply modeled as a binomial event with a probability and average amount for each year, using the HRS data.[70] This is due to the relatively low probabilities and low dollar amounts documented in Table 3 compared to the impact of non-family risks above. To be precise, the amount of transfer F_t at age t is

[68] The longevity and health risks from the head and the spouse are assumed to be independent.
[69] The family transfers in the model are modeled as shocks and expenses during the underlying period and are not included in the consumption and utility function.[69]
[70] The HRS collects the family transfer data for two-year period. Assuming the independency in each year, this paper calculates the corresponding annual probability and transfer amount. Similar procedure is taken for subjective questions which asks for next ten years.

a random variable taking values of F_1, F_2, and F_3, respectively, for the age ranges 65-74, 75-84, and 85+ with corresponding probabilities of φ_1, φ_2, and φ_3, and taking the value of zero otherwise. On the subjective side, the probability of having a family transfer at the given age ranges (i.e., φ_1, φ_2 and φ_3) is based on the subjective expectations in HRS data. Due to data limitations, the transfer values F_1, F_2, or F_3 remain the same as in the empirical data.

3.5 POLICY RISK

It is difficult to model Social Security benefit reform because there is not much historical data for this. Therefore, this project relies on Social Security history and expert opinions (e.g., Diamond 2018) for the best predictions.[71] In the objective settings, the benefit reduction is modeled as a one-time COLA delay that randomly happens between now and 2035. That means the benefit will be 2 percent lower in real term for the rest of the life once the policy has changed. The year to start the lower benefit follows a hazard probability model, with the probability of zero at the initial period gradually (linearly) increasing over a 15-year period to 100 percent in 2035, when the Social Security trust fund is projected to run out. Other types of adjustments – including the financial impact of a benefit cut on a person who retires at age 65 if the Normal Retirement Age (NRA) increased to age 70 or a harsh 25 percent benefit cut to restore trust fund insolvency – are shown as the robustness check in the appendix.[72]

[71] The assumption is also based on the conversion with Alicia Munnell.
[72] For birth cohort 1960 or later, the Social Security benefit is 100 percent for retirement age 67 (the FRA). If the retirement age is 65, or two years earlier than FRA, the benefit is 86.67 percent of the full amount; if

The subjective assumption relies on the self-reported expectations of benefit cuts in the HRS. The annual probability is taken from the average expectation.[73] The magnitude of the expectations of a benefit cut is modeled in the same way as the objective setting.

3.6 SOLVING THE MODEL

This paper first solves the life cycle optimization model that uses all of the sources of risk following the empirical settings discussed above. The product of this step is an optimized policy function indicating how much to consume and invest over the life cycle, and an associated expected lifetime utility serving as a benchmark. The second step is to quantify each source of objective risk by solving the alternative models with one risk removed at a time and comparing the result to the benchmark lifetime utility. The final step is to repeat the exercise above but using subjective risk distributions calibrated using the expectations in the survey instead of the objective risk distributions from empirical data.

For simplicity, this section demonstrates the optimization model using the simplified notation for singles.[74] Following the life cycle model literature, the optimization problem

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five years earlier, the benefit is only 70 percent. If FRA increases to 70, the current retirement age 65 in the model of this paper is five years earlier than the new FRA. The benefit cut is equivalent to 1 – 70% / 86.67% = 19.2%

[73] This project takes the sample average in the 2016 HRS, because the result does not vary much across demographic groups.

[74] The full version of the model for couples can be found in the appendix.

is to maximize V_t in the following Bellman equation, where time preference ρ is assumed to be 0.96 and bequest motive b is assumed to be 2 as commonly used in the literature (e.g., Horneff et al. 2020).[75]

$$V_t = U_t(C_t) + \rho\, E_t\left[p_t\, V_{t+1} + (1 - p_t)\, b\, U_t\left(\frac{1}{b} B_t\right)\right] \tag{6}$$

Adapting Deaton (1991), the household's total cash-in-hand is denoted as X_t and defined as the sum of all wealth resources including liquid cash, retirement savings and housing wealth. The budget constraints are given by:

$$X_t = H_t + K_t + L_t \tag{7}$$

$$H_{t+1} = H_t * R^h_{t+1} \tag{8}$$

$$K_{t+1} = (K_t - D_t) * (S_t R^e_{t+1} + (1 - S_t) R^f) \tag{9}$$

$$L_{t+1} = (L_t + D_t - C_t) * (S_t R^e_{t+1} + (1 - S_t) R^f) \tag{10}$$

$$X_{t+1} = H_{t+1} + K_{t+1} + L_{t+1} + Income_{t+1} - Expense_{t+1} - Tax_{t+1} \tag{11}$$

[75] The CRRA risk aversion parameter $\gamma = 5$ in the benchmark model. According to Horneff et al. (2020), those parameter values are also in line with those used in prior work on life-cycle portfolio choice. For simplicity, the benchmark result has been done without bequest motive. Appendix shows sensitivity test for other parameter values.

Household income $Income_{t+1}$ includes 1) Social Security benefits $Y_{t+1} = A_{t+1}\bar{Y}$, where $\bar{Y}$ is the base level of annual benefit for a typical worker retired at 65 in 2020, and A_{t+1} is the benefit adjustment status equals to 1 if no policy changes and less than 1 if benefit cut happens; and 2) the proceeds from selling the house if the liquid assets are not sufficient to cover a financial shock such as unexpected, large medical expenditures.[76] The expense term $Expense_{t+1}$ includes: 1) medical expenditures M_{t+1}; 2) the family transfer F_{t+1} if it happens; and 3) the rent payment if the house has been sold.[77] A flat marginal tax rate of 15 percent is assumed.[78]

In real life, households that lack sufficient wealth to cover their large medical expenses might rely on Medicaid or other means-tested government programs. The literature typically imposes no borrowing constraints and assumes a minimum consumption floor guaranteed by public transfers.[79] In this model, households who exhaust their assets are assumed to have a consumption floor of $10,000 per year, corresponding roughly to the income which would allow them to meet the Medicaid eligibility criteria.[80]

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[76] If there is a balance in the retirement savings account, the model assumes to make withdrawals to cover the shortage. If still not enough, the house will be sold.

[77] The rent payment is assumed to be 20% of the household Social Security benefit if the house has not been sold. One subtle improvement of the current model is to assume that homeowners facing a random maintenance cost (such as roof repair) modeled as a percentage of housing value.

[78] The taxable income in this project is defined as adjusted gross income plus nontaxable interest plus half of Social Security benefits. Since the model does not distinguish between capital gains and yield on risky assets, there is no differential taxation on dividend and capital gains. To apply the current progressive tax system with seven income tax brackets 10%, 12%, 22%, 24%, 32%, 35% and 37% (IRS 2019) instead of a flat marginal rate assumption has no significant change to the result.

[79] The consumption floor plays the role as a valuable safeguard against catastrophic medical costs. This assumption has limited affect for the purpose of this study, i.e., quantifying the risk for a typical household. Hubbard, Skinner, and Zeldes (1995) find that such social insurance programs discourage saving at the bottom of the wealth distribution, but have little effect on the wealth accumulation trajectory of more affluent individuals.

[80] See Centers for Medicare & Medicaid Services (2020). For an individual over age 65 in 2020, eligibility for institutional / nursing home Medicaid begins at $1,061 per month. Individuals above the Federal

To sum up, the state variables in this optimization problem are: age t, total wealth X_t, housing value H_t, retirement saving balance K_t, the level of permanent shock P_t as a proxy for health status, and the Social Security benefit adjustment status A_t. There are three choice variables: consumption C_t; withdrawal D_t from a retirement savings account; and the share invested in risky assets S_t. The stochastic shocks considered in this model include stock return R_{t+1}^e, housing return R_{t+1}^h, the innovation of permanent shock ε_{t+1}^{perm} and transitory shock ε_{t+1}^{tran} for medical expenditures M_{t+1}, family transfers F_{t+1}, and the Social Security policy change α_{t+1}.

As the number of state variables grows, the required computation increases exponentially; this creates a numerical burden called the "curse of dimensionality." A standard operation in the literature to solve this problem is to exploit the scale independence in the maximization problem by normalizing all variables with respect to one state variable, for example, permanent income (e.g., Cocco et al. 2005; Pang and Warshawsky, 2010; Horneff et al. 2020), or homogenous total wealth (e.g., Yogo 2018). However, there is no free lunch in using this approach. This approach works only if all of the shocks follow a random walk. If the underlying variable follows an autoregressive process such as the AR(1) process for health risk in this model, this approach can't be applied. Moreover, some policy rules, such as the Medicaid requirement, have fixed amounts. To apply those rules, the state variable still needs to be tracked. To mitigate

Poverty Line may also face cost sharing of 10 percent of costs (see Kaiser Family Foundation 2017); consequently, they will retain roughly $10,000 per year.

the computational issue, this paper takes a different approach by exploiting the parallel computing techniques with distributed clusters (Linux cluster servers).[81] Other numerical skills to speed up the backward induction process include discretizing the continuous state variables, multidimensional Cubic Spline interpolations, and Gaussian quadrature for numerical integrations (Judd et al. 2011). The detail of the solution method is provided in the appendix.

3.7 ALTERNATIVE MODELS AND UTILITY-EQUIVALENT WEALTH

The alternative objective and subjective models are solved in the same way as their respective benchmark models – with one risk removed at a time (while other risks stay the same) by the following way: 1) the longevity risk will be removed by fixing the life span of the model at the life expectancy; 2) the market risk, health risk and family risk will each be removed independently by using the mean level to replace the random shocks; and 3) the policy risk is removed by fixing the starting year of the Social Security benefit adjustment.[82] After solving the model with, for example, the subjective health risk removed, the risk-averse retiree have a higher-level lifetime expected utility and will be better off. Then, this project calculates the required initial wealth under this circumstance to reach the same level of lifetime expected utility as in the benchmark with all the risks. The required initial wealth is lower due to the risk aversion assumption, and

[81] Under multiprocessing, the full version of the model runs about 25 hours.

[82] This is similar to the life span fixed at the life expectancy. The starting year of the benefit adjustment is the random variable, and it is assumed fixed at the expectation under the no risk alternative.

the decrease of the wealth is then used as the measurement to quantify this risk.[83] The process is repeated for all risks using either objective or subjective risk distribution to obtain two sets of the rankings.

[83] It essentially interprets the welfare gain by calculating the wealth required to reach the same maximized utility in the optimization model. Many other measurements and methodologies are essentially based on the same spirit. For example, annuity equivalent wealth (AEW) such as in Kotlikoff and Spivak (1981), Brown (2001), and Milevsky and Huang (2018), and average certainty equivalent consumption (ACE) such as in Warshawsky (2017).

4 RESULTS

This section has three parts. The first section compares the empirical risk distributions and the estimated subjective risk distributions. The second section illustrates the lifecycle path for typical households. The third section ranks the retirement risks from both objective and subjective perspectives and discusses the policy implication.

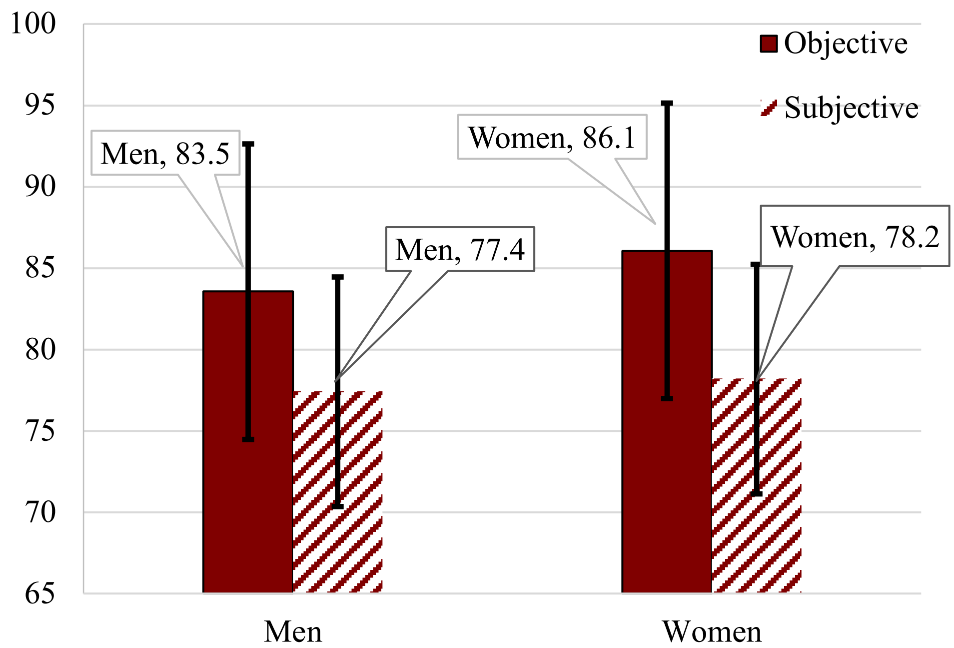
4.1 COMPARISON OF RISK DISTRIBUTIONS

First, Figure 4 compares the life expectancy and standard deviation calculated from the population life tables (SSA, 2019) with the parametric model estimated from subjective data in the HRS. Based on the life table, the life expectancies for men and women at age 65 in 2020 are 84 and 86, with a standard deviation of 10 years. However, in the estimation of subjective expectations, life expectancy is only 77 for men and 78 for women, with a smaller standard deviation of 7 years. This pessimistic subjective expectation and smaller fluctuation is consistent with the findings in O'Dea and Sturrock (2018).[84] It is not surprising, because parental longevity has been shown to be an important source of subjective life expectancy (Griffin et al 2013).[85] The average parental death age for people who are around age 65 in the HRS 2016 is about 76.5, which is very close to the subjective estimation above. A lower subjective life expectancy and smaller

[84] The estimation of subjective life expectancy is slightly lower than O'Dea and Sturrock (2018).
[85] Griffin et al 2013 have a discussion of other factors such as 1) biomedical and genetic factors; 2) socioeconomic factors; 3) health behaviors; and 4) psychosocial factors.

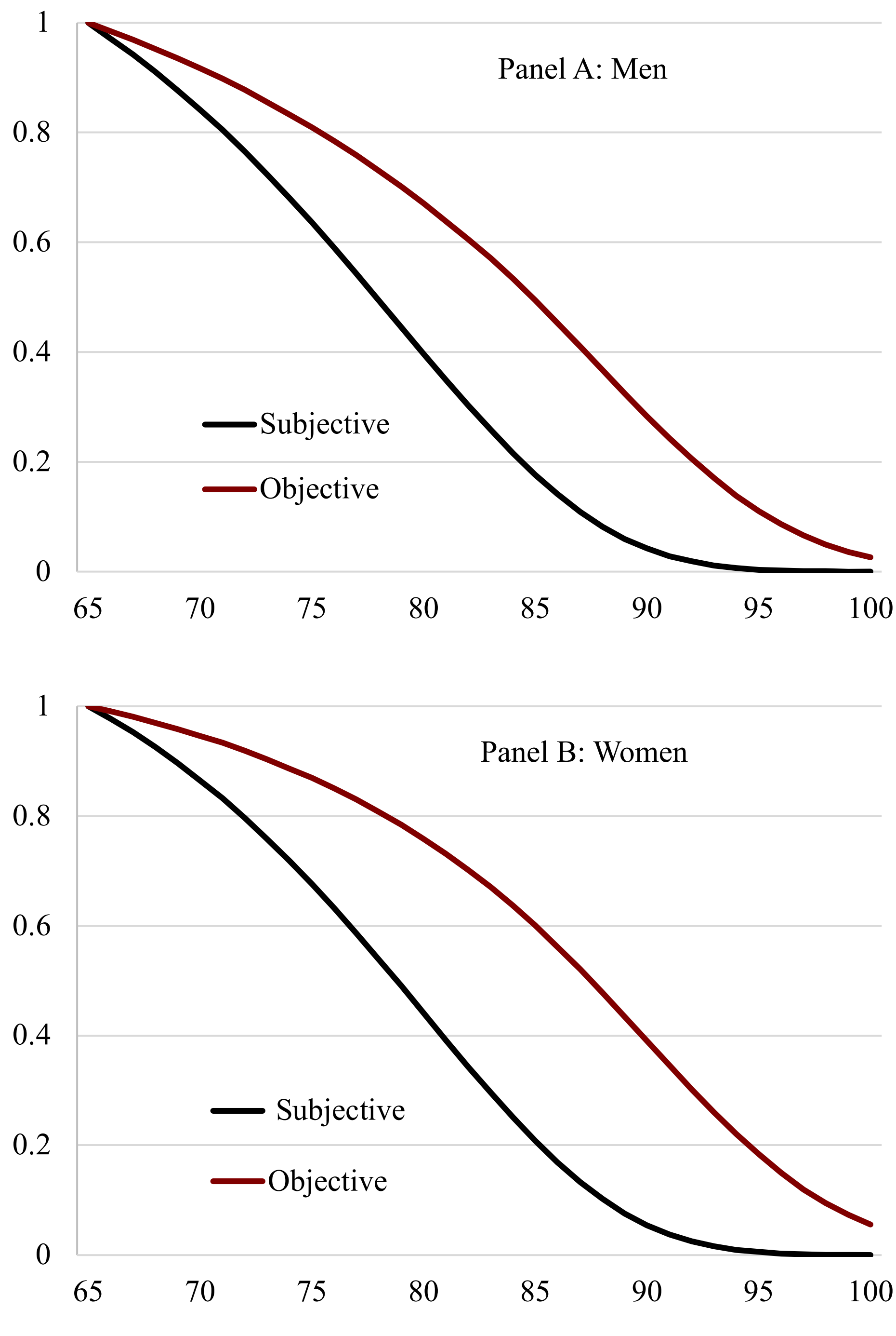
standard deviation may also be one factor explaining why annuities are not popular (e.g., O'Dea and Sturrock 2019).

Figure 4. *Life Expectancy and Standard Deviation.*



Source: author's calculation.
Note: The error bars are the standard deviations.

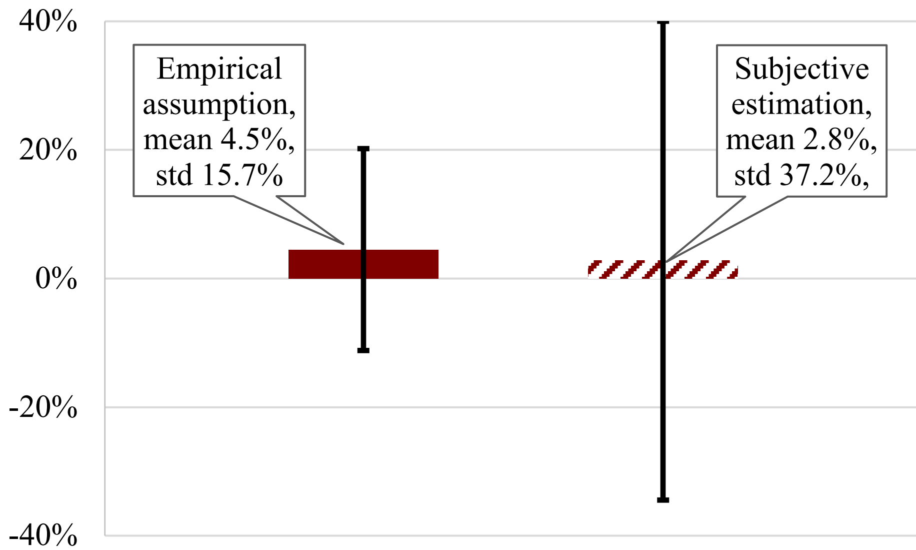
Figure 5. *Survival Curve at Age 65.*



Source: author's calculation.

Second, consistent with the literature and the data summarized in the previous sections, the estimation of subjective expectations for both the stock market and housing market are pessimistic and have a large standard deviation. Figure 6 shows that the estimated mean of annual return using subjective expectations is 2.8 percent in real terms, smaller than the 4.5 percent in the objective model, and the standard deviation for subjective expectations is 37.2 percent, more than double of 15.7 percent from the empirical data.

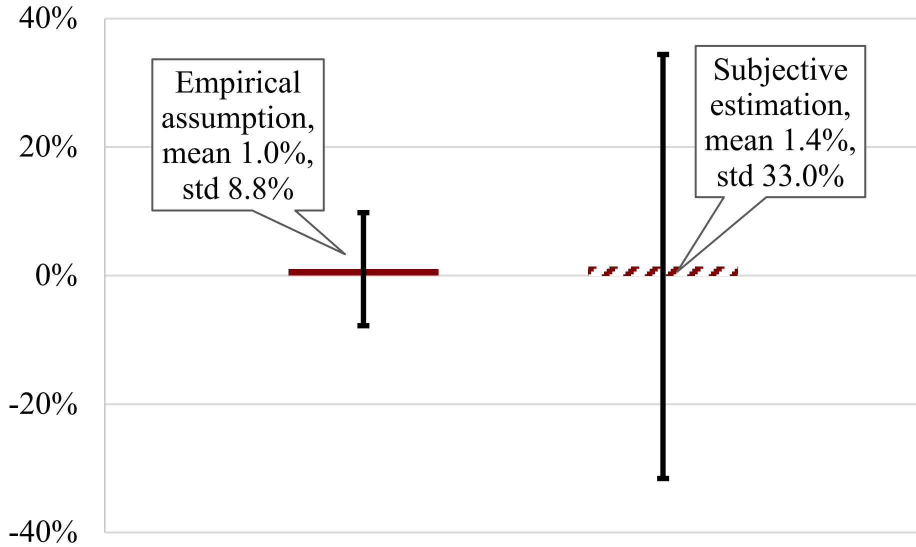
Figure 6. *Stock Market Returns, Empirical Assumption vs. Subjective Estimation*.



Source: author's calculation.

The estimate for the housing returns in Figure 7 shows similar pattern. One might blame this pessimistic perspective and large standard deviation on the after effects of the 2008-09 financial crisis. However, Heiss et al. (2019) study the subjective expectations over the period of the crisis and find a similar result. Given such a large standard deviation, it is reasonable to speculate a much higher ranking for market risk on the subjective list.

Figure 7. *Housing Market Returns, Empirical Assumption vs. Subjective Estimation.*

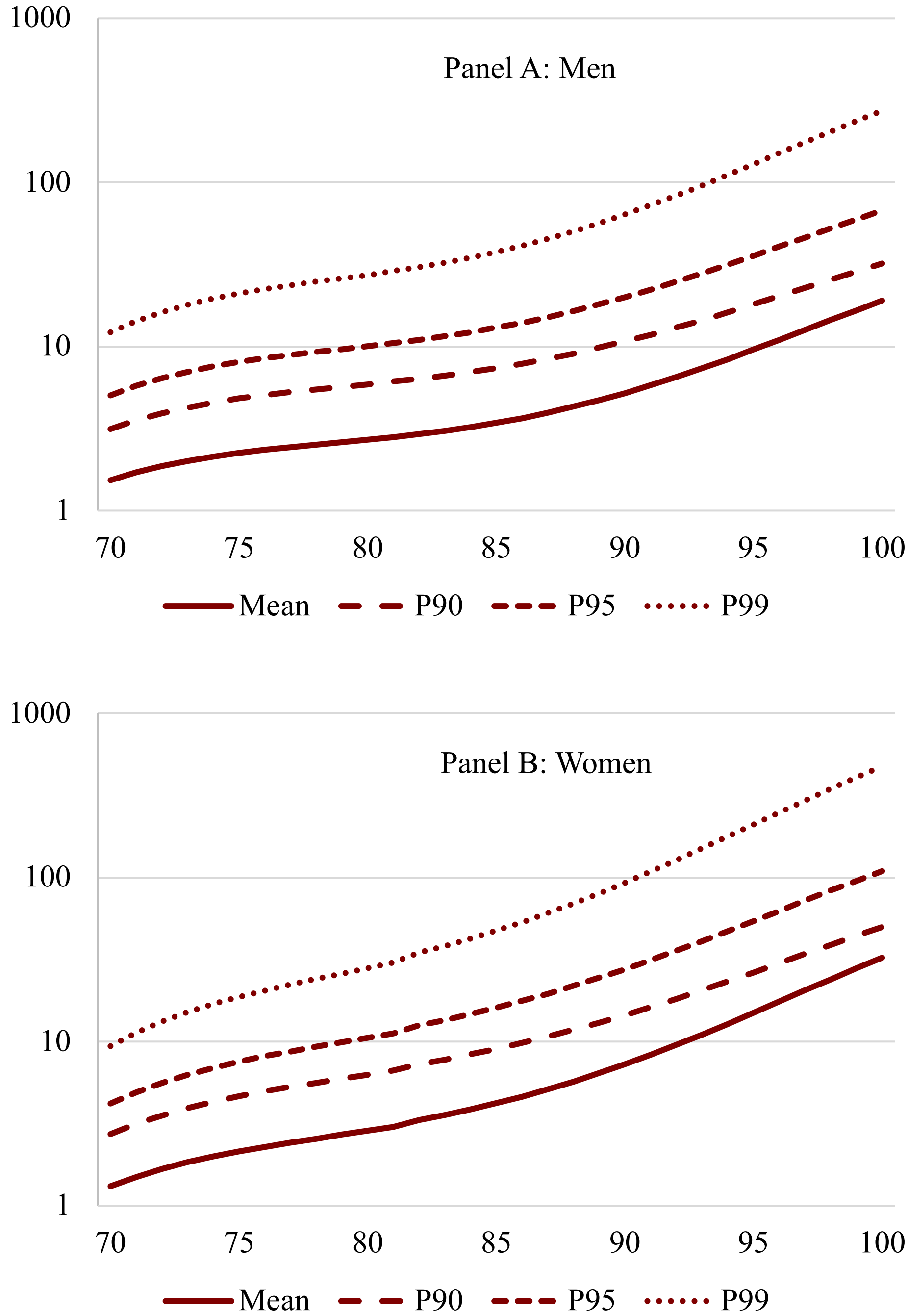


Source: author's calculation.

Interestingly, the estimation of medical expenditures shows mixed result. While the empirical model shows a clear upward trend of health spending in Figure 8 for men and women after age 70, the estimation based on subjective expectations in Figure 9 shows a flat pattern as people age. Comparing Figure 8 and Figure 9, the result suggests that retirees overestimate their medical spending at the beginning of their retirement years, and it turns out that those who survive to old ages are biased toward underestimating their medical costs in late life. This might explain one of the reasons people don't buy long-term care insurance (see Henning-Smith and Shippee, 2015).[86]

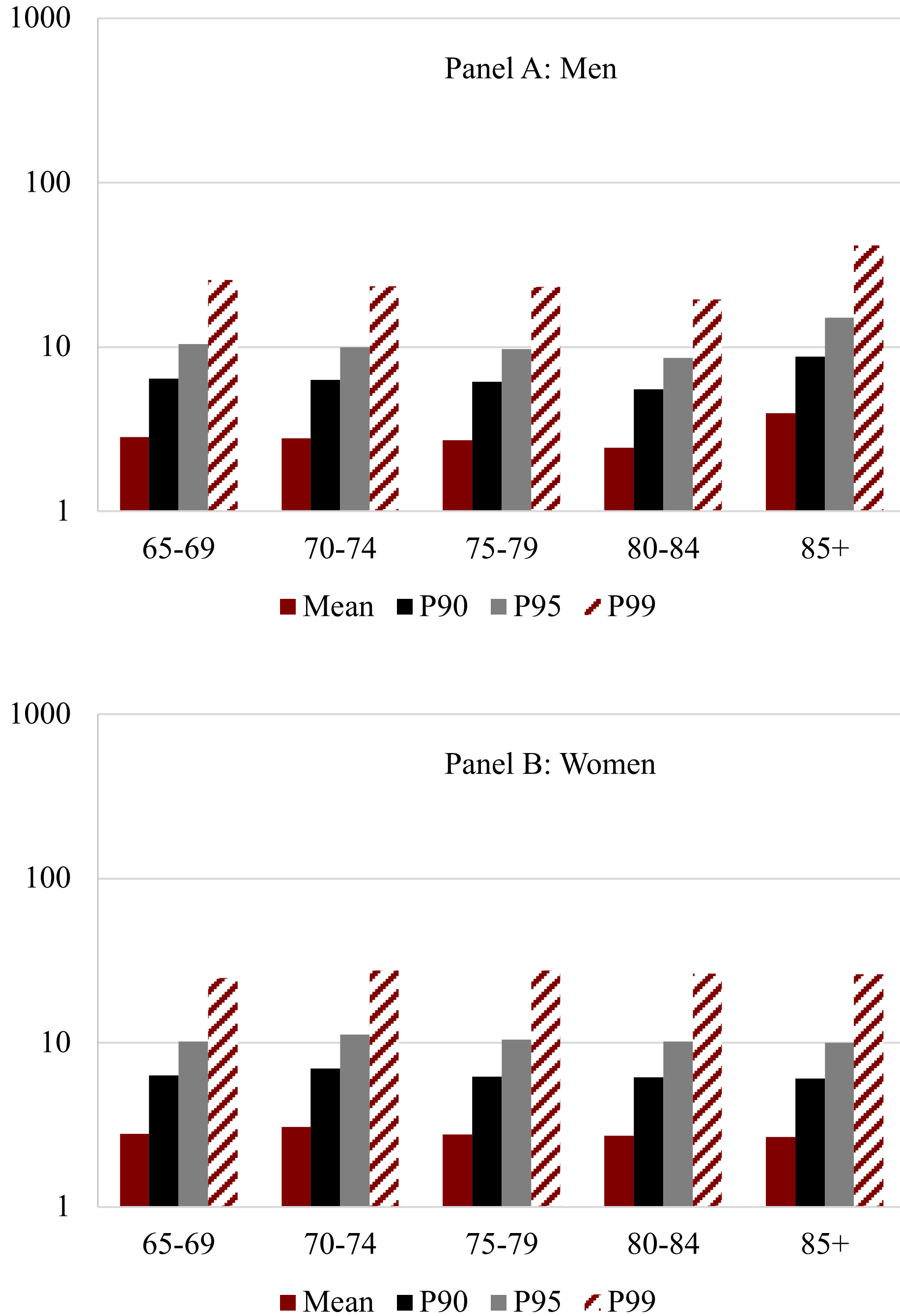
[86] They find that 60 percent of respondents believed that they were unlikely to need long-term services and supports in the future, whereas the evidence suggests that nearly 70 percent of older adults will need them at some point.

Figure 8. *Medical Expenditure Estimated from Empirical Data, by Age and Gender.*



Source: author's calculation.

Figure 9. *Medical Expenditure from Subjective Estimation.*

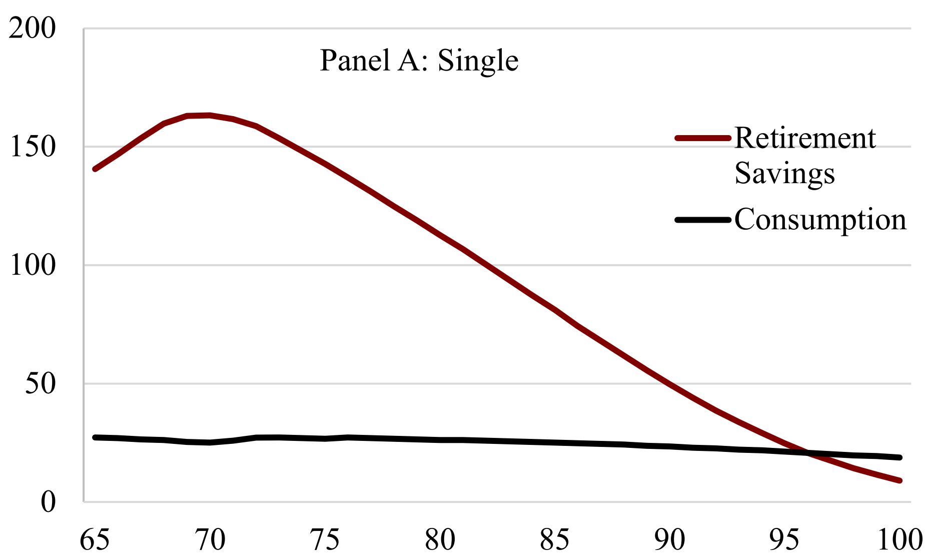


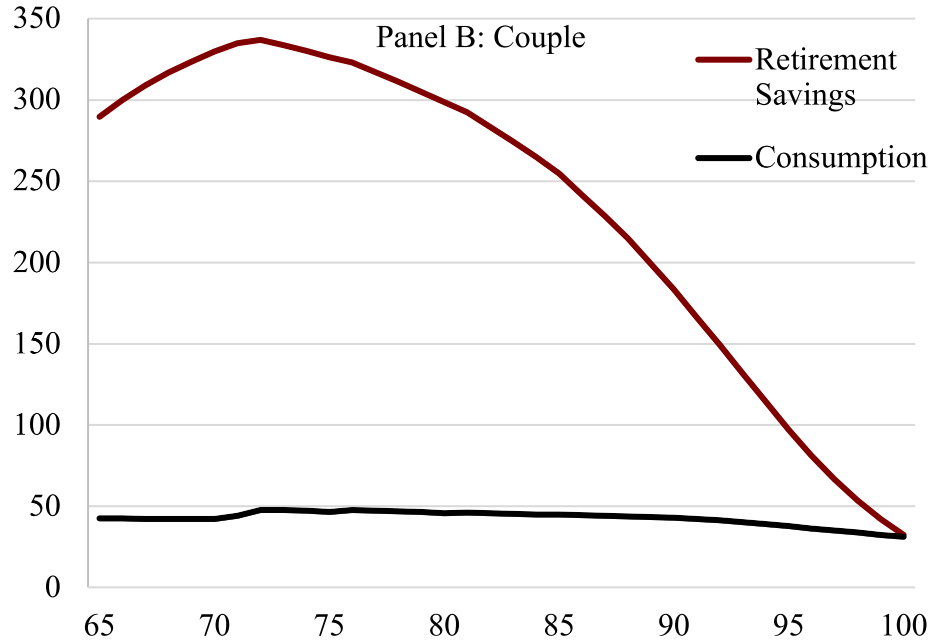
Source: author's calculation.

4.2 LIFE CYCLE PATH SIMULATION

Solving the life cycle model is a complicated process. And its product, the optimized policy function indicating how much to consume and invest over the life cycle, is often a multi-dimensional function that is not intuitive to visualize. Therefore, it is better to perform Monte Carlo simulations and look at the simulated life cycle paths for consumption and wealth. The first step is to apply the empirical risk distributions of all five risks to the benchmark model in the objective analysis. Figure 10 illustrates the average optimal life cycle patterns for a single man retiring at age 65 with initial wealth calibrated using the data in Table 1. The retirement savings increase in the beginning years of retirement and start declining with substantial withdrawals around early 70s when the RMD rule kicks in. The patterns of life cycle path for a typical married couple is similar.

Figure 10. *Life Cycle Path for Consumption and Retirement Savings.*



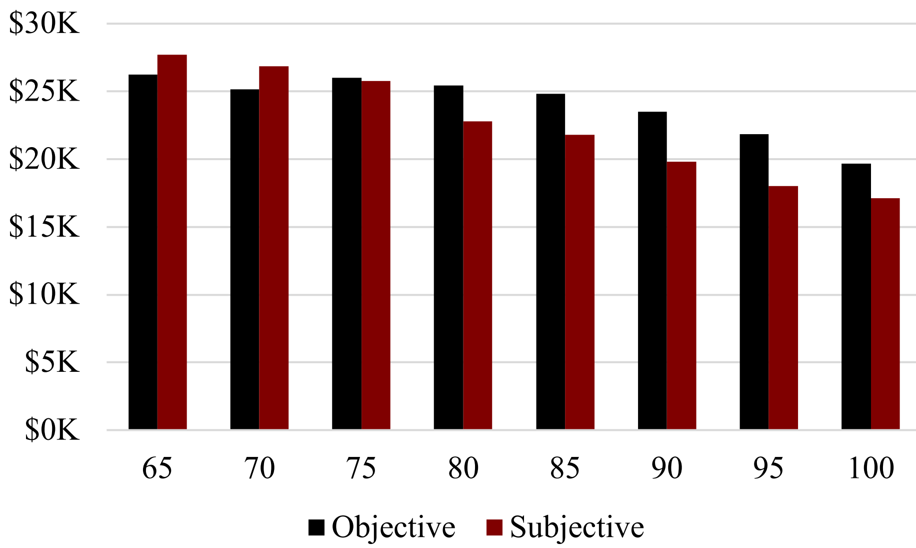


Source: author's calculation.

The next step is to solve the subjective benchmark model with the risk input from subjective risk distributions. The shape of life cycle patterns is similar to the objective analysis; however, two differences are noticeable. First, due to the shorter expected life span in the subjective model, the consumptions in early ages are slightly higher than the objective model, and significantly lower in late life, as shown in Figure 11. Second, the share of the financial assets invested in risky assets is much lower in the subjective model (see Figure 12), which is not surprising because of the pessimistic perspective on the market returns and large expected volatilities.[87] In the objective model, the share invested in stocks declines from 85 percent at age 65 to 52 percent at age 100; while in the same period of life, the percentage drops from 45 to 12 in the subjective model.

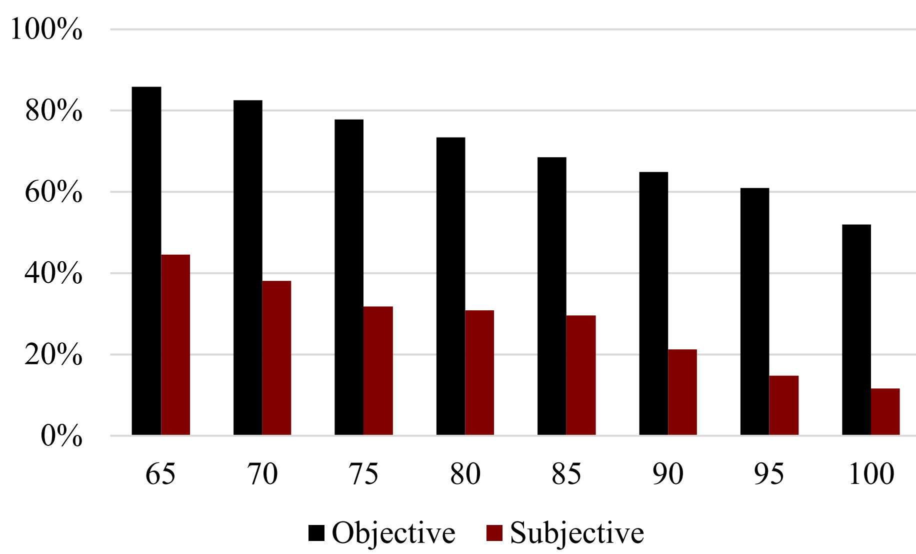
[87] The financial assets here include both the retirement savings and liquid assets.

Figure 11. *Lifetime Consumption Pattern, Objective Model vs. Subjective Model*.



Source: author’s calculation.

Figure 12. *Portfolio Share Invested in Stocks, Objective Model vs. Subjective Model.*



Source: author’s calculation.

4.3 COMPARISON OF RISK DISTRIBUTIONS

The final step is to compare the rankings of the risks that used the empirical data as inputs with the risks perceived by retirees. Each risk is measured using the method of *utility-equivalent wealth*. As the result of removing one risk, a risk-averse retiree would need less initial retirement wealth to reach the same lifetime utility level, and this wealth decease quantifies the economic value of the risk. The ranking and the value of each source of risks for single men can be found in Table 10.

Table 10. *Objective Risk Ranking for Single Men.*

Ranking	Source	Value
1	Longevity Risk	27.2%
2	Health Risk	14.0%
3	Market Risk	10.8%
4	Family Risk	3.2%
5	Policy Risk	0.1%

Source: author's calculation.

The three main sources of objective risk, from highest to lowest, are longevity risk, health risk, and market risk. It is not surprising that longevity risk is at the top of the list, because it affects the planning time horizon for retirement life. Interestingly, the value of 27 percent for the longevity risk is close to the 30 percent suggested in the literature (e.g., Mitchell et al. 1999; Milevsky and Young 2018). Health risk ranks in second place, mainly due to the unpredictability of medical expenditures in late life, particularly the cost of long-term care. Market risk ranks third, thanks to retirees' relatively long investment horizon, which is about 20 years for average life expectancy. Family risk and policy risk are the smallest risks. One big reason the policy risk is small is that Social Security reform is unlikely to have a significant impact on people who have already retired. For younger cohorts who have not retired yet, this risk is likely to be much larger. The risk ranking for married couples mirrors the result in singles, as shown in Table 11. Because of the existence of the spouse, the relative value of the risks is larger overall.

Table 11. *Objective Risk Ranking for Married Couples.*

Ranking	Source	Value
1	Longevity Risk	33.4%
2	Health Risk	28.5%
3	Market Risk	22.2%
4	Family Risk	9.1%
5	Policy Risk	0.1%

Source: author's calculation.

Table 12. *Subjective Risk Ranking for Single Men.*

Ranking	Source	Value
1	Market Risk	31.0%
2	Longevity Risk	14.6%
3	Health Risk	9.6%
4	Family Risk	1.1%
5	Policy Risk	0.3%

Source: author's calculation.

To complete the analysis, Table 12 shows the risk ranking from the subjective model. Given the large volatility of subjective expectations, it is not surprising to see that market risk is now at the top of the list. The health risk is not as large as in objective ranking, because retirees significantly underestimate the medical expenses in old ages. Due to the pessimistic and relatively certain subjective life expectation comparing to what the life table implies, the longevity risk is smaller in subjective analysis. A shorter expected life span also intensifies the market risk expectation because of a shorter investment horizon and reduces the subjective health risk due to lower chance facing the uncertain medical expenses in late life.

The policy implications of this paper are threefold. First, the rankings from the objective and subjective perspectives paint a clear picture: retirees do not have an accurate understanding of their true retirement risks. This finding highlights the importance of educating the public on the actual sources of retirement risks, as outlined in the financial literacy literature (e.g., Mitchell and Lusardi 2011). Second, this paper provides unique insight into the need for lifetime income products, such as annuities, which hedge longevity risk and market risk at the same time. Policymakers should facilitate the inclusion of annuities in retirement plans and makes annuities portable between employer retirement plans.[88] Finally, long-term care is also a significant risk faced by retirees, but one they often underestimate. Better designed public programs and private products, possibly integrated with life annuities, could be encouraged to protect retirees with limited financial resources from this potentially cartographic risk.

[88] The recent passed Setting Every Community Up for Retirement Enhancement (SECURE) Act is a good example.

5 CONCLUSION

Planning for retirement has always been challenging, because retirees with limited financial resources face numerous risks, including out-living their money (longevity risk), investment losses (market risk), unexpected health expenses (health risk), the unforeseen needs of family members (family risk), and even retirement benefit cuts (policy risk). First, it is challenging to analyze these risks within a single framework, because they affect retirees through multiple dimensions, such as their planning horizons, the value of their investment holdings, unexpected expenditures, and income disruptions. It is also unclear whether retirees perceive their risks accurately, because their beliefs about those risks often deviate from what the empirical data show.

This paper develops a life cycle model of a typical retired household facing the five categories of risk discussed above. To perform the parallel analyses from both the *objective* and *subjective* perspectives, this study first applies the *objective* risk distributions from the empirical data, such as life tables and historical market returns, and, in a second step, estimates the *subjective* risk distributions from the survey data in the HRS. Using the method of *utility-equivalent wealth*, the parallel analyses quantify the five risks to generate two rankings – one for objective and one for subjective risk. The biggest risk in the objective ranking is longevity risk, followed by health risk and market risk. Policy risk ranks at the bottom, because Social Security reform is unlikely to have a significant impact on people who have already retired. At the top of the subjective ranking is market risk, which reflects retirees' exaggerated assessments of market volatility. Perceived longevity risk and health risk rank lower, because retirees are pessimistic about their survival probabilities and often underestimate their health costs in late life. The results highlight the importance of educating retirees on the sources of their retirement risks. Moreover, this paper provides a unique angle to encourage the use of annuities to hedge both the longevity risk and market risk and to emphasize the demand for long-term care insurance to cover the risk of high medical costs in late life.

This paper provides three possible avenues for future research. First, this model estimates the risks for the typical retired household. The model and methodology could also be applied to various household types to obtain a comprehensive picture of the perception gap based on socioeconomic status and other demographics. Second, the risks were independent in this model but that is not the reality. For example, mortality risk is highly correlated with health status, which determines the risk of large medical expenditure. It is therefore important to explore the interactions between different sources of risk and how these interactions complicate the task of retirement planning. Finally, more work needs to be done to improve the estimation of the subjective risk distributions. For example, which type of distribution would best represent the risk expectations in people's minds? How can the estimation of the rounding standard be improved using the survey data? And could a learning paradigm (Athey, 2018) be embedded in the analysis that would allow retirees' expectations and resulting decision-making to evolve as they experience real-life risks?

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APPENDIX

Table A - 1. *Current-Law Scheduled Benefits and Replacement Rates for Hypothetical Retired Workers in their First Year of Benefit Receipt at Age 65.*

Year of birth	Year attain age 65	Wage-indexed 2019 dollars	Percent of career average earnings
Scaled very low earnings: (career-average earnings for 2018 equal $12,949)			
1953	2018	$9,307	71.1
1954	2019	9,518	73.5
1955	2020	9,431	73.3
1956	2021	9,092	70.5
1957	2022	8,904	68.9
Scaled low earnings: (career-average earnings for 2018 equal $23,308)			
1953	2018	12,183	51.7
1954	2019	12,451	53.4
1955	2020	12,348	53.3
1956	2021	11,908	51.3
1957	2022	11,657	50.1
Scaled medium earnings: (career-average earnings for 2018 equal $51,795)			
1953	2018	20,076	38.4
1954	2019	20,538	39.7
1955	2020	20,355	39.6
1956	2021	19,627	38.1
1957	2022	19,222	37.2
Scaled high earnings: (career-average earnings for 2018 equal $82,872)			
1953	2018	26,605	31.8
1954	2019	27,208	32.8
1955	2020	26,971	32.8
1956	2021	25,993	31.5
1957	2022	25,447	30.8
Steady maximum earnings: (career-average earnings for 2018 equal $127,061)			
1953	2018	32,385	25.3
1954	2019	33,134	26.1
1955	2020	32,875	26.0
1956	2021	31,721	25.0
1957	2022	31,069	24.4

Source: Clingman, Burkhalter, and Chaplain (2019).

Note: Average of highest 35 years of wage-indexed earnings through the year prior to retirement. The value is for retirement in 2019. Thus, the annual earnings used for this average are wage-indexed to 2018. The result is based on intermediate assumptions of the 2019 OASDI Trustees Report.

Table A - 2. *Family Transfer over Two-year Period, by Transfer Types*.

Panel A. Total transfer (net)

Age	All households		Among households who made family transfer					
	Samples	Made transfers	Samples	Mean	P50	P75	P90	P95
50-64	7,784	52.6%	3,890	$13,195	$3,400	$10,000	$30,000	$57,622
65-74	4,713	42.8	1,918	9,580	3,000	10,000	22,651	38,000
75-84	3,973	34.0	1,302	11,684	2,800	10,000	25,000	50,000
85+	1,325	28.3	387	9,261	2,000	10,200	33,500	58,736
Total	17,795	45.6	7,497	11,901	3,000	10,000	27,000	50,000

Panel B. Transfer to children

Age	All households		Among households who made family transfer					
	Samples	Made transfers	Samples	Mean	P50	P75	P90	P95
50-64	6,908	47.7%	2,899	$15,719	$4,000	$12,500	$33,000	$68,000
65-74	4,377	39.1	1,616	10,377	3,700	10,000	24,000	37,977
75-84	3,733	32.6	1,147	13,294	3,000	10,000	25,000	50,000
85+	1,240	28.2	359	10,940	1,500	10,000	31,000	60,000
Total	16,258	41.7	6,021	13,760	3,700	11,500	30,000	55,000

Panel C. Transfer to parents

Age	All households		Among households who made family transfer					
	Samples	Made transfers	Samples	Mean	P50	P75	P90	P95
50-64	7,784	11.8%	1,078	$3,157	$2,000	$4,000	$7,000	$12,000
65-74	4,713	5.1	215	4,247	1,900	5,000	10,000	12,400
75-84	3,973	0.7	32	4,148	2,800	8,000	10,000	15,000
85+	1,325	0.1	2	845	1,000	1,000	1,000	1,000
Total	17,795	7.6	1,327	3,387	2,000	4,000	8,000	12,000

Panel D. Transfer to relatives

Age	All households		Among households who made family transfer					
	Samples	Made transfers	Samples	Mean	P50	P75	P90	P95
50-64	7,654	12.6%	907	$4,506	$2,000	$4,000	$10,000	$20,000
65-74	4,662	11.3%	447	4,786	$1,500	$3,000	$8,000	$10,000
75-84	3,930	7.2	226	5,429	$1,500	$4,000	$10,000	$25,000
85+	1,307	7.8	82	4,013	$1,000	$3,000	$12,000	$20,000
Total	17,553	11.1	1,662	4,659	$1,800	$4,000	$10,000	$20,000

Panel E. Transfer from children

Age	All households	Among households who made family transfer

	Samples	Made transfers	Samples	Mean	P50	P75	P90	P95
50-64	6,930	5.1%	479	$3,492	$1,900	$4,000	$7,000	$16,000
65-74	4,391	4.8	249	4,381	2,000	4,000	8,000	15,500
75-84	3,762	6.2	262	5,972	2,000	5,000	10,000	20,000
85+	1,245	7.1	95	6,305	2,500	5,000	12,000	28,000
Total	16,328	5.3	1,085	4,392	2,000	4,000	8,500	18,960

Panel F. Transfer from relatives

Age	All households		Among households who made family transfer					
	Samples	Made transfers	Samples	Mean	P50	P75	P90	P95
50-64	7,661	4.7%	331	$9,939	$2,500	$6,000	$20,000	$50,000
65-74	4,663	1.9	80	7,212	2,000	5,500	10,000	25,000
75-84	3,937	1.5	56	7,646	1,500	5,000	14,000	20,000
85+	1,311	2.6	25	5,070	1,000	4,300	12,000	30,000
Total	17,572	3.3	492	9,139	2,000	5,500	15,000	30,000

Source: HRS 2014.
Note: In 2014 dollars.

Table A - 3. *The Expectation Questions in the HRS.*

Risk type	Wording in the survey
Longevity Risk	What is the percent chance that you will live to be [75/80/85/90/95/100] or more?
Market Risk	By next year at this time, what is the percent chance that mutual fund shares invested in blue chip stocks like those in the Dow Jones Industrial Average will be worth more than they are today?
Market Risk	By next year at this time, what is the percent chance that mutual fund shares invested in blue chip stocks (like those in the Dow Jones Industrial Average) will have [gained/ fallen] in value by more than 20 percent compared to what they are worth today?

Market Risk	What do you think is the percent chance that by next year at this time your home will be worth [more/less] than it is today?
Market Risk	By this time next year, what is the percent chance that the value of your home will have [fallen/gained] in value by more than [10/20/30/40] percent compared to what it is worth today?
Health Risk	What are the chances that you will spend out-of-pocket for your own medical expenses more than [$500/$1,500/$3,000/$8,000] during the coming year?
Health Risk	What is the percent chance that you will move to a nursing home in the next five years?
Policy Risk	what do you think is the percent chance that the benefits you yourself are receiving from Social Security will be cut some time over the next 10 years?
Policy Risk	what do you think is the percent chance that over the next 10 years there will be changes to Social Security that will reduce your future benefits compared to what you would get under the current system?

Source: HRS 2010 – 2016.

Table A - 4. *Expectation of Housing Price Change in the Next Year.*

	Loss 40% more	Loss 30% more	Loss 20% more	Loss 10% more	Worth more	Gain 10% more	Gain 20% more	Gain 30% more	Gain 40% more
All	15.8%	18.0 %	20.0%	22.0%	52.6%	35.4%	27.1%	22.8%	19.1%
By gender:									
Men	13.2	14.1	16.8	19.7	53.7	33.6	23.1	19.0	16.1
Women	18.1	21.7	23.1	23.9	51.5	37.2	30.6	26.6	22.1
By year:									
2012	15.2	19.2	21.4	23.1	49.2	32.0	26.6	21.1	18.0
2014	14.6	15.7	19.1	18.8	47.8	35.3	27.0	23.3	20.0
2016	17.6	19.2	19.4	24.4	50.0	37.8	27.5	24.0	19.0
By age:									
65-69	14.6	16.5	20.3	22.9	53.7	37.2	26.6	22.5	18.4
70-74	15.6	18.9	20.1	21.8	51.5	34.8	26.8	23.9	18.5
75-79	16.2	18.4	18.9	21.3	51.8	38.5	28.5	23.2	20.1
80-84	14.5	19.6	19.6	21.2	53.3	30.6	28.0	22.2	21.7
85+	20.8	17.9	20.9	22.1	52.1	31.0	25.6	21.2	18.4

Source: HRS 2012 - 2016.

Table A - 5. *Expectation of Medical Spending in Next Year.*

	Spend \$1500+	Spend \$3000+	Spend \$8000+
All	42.7%	23.6%	10.8%
By gender:			
Men	44.0	24.2	10.6
Women	41.6	23.1	11.0
By year:			
2010	40.8	22.0	9.8
2012	43.0	23.7	10.7
2014	42.4	23.5	11.0
2016	44.2	24.8	11.7
By age:			
65-69	44.1	24.7	11.1
70-74	45.0	24.7	11.4
75-79	41.4	22.5	10.2
80-84	40.2	22.0	10.1
85+	37.3	20.8	10.3

Source: HRS 2010 - 2016.

Table A - 6. *Expectation of Family Transfers $5,000 or more in Next 10 Years*.

	Samples	Mean	Std
All	46,439	34.8%	37.5%
By gender:			
Men	19,066	41.5	38.8
Women	27,373	29.5	35.7
By year:			
2002	14,446	34.4	37.6
2004	16,642	35.1	37.5
2006	15,351	34.7	37.6
By age:			
65-74	16,092	30.8	36.1
75-84	9,005	26.5	36.1
85+	2,666	22.5	35.4

Source: HRS 2002-2006

Table A - 7. *Expectation of Social Security Benefit Reduction in Next 10 Years.*

	Samples	Mean	Std
All	48,966	43.3%	31.0 %
By gender:			
Men	20,703	41.2	31.5
Women	28,263	44.9	30.6
By year:			
2006	8,056	38.8	29.5
2008	8,171	43.8	29.6
2010	8,293	51.6	31.7
2012	8,121	49.6	31.2
2014	8,299	38.8	30.6
2016	8,026	38.2	30.3
By age:			
65-69	12,475	44.4	30.8
70-74	13,144	43.2	30.7
75-79	10,962	42.7	30.9
80-84	7,057	42.0	31.7
85+	5,328	42.6	31.9

Source: HRS 2006-2016.

Table A - 8. *United States Life Table Functions for Cohort born in 1955.*

Panel A: Male

x	q(x)	l(x)	d(x)	L(x)	T(x)	e(x)
0	0.029631	100000	2963	97359	7376073	73.76
1	0.001886	97037	183	96945	7278714	75.01
2	0.001174	96854	114	96797	7181768	74.15
3	0.000912	96740	88	96696	7084971	73.24
4	0.000740	96652	71	96616	6988275	72.30
5	0.000666	96580	64	96548	6891659	71.36
6	0.000564	96516	54	96489	6795111	70.40
7	0.000512	96462	49	96437	6698622	69.44
8	0.000471	96412	45	96389	6602185	68.48
9	0.000419	96367	40	96347	6505796	67.51
10	0.000374	96326	36	96308	6409450	66.54
11	0.000371	96290	36	96272	6313141	65.56
12	0.000433	96255	42	96234	6216869	64.59
13	0.000612	96213	59	96184	6120635	63.62
14	0.000875	96154	84	96112	6024451	62.65
15	0.001128	96070	108	96016	5928339	61.71
16	0.001402	95962	135	95894	5832324	60.78
17	0.001646	95827	158	95748	5736429	59.86
18	0.001837	95669	176	95582	5640681	58.96
19	0.001867	95494	178	95405	5545099	58.07
20	0.001929	95315	184	95224	5449695	57.18
21	0.001941	95132	185	95039	5354471	56.28
22	0.002024	94947	192	94851	5259432	55.39
23	0.002038	94755	193	94658	5164581	54.50
24	0.002033	94562	192	94466	5069923	53.62
25	0.002014	94369	190	94274	4975457	52.72
26	0.001910	94179	180	94089	4881183	51.83
27	0.001732	94000	163	93918	4787094	50.93
28	0.001667	93837	156	93759	4693176	50.01
29	0.001697	93680	159	93601	4599417	49.10
30	0.001800	93521	168	93437	4505816	48.18
31	0.002066	93353	193	93257	4412379	47.27
32	0.002143	93160	200	93060	4319123	46.36
33	0.002287	92960	213	92854	4226062	45.46
34	0.002440	92748	226	92635	4133208	44.56
35	0.002555	92522	236	92403	4040573	43.67

36	0.002695	92285	249	92161	3948170	42.78
37	0.002821	92036	260	91907	3856009	41.90
38	0.003021	91777	277	91638	3764102	41.01
39	0.003214	91500	294	91353	3672464	40.14
40	0.003401	91206	310	91050	3581112	39.26
41	0.003265	90895	297	90747	3490061	38.40
42	0.003133	90599	284	90457	3399314	37.52
43	0.003299	90315	298	90166	3308858	36.64
44	0.003550	90017	320	89857	3218692	35.76
45	0.003903	89697	350	89522	3128835	34.88
46	0.004278	89347	382	89156	3039313	34.02
47	0.004560	88965	406	88762	2950157	33.16
48	0.004937	88559	437	88341	2861394	32.31
49	0.005210	88122	459	87893	2773054	31.47
50	0.005719	87663	501	87412	2685161	30.63
51	0.006144	87162	536	86894	2597749	29.80
52	0.006447	86626	558	86347	2510855	28.98
53	0.006868	86068	591	85772	2424508	28.17
54	0.007347	85476	628	85162	2338736	27.36
55	0.007806	84848	662	84517	2253574	26.56
56	0.008502	84186	716	83828	2169056	25.76
57	0.009124	83470	762	83090	2085228	24.98
58	0.009801	82709	811	82304	2002138	24.21
59	0.010588	81898	867	81465	1919835	23.44
60	0.011468	81031	929	80566	1838370	22.69
61	0.012434	80102	996	79604	1757803	21.94
62	0.012967	79106	1026	78593	1678200	21.21
63	0.013770	78080	1075	77542	1599607	20.49
64	0.014474	77005	1115	76448	1522064	19.77
65	0.015217	75890	1155	75313	1445617	19.05
66	0.016070	74735	1201	74135	1370304	18.34
67	0.017043	73535	1253	72908	1296169	17.63
68	0.018166	72281	1313	71625	1223261	16.92
69	0.019448	70968	1380	70278	1151636	16.23
70	0.020942	69588	1457	68859	1081358	15.54
71	0.022617	68131	1541	67360	1012499	14.86
72	0.024404	66590	1625	65777	945138	14.19
73	0.026289	64965	1708	64111	879361	13.54
74	0.028349	63257	1793	62360	815250	12.89
75	0.030824	61464	1895	60516	752890	12.25

76	0.033712	59569	2008	58565	692374	11.62
77	0.036788	57561	2118	56502	633809	11.01
78	0.039991	55443	2217	54335	577307	10.41
79	0.043479	53226	2314	52069	522972	9.83
80	0.047440	50912	2415	49704	470903	9.25
81	0.052183	48497	2531	47231	421199	8.69
82	0.057988	45966	2665	44633	373967	8.14
83	0.065133	43300	2820	41890	329334	7.61
84	0.073579	40480	2978	38991	287444	7.10
85	0.083119	37502	3117	35943	248453	6.63
86	0.093521	34385	3216	32777	212510	6.18
87	0.104612	31169	3261	29539	179733	5.77
88	0.116313	27908	3246	26285	150195	5.38
89	0.128659	24662	3173	23076	123909	5.02
90	0.141724	21489	3046	19966	100834	4.69
91	0.155618	18444	2870	17009	80867	4.38
92	0.170464	15573	2655	14246	63859	4.10
93	0.186378	12919	2408	11715	49613	3.84
94	0.203472	10511	2139	9442	37898	3.61
95	0.220223	8372	1844	7450	28456	3.40
96	0.236283	6529	1543	5757	21006	3.22
97	0.251288	4986	1253	4359	15249	3.06
98	0.264876	3733	989	3239	10889	2.92
99	0.276698	2744	759	2365	7650	2.79
100	0.289052	1985	574	1698	5286	2.66
101	0.301963	1411	426	1198	3588	2.54
102	0.315455	985	311	830	2390	2.43
103	0.329557	674	222	563	1560	2.31
104	0.344294	452	156	374	997	2.20
105	0.359696	296	107	243	623	2.10
106	0.375793	190	71	154	379	2.00
107	0.392617	118	47	95	225	1.90
108	0.410202	72	30	57	130	1.81
109	0.428580	42	18	33	73	1.72
110	0.447790	24	11	19	40	1.63
111	0.467868	13	6	10	21	1.55
112	0.488855	7	3	5	10	1.46
113	0.510791	4	2	3	5	1.39
114	0.533720	2	1	1	2	1.31
115	0.557688	1	0	1	1	1.24

116	0.582742	0	0	0	0	1.17
117	0.608930	0	0	0	0	1.10
118	0.636306	0	0	0	0	1.04
119	0.664924	0	0	0	0	0.97

Panel B: Female

x	q(x)	l(x)	d(x)	L(x)	T(x)	e(x)
0	0.023076	100000	2308	97970	7997073	79.97
1	0.001718	97692	168	97608	7899103	80.86
2	0.000964	97525	94	97478	7801495	80.00
3	0.000761	97431	74	97394	7704017	79.07
4	0.000623	97356	61	97326	7606624	78.13
5	0.000522	97296	51	97270	7509297	77.18
6	0.000427	97245	42	97224	7412027	76.22
7	0.000389	97203	38	97184	7314803	75.25
8	0.000331	97166	32	97149	7217618	74.28
9	0.000300	97133	29	97119	7120469	73.31
10	0.000267	97104	26	97091	7023350	72.33
11	0.000261	97078	25	97066	6926259	71.35
12	0.000272	97053	26	97040	6829193	70.37
13	0.000322	97027	31	97011	6732154	69.38
14	0.000415	96995	40	96975	6635143	68.41
15	0.000486	96955	47	96932	6538168	67.44
16	0.000586	96908	57	96880	6441236	66.47
17	0.000637	96851	62	96820	6344357	65.51
18	0.000671	96790	65	96757	6247536	64.55
19	0.000626	96725	61	96694	6150779	63.59
20	0.000631	96664	61	96634	6054085	62.63
21	0.000623	96603	60	96573	5957451	61.67
22	0.000641	96543	62	96512	5860878	60.71
23	0.000662	96481	64	96449	5764366	59.75
24	0.000641	96417	62	96386	5667917	58.79
25	0.000646	96355	62	96324	5571531	57.82
26	0.000654	96293	63	96261	5475207	56.86
27	0.000627	96230	60	96200	5378946	55.90
28	0.000640	96170	62	96139	5282746	54.93
29	0.000652	96108	63	96077	5186607	53.97
30	0.000700	96045	67	96012	5090530	53.00
31	0.000778	95978	75	95941	4994519	52.04
32	0.000841	95903	81	95863	4898578	51.08

33	0.000883	95823	85	95780	4802715	50.12
34	0.000948	95738	91	95693	4706934	49.16
35	0.001002	95647	96	95599	4611242	48.21
36	0.001093	95552	104	95499	4515642	47.26
37	0.001170	95447	112	95391	4420143	46.31
38	0.001285	95335	123	95274	4324752	45.36
39	0.001391	95213	132	95147	4229478	44.42
40	0.001527	95080	145	95008	4134331	43.48
41	0.001598	94935	152	94859	4039323	42.55
42	0.001690	94783	160	94703	3944464	41.62
43	0.001806	94623	171	94538	3849760	40.69
44	0.001964	94452	185	94360	3755222	39.76
45	0.002145	94267	202	94166	3660863	38.84
46	0.002402	94065	226	93952	3566697	37.92
47	0.002633	93839	247	93715	3472745	37.01
48	0.002825	93592	264	93460	3379030	36.10
49	0.002996	93327	280	93188	3285570	35.20
50	0.003286	93048	306	92895	3192383	34.31
51	0.003516	92742	326	92579	3099488	33.42
52	0.003745	92416	346	92243	3006909	32.54
53	0.004000	92070	368	91886	2914666	31.66
54	0.004296	91701	394	91504	2822781	30.78
55	0.004520	91307	413	91101	2731276	29.91
56	0.004926	90895	448	90671	2640175	29.05
57	0.005344	90447	483	90205	2549504	28.19
58	0.005759	89964	518	89705	2459299	27.34
59	0.006266	89446	560	89165	2369594	26.49
60	0.006735	88885	599	88586	2280429	25.66
61	0.007358	88286	650	87962	2191843	24.83
62	0.007504	87637	658	87308	2103881	24.01
63	0.008036	86979	699	86630	2016573	23.18
64	0.008615	86280	743	85909	1929944	22.37
65	0.009285	85537	794	85140	1844035	21.56
66	0.010041	84743	851	84317	1758895	20.76
67	0.010879	83892	913	83435	1674578	19.96
68	0.011795	82979	979	82490	1591142	19.18
69	0.012807	82000	1050	81475	1508653	18.40
70	0.014005	80950	1134	80383	1427177	17.63
71	0.015371	79817	1227	79203	1346794	16.87
72	0.016805	78590	1321	77929	1267591	16.13

73	0.018288	77269	1413	76562	1189661	15.40
74	0.019898	75856	1509	75101	1113099	14.67
75	0.021817	74347	1622	73536	1037998	13.96
76	0.024092	72725	1752	71848	964462	13.26
77	0.026614	70972	1889	70028	892614	12.58
78	0.029366	69084	2029	68069	822586	11.91
79	0.032429	67055	2175	65968	754517	11.25
80	0.035959	64880	2333	63714	688549	10.61
81	0.040081	62547	2507	61294	624835	9.99
82	0.044876	60040	2694	58693	563541	9.39
83	0.050495	57346	2896	55898	504848	8.80
84	0.057014	54450	3104	52898	448950	8.25
85	0.064428	51346	3308	49692	396052	7.71
86	0.072694	48038	3492	46292	346360	7.21
87	0.081757	44546	3642	42725	300069	6.74
88	0.091586	40904	3746	39031	257344	6.29
89	0.102186	37158	3797	35259	218313	5.88
90	0.113584	33361	3789	31466	183054	5.49
91	0.125823	29571	3721	27711	151588	5.13
92	0.138960	25851	3592	24054	123877	4.79
93	0.153050	22258	3407	20555	99823	4.48
94	0.168151	18852	3170	17267	79268	4.20
95	0.183270	15682	2874	14245	62001	3.95
96	0.198142	12808	2538	11539	47756	3.73
97	0.212480	10270	2182	9179	36217	3.53
98	0.225985	8088	1828	7174	27038	3.34
99	0.238357	6260	1492	5514	19864	3.17
100	0.251410	4768	1199	4169	14350	3.01
101	0.265183	3569	947	3096	10182	2.85
102	0.279715	2623	734	2256	7086	2.70
103	0.295049	1889	557	1610	4830	2.56
104	0.311228	1332	414	1125	3219	2.42
105	0.328300	917	301	767	2095	2.28
106	0.346315	616	213	509	1328	2.16
107	0.365324	403	147	329	819	2.03
108	0.385383	256	99	206	490	1.92
109	0.406550	157	64	125	283	1.80
110	0.428887	93	40	73	158	1.69
111	0.452459	53	24	41	85	1.59
112	0.477334	29	14	22	44	1.49

113	0.503585	15	8	11	21	1.40
114	0.531289	8	4	6	10	1.31
115	0.557688	4	2	3	4	1.24
116	0.582742	2	1	1	2	1.17
117	0.608930	1	0	0	1	1.10
118	0.636306	0	0	0	0	1.04
119	0.664924	0	0	0	0	0.97

Source: U.S. Social Security Administration. 2019. “The Annual Report of the Board of Trustees of the Federal Old- Age and Survivors Insurance and Federal Disability Insurance Trust Funds.”
Note: Based on the Alternative 2 mortality probabilities used in the 2019 Trustees Report.

Table A - 9. *Subjective Mortality Model Estimation.*

	Coefficient	Std
Male	0.121	(0.031)
Black	-0.004	(0.042)
Hispanic	0.311	(0.062)
High school	-0.313	(0.036)
College	-0.599	(0.037)
Ever smoked	0.182	(0.035)
Constant	-5.133	(0.081)
γ	0.115	(0.004)
ς^{-1}	1.096	(0.042)

Source: Bissonnette et al. (2017)

Table A - 10. *Subjective Housing Return Estimation by Distribution Types, for Men*.

Ranking	Distribution Name	Mean	Std	Loss
1	Double Weibull	1.023738	0.559269	0.010705
2	Double Gamma	1.024124	0.463452	0.011706
3	Log Double Exponential (Log-Laplace)	1.046921	0.344028	0.017427
4	Laplace (Double Exponential, Bilateral Exponential)	1.033428	0.338347	0.017731
5	Hyperbolic Secant	1.035402	0.308437	0.024623

6	Von Mises	1.035695	0.280165	0.026476
7	Mielke’s Beta-Kappa	1.040389	0.296107	0.027782
8	Burr	1.040384	0.296105	0.027782
9	Fisk (Log Logistic)	1.040663	0.294630	0.027955
10	Generalized Logistic	1.035555	0.294055	0.028058
11	Logistic	1.035931	0.293930	0.028059
12	Exponentiated Weibull	1.037776	0.275568	0.032513
13	Power Log Normal	1.037474	0.275473	0.032696
14	Reciprocal Inverse Gaussian	1.039070	0.275084	0.032730
15	Inverted Gamma	1.038295	0.275085	0.032857
16	**Log Normal**	**1.038158**	**0.275059**	**0.032859**
17	Johnson SB	1.038112	0.275053	0.032860
18	Fatigue Life (Birnbaum-Saunders)	1.038033	0.275043	0.032861
19	Gamma	1.037898	0.275025	0.032863
20	Chi-squared	1.037909	0.275026	0.032863
21	Power Normal	1.035098	0.275233	0.032866
22	Generalized Gamma	1.037785	0.274975	0.032877
23	Beta Prime	1.039807	0.275328	0.032881
24	Rice	1.036388	0.274967	0.032887
25	Normal	1.036384	0.274966	0.032887
26	Log Gamma	1.036280	0.274967	0.032891
27	Beta	1.037777	0.274928	0.032891
28	Inverse Normal (Inverse Gaussian)	1.041149	0.275551	0.032954

29	Gauss Hypergeometric	1.037651	0.274421	0.033050
30	Generalized Extreme Value	1.041311	0.270896	0.034167
31	Weibull Minimum Extreme Value	1.033608	0.270673	0.034744
32	Maxwell	1.051646	0.277288	0.037388
33	Cosine	1.036534	0.263967	0.037866
34	Gumbel (Log Weibull, Fisher-Tippetts, Type I Extreme Value)	1.071183	0.304547	0.038922
35	Inverted Weibull	1.071481	0.305158	0.038987
36	Exponential Power	1.030982	0.264326	0.039957
37	Anglit	1.036439	0.260470	0.041800
38	Gumbel Left-skewed	1.002819	0.308583	0.041844
39	Rayleigh	1.057003	0.281824	0.041981
40	Generalized Exponential	1.057045	0.281777	0.041993
41	KStwo	1.066515	0.288116	0.042349
42	Semicircular	1.035914	0.259532	0.048512
43	Generalized Half-Logistic	1.033517	0.263782	0.051440
44	Power-function	1.031632	0.263854	0.057140
45	Half Normal	1.073635	0.251620	0.057263
46	Folded Normal	1.073636	0.251621	0.057263
47	Gompertz (Truncated Gumbel)	1.069682	0.242163	0.058138
48	Generalized Pareto	1.047993	0.246542	0.058600
49	Truncated Exponential	1.046373	0.243580	0.060858
50	Bradford	1.045949	0.242809	0.061285
51	Ksone	1.032440	0.266399	0.061976

52	Uniform	1.044617	0.242229	0.063116
53	Half-Logistic	1.091151	0.345673	0.063809
54	Exponential	1.107861	0.340755	0.064522
55	Pareto Second Kind (Lomax)	1.107861	0.340755	0.064522
56	Wald	1.139846	0.428259	0.065563
57	Gilbrat	1.167066	0.558812	0.067000
58	Noncentral Chi-squared	1.117906	0.306401	0.067772
59	Pareto	1.125868	0.436739	0.084718
60	Arcsine	1.022925	0.107593	0.181072
61	R-distribution	0.362800	0.792577	0.609748

Source: HRS 2012-2016 and author's calculation.

Table A - 11. *Objective Health Model Estimation.*

Panel A: Dynamics

Variable	Parameter	Estimate	Std
Autocorrelation, persistent part	η	0.922	(0.010)
Innovation variance, persistent part	$\sigma^2_{\varepsilon,perm}$	0.050	(0.008)
Innovation variance, transitory part	$\sigma^2_{\varepsilon,tran}$	0.665	(0.014)

Panel B: Mean and variance of the log of medical expenses

	Male		Female	
Age t	$m(t)$	$\sigma(t)$	$m(t)$	$\sigma(t)$
70	5.93657	1.37624	5.94819	1.25083
71	6.01512	1.39834	6.03638	1.28382
72	6.08147	1.41515	6.11238	1.31064
73	6.13728	1.42795	6.17783	1.33284
74	6.18411	1.43783	6.23430	1.35169
75	6.22343	1.44576	6.28327	1.36830
76	6.25663	1.45262	6.32611	1.38362
77	6.28503	1.45917	6.36415	1.39849

78	6.30981	1.46609	6.39858	1.41362
79	6.33213	1.47400	6.43055	1.42964
80	6.35301	1.48339	6.46107	1.44704
81	6.37342	1.49469	6.49112	1.46625
82	6.39420	1.50824	6.52154	1.48756
83	6.41615	1.52427	6.55314	1.51121
84	6.43994	1.54294	6.58658	1.53731
85	6.46620	1.56431	6.62248	1.56589
86	6.49542	1.58836	6.66134	1.59691
87	6.52804	1.61498	6.70361	1.63024
88	6.56440	1.64400	6.74961	1.66570
89	6.60476	1.67520	6.79962	1.70306
90	6.64927	1.70826	6.85377	1.74200
91	6.69803	1.74287	6.91217	1.78222
92	6.75100	1.77865	6.97479	1.82334
93	6.80813	1.81518	7.04156	1.86499
94	6.86919	1.85203	7.11227	1.90673
95	6.93395	1.88875	7.18667	1.94815
96	7.00202	1.92485	7.26439	1.98878
97	7.07298	1.95985	7.34499	2.02817
98	7.14628	1.99320	7.42793	2.06582
99	7.22131	2.02438	7.51261	2.10123
100	7.29736	2.05281	7.59830	2.13386
101	7.37364	2.07791	7.68423	2.16318
102	7.44925	2.09902	7.76949	2.18857

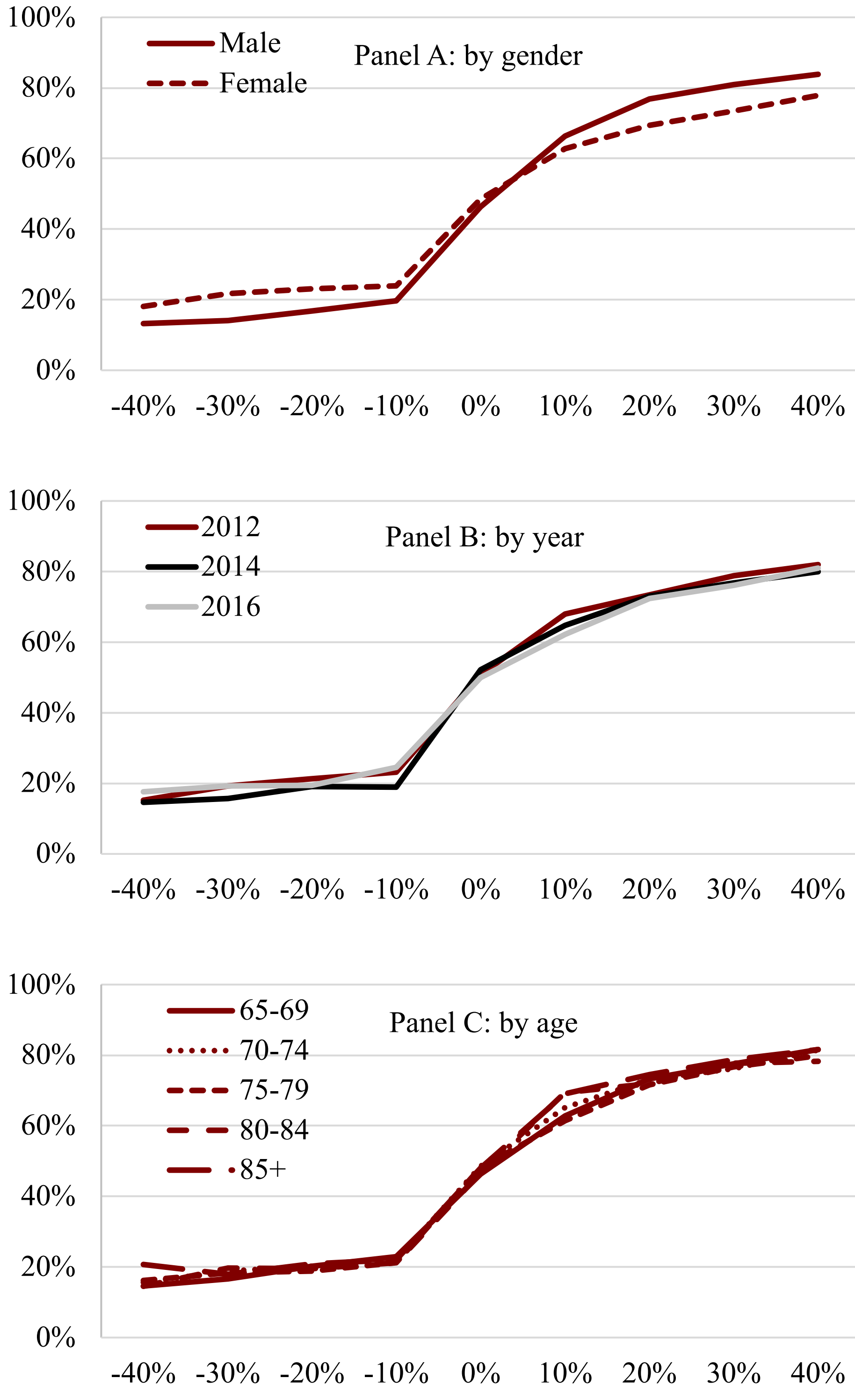
Source: De Nardi et al. (2010) and author's calculation.

Table A - 12. *Alternative Assumptions of Social Security Benefit Cut, for Single Men*.

Assumption	Risk Value
COLA change	0.1%
FRA to 70	1.0
25 percent cut	1.2

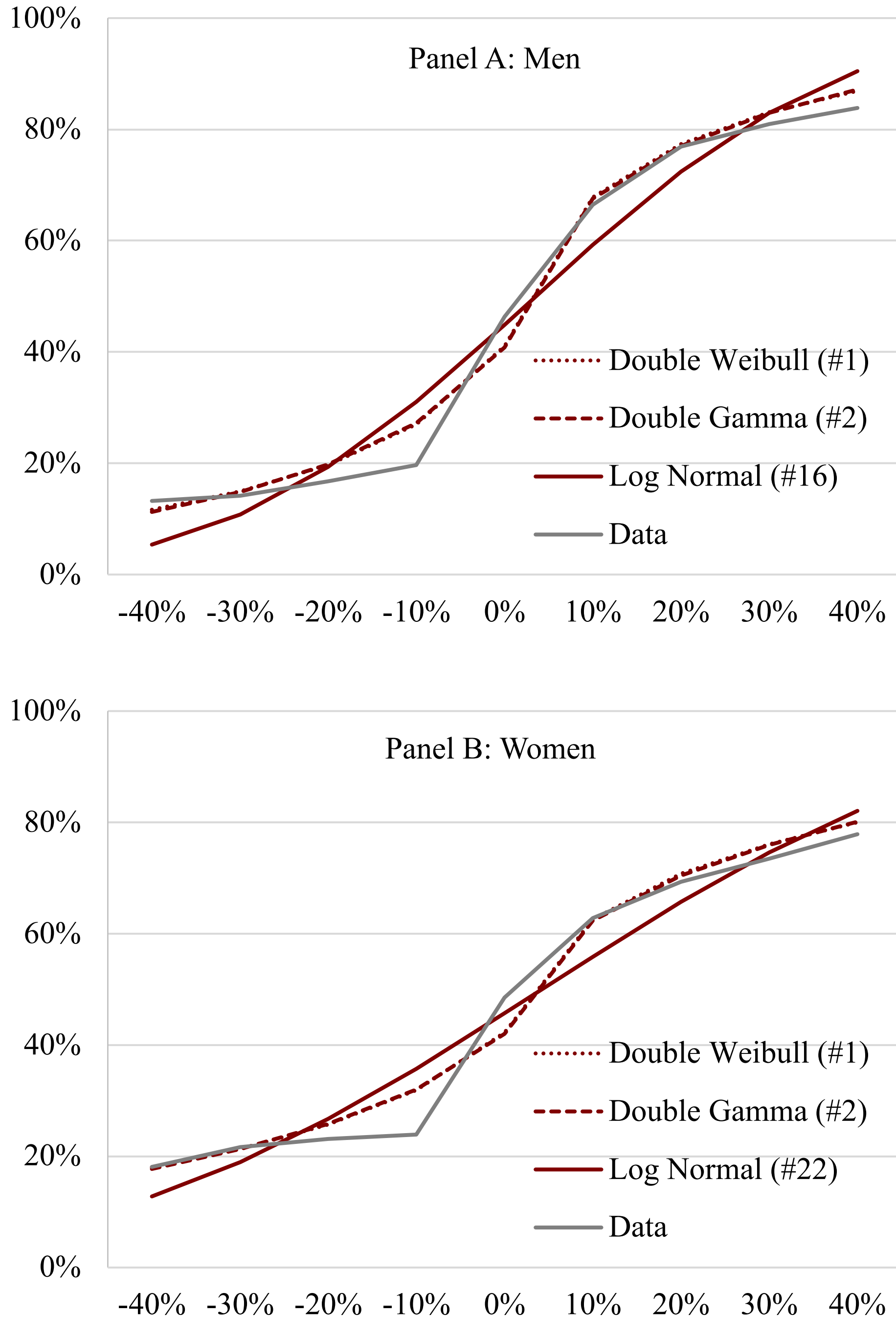
Source: author's calculation.

Figure A - 1. *Subjective CDF of Housing Price Change, by Gender, Year, and Age.*



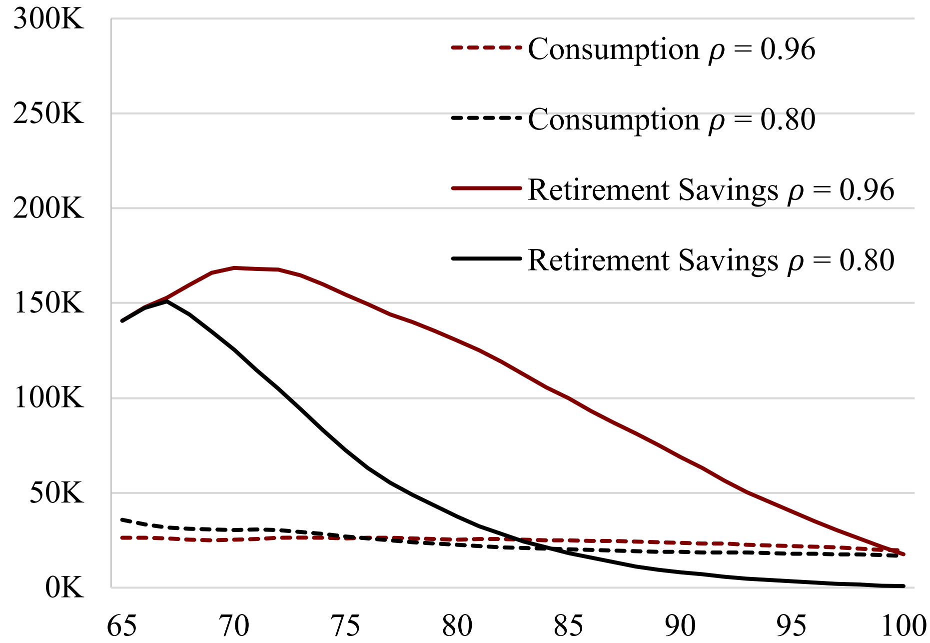
Source: HRS 2012-2016 and author's calculation.

Figure A - 2. *Estimated CDF of Housing Price Change using Subjective Data*.



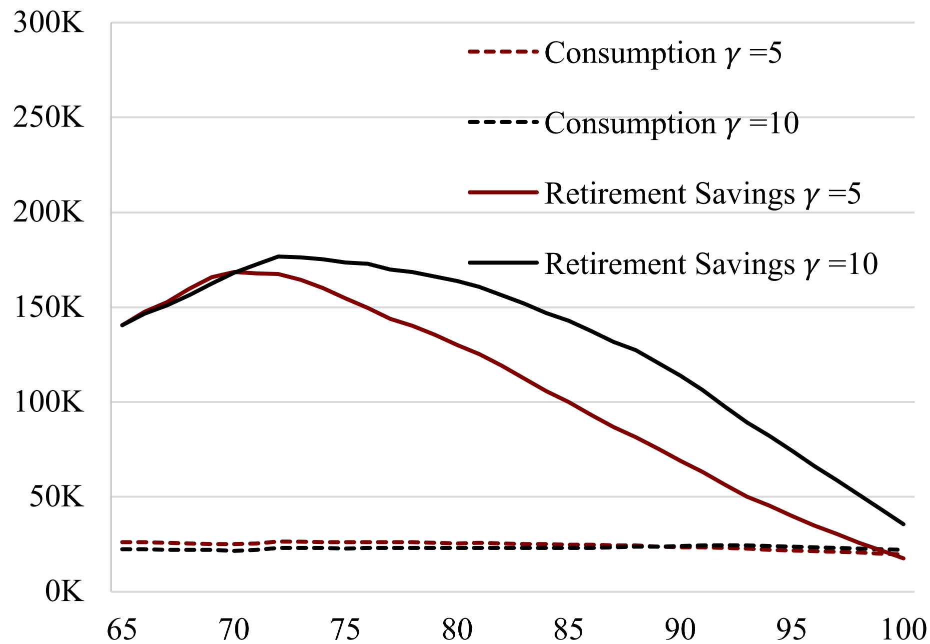
Source: HRS 2012-2016 and author's calculation.

Figure A - 3. *Life Cycle Path for Single Men, by Different Values of Time Preference.*



Source: author's calculation.

Figure A - 4. *Life Cycle Path for Single Men, by Different Values of Risk Aversion.*



Source: author's calculation.

TECHNICAL APPENDIX

Solving the Couple's model

In the full version of the model for married couples, the optimization problem is solved with the number of state variables, choice variables, and shock variables as $8 \times 3 \times 8$. The state variables are: age $t = 65 \ldots 119$, total wealth X_t, housing value H_t, retirement saving balance K_t, permanent health shock level P^h for the head and P^s for the spouse, number of family members $N = 2$ if the spouse still alive and 1 if dead, and the Social Security benefit adjustment status $A = 1$ if no benefit change and less than 1 if the benefit cut happens. Except three discrete variables, age t, binary N and binary A, the rest are continuous ones and have to be discretized. For the order of X, H, K, P^h and P^s, this paper uses a 1000 ×100 ×100 ×10 ×10 grid with a log-scale for numerical solutions. There are three choice variables at household level: consumption C_t; withdrawal D_t from a retirement savings account; and the share invested in risky assets S_t. The stochastic shocks considered in the couple's model include stock return R^e_{t+1}, housing return R^h_{t+1}, the innovation of permanent health shock $\varepsilon^{h,perm}_{t+1}$ $\varepsilon^{s,perm}_{t+1}$ for the head and the spouse, the innovation of transitory shock $\varepsilon^{h,tran}_{t+1}$ $\varepsilon^{s,tran}_{t+1}$, family transfers F_{t+1}, spousal mortality Q^s_{t+1} from the life table, and the Social Security policy change α_{t+1}. Except the last two which are binary shocks, the rest six of the eight shocks are all continuous. Therefore, the expectation part of the objective function can be rewritten as multiple integral form with respect of those six continuous variables and are solved with multidimensional *Gauss-Hermite Quadrature* method, as describe later. In order to attain the value function from the future period, this paper uses cubic-splines interpolation, a piecewise cubic polynomial which is twice continuously differentiable. To do that, the model is first solved in the last period $t = 119$ and generates a value function (policy function) with eight state variables and the associated optimal utility value V_{119}. This gives the mapping system at each of the 1000 ×100 ×100 ×10 ×10 ×2 ×2 grid point at age 119. In the backward induction process for current age t, the future value of V_{t+1} in the objective function is interpolated among the grid points by the state variables at age $t + 1$ calculated using the realized shocks and the mapping of V_{t+1} that have been solved. This paper uses the cubic splines interpolation class in the SciPy package for Python with the "natural" type (the second derivative at curve ends are zero). The backward induction uses Multiprocessing package for Python to do parallel computing on Boston College's Linux Cluster server. The running time to solve the couple's model is about 25 hours.

Gauss-Hermite Quadrature

The Gauss-Hermite quadrature method provides a set of integration modes $\{\epsilon_j\}_{j=1,\dots,J}$ and weights $\{\omega_j\}_{j=1,\dots,J}$ for approximation of the integral in the expectation calculation. To approximate a multidimensional integral by multidimensional Gauss-Hermite quadrature rule:

$$E[G(\epsilon)] = \int_{\mathbb{R}^N} G(\epsilon) * w(\epsilon)\, d\epsilon \approx \sum_{j_1=1}^{J_1} \dots \sum_{j_N=1}^{J_N} \omega_{j_1}^1 \dots \omega_{j_N}^N * G(\epsilon^1, \dots, \epsilon^N)$$

where $\epsilon \equiv (\epsilon^1, \dots, \epsilon^N)^{\mathrm{T}} \in \mathbb{R}^N$ is a vector of uncorrelated variables; $\{\omega_{j_h}^h\}_{j_h=1,\dots,J_h}$ and $\{\epsilon_{j_h}^h\}_{j_h=1,\dots,J_h}$are weights and nodes in a dimension h derived from the unidimensional Gauss-Hermite quadrature rule, denoted by $Q(J)$. This paper uses a three-node rule $Q(3)$

for the normal distribution shocks with nodes $\epsilon_{t+1,1} = 0$, $\epsilon_{t+1,2} = \sigma\sqrt{\frac{3}{2}}$, $\epsilon_{t+1,3} = -\sigma\sqrt{\frac{3}{2}}$ and weights $\omega_{t+1,1} = \frac{2\sqrt{\pi}}{3}$, $\omega_{t+1,2} = \omega_{t+1,3} = \frac{\sqrt{\pi}}{6}$. See Chapter 7 in *Handbook of Computational Economics* (Volume 3 by Schmedders and Judd, 2013).