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Health Heterogeneity, Portfolio Choice and Wealth Inequality*

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Abstract

In this paper we first provide empirical evidence on the long-lasting effects of poor health on stock market participation, asset portfolio composition, and the wealth gap over the lifecycle in the U.S. To quantify the importance of this health-wealth portfolio channel we formulate a structural lifecycle model that incorporates elastic labor supply, asset portfolio choice, and household heterogeneity in health status, health expenditure, health insurance, and earnings ability. Through counterfactual simulations, we demonstrate that the health-wealth portfolio channel plays a significant role in explaining variations in wealth gaps across groups and over the lifecycle. Finally, our findings highlight the important role of the health insurance system in reducing wealth inequality.

JEL: G41, G51, G52, E21, H21, I13, I14

Keywords: Health and income risks, Health insurance, Heterogeneity, Lifecycle savings, Risky and safe assets, Asset portfolio, Inequality.

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1 Introduction

Recent studies have identified health shocks as an important source of economic inequality that operate either directly through earnings effects or indirectly through human capital accumulation, labor supply and savings channels (e.g., [Hosseini, Kopecky and Zhao](#page-39-0) [2021;](#page-39-0) [Capatina and Keane](#page-37-0) [2024;](#page-37-0) [De Nardi, Pashchenko and](#page-37-1) [Porapakkarm](#page-37-1) [2024;](#page-37-1) [Mahler and Yum](#page-40-0) [2024\)](#page-40-0). [De Nardi, Pashchenko and Porapakkarm](#page-37-1) [\(2024\)](#page-37-1) in particular highlight that the gap in wealth by health status starts at a relatively young age and subsequently grows to become large by retirement time. However, prior studies in the health-macro literature typically assume that individuals can only invest in a common risk-free asset which effectively assumes away the impact of health on stock market participation and asset portfolio composition. This assumption neglects the role of heterogeneity in rates of return in generating wealth inequality (e.g., [Benhabib, Bisin and Zhu](#page-36-0) [2015;](#page-36-0) [Gabaix, Lasry, Lions](#page-38-0) [and Moll](#page-38-0) [2016;](#page-38-0) [Benhabib, Bisin and Luo](#page-36-1) [2019\)](#page-36-1), which is central to our study.

Arguably, health can affect stock market participation through several channels, including life expectancy, out-of-pocket medical expenses, earning capacity, risk adjustments and changes in risk perception—all of which influence an individual's ability or willingness to invest in risky assets. For instance, according to the background risk literature (e.g., [Gollier and Pratt](#page-38-1) [1996;](#page-38-1) [Kimball](#page-40-1) [1990;](#page-40-1) [Pratt and Zeckhauser](#page-41-0) [1987\)](#page-41-0), individuals facing undesirable risk are less willing to take on other types of risk. Accordingly, individuals in poor health exhibit a reduced inclination to invest in portfolios offering higher returns due to concerns regarding elevated risk exposure. The early experience of poor health setbacks can therefore substantially impact an individual's wealth portfolio composition. Such variations in asset portfolio composition directly translate into variations in asset returns. Heterogeneity in asset returns subsequently impacts wealth accumulation and contributes to wealth inequality between individuals with varying health conditions.

In this study we argue that variations in the timing and realization of health shocks contribute to the buildup of wealth inequality through a previously unexplored health-wealth portfolio channel, resulting from differences not only in how much sick and healthy individuals save for retirement, but also in the types of assets they choose to invest in.

To do so we first document the empirical relationship between the onset of health shocks at a point where many individuals begin to significantly accumulate wealth—typically in the early to mid forties—and the lifecycle patterns of stock market participation, wealth portfolio composition and wealth accumulation. To do so, we use two panel data samples from the Health and Retirement Study from 1992–2018 and the Panel Study of Income Dynamics (PSID) from 1984–2019 and form two groups of individuals differentiated by the timing of being exposed to bad health: (*i*) sick type who reports poor health in at least one of the survey years between the ages of 45 and 55 (treatment group); and (*ii*) a healthy type who consistently reports good health during the same age range.^{[1](#page-2-0)} We track these two groups over their life course and document differences in age profiles of income, savings, and investment portfolio composition, and wealth disparities at retirement.^{[2](#page-2-1)}

¹When we refer to health state in the discussion that follows we always mean "health states at peak earnings age between 45–55" and not current health status unless otherwise specified. The 45–55 age range is selected because it represents the peak earnings period, during which individuals typically accumulate significant wealth. We obtain similar patterns from PSID when moving the age range to the ages of 35 and 45 or the age of 30 and 40.

²The contemporaneous effects of poor health on portfolio choice have been documented in empirical studies (e.g., see [Rosen and](#page-41-1) [Wu](#page-41-1) [2004;](#page-41-1) [Edwards](#page-38-2) [2008;](#page-38-2) [Bressan, Pace and Pelizzon](#page-36-2) [2014\)](#page-36-2). While we observe similar contemporaneous effects in the HRS and PSID samples, our focus is on the dynamic and long-term effects of poor health on wealth portfolio composition and, by extension, on wealth accumulation and disparity over the life cycle.

Our empirical analysis reveals several key patterns. *First*, initially there are no significant wealth gaps by health status (as defined above) among individuals in their early 40s. However, these gaps begin to widen around age 45, increase markedly until retirement age at 65, and subsequently stabilize until age 80. *Second*, two distinct lifecycle patterns emerge for the portfolio share of risky assets by health status. The share of risky assets increases for healthy individuals and decreases for those in poor health. *Third*, the participation rates in risky asset investments are consistently higher for healthy individuals over the entire age profile, ranging between 40–58 percent, compared to 15–25 percent for sick individuals (participation/extensive margin). *Fourth*, conditional on participating in risky (stock) investments, there are only negligible differences in the portfolio shares of risky assets by health status (i.e., intensive margin). This implies that the health effect on investing in risky assets primarily works through the extensive, or participation, margin. *Fifth*, wealth mobility is low and decreases with age for sick individuals.

Our empirical results show how risk associated with health status strongly affects asset portfolio composition. Our panel data regressions additionally highlight the long-run relationship of poor health at ages 45–55 and the wealth portfolio levels and composition at retirement age. However, the magnitudes of these effects are difficult to assess with reduced form empirical approaches due to potential omitted variables biases. We therefore construct a structural lifecycle model with elastic labor supply and asset portfolio choice in order to quantify the impact of the health-wealth portfolio channel on wealth accumulation over the lifecycle as well as wealth inequality. We specifically focus on the cumulative long-run effects of poor health in middle age on wealth holdings and portfolio composition at the point of retirement. In our model individuals have a life span from ages 40–94 and differ by skill, labor productivity, health status, and wealth portfolio. Health is an important source of household heterogeneity as it directly affects mortality, earnings ability and medical expenses. Within this framework, individuals make decisions regarding savings levels and the choice of savings vehicles, which may include safe or risky assets, or a combination of both. This framework underscores four channels through which health and health shocks can impact wealth inequality: mortality risk, labor earnings, out-of-pocket health expenditure, and asset portfolio composition. The first three channels have been identified as significant sources of inequality in previous studies (e.g., [Hosseini, Kopecky and Zhao](#page-39-0) [2021;](#page-39-0) [Capatina and](#page-37-0) [Keane](#page-37-0) [2024;](#page-37-0) [De Nardi, Pashchenko and Porapakkarm](#page-37-1) [2024\)](#page-37-1), while the fourth channel introduces a novel dimension, leveraging compounding of interest income at different rates of return. These returns, we argue, are strongly affected by health.

We discipline the structural model using US data, following a two-step calibration strategy. Our benchmark model is capable of replicating the observed lifecycle profiles of stock market participation, asset holdings, the distribution of financial assets based on data from the Panel Study of Income Dynamics (PSID), and the Health and Retirement Study (HRS) as well as health expenditure and insurance take-up profiles based on data from the Medical Expenditure Panel Survey (MEPS). Subsequently, we employ the structural model to quantify the extent to which the presence of the health-wealth portfolio channel determines wealth inequality through counterfactual simulations.

We begin with an investigation of the impact of health on wealth accumulation as well as the wealth portfolio composition. This involves a counterfactual scenario in which individuals unexpectedly enjoy good health during their peak earning years between ages 45–55, akin to the analysis in [De Nardi, Pashchenko and Pora](#page-37-1)[pakkarm](#page-37-1) [\(2024\)](#page-37-1). Our results indicate that remaining in best health during the prime earning years of 45–55

generates an average annual monetary benefit of approximately \$3,280, accompanied by welfare gains expressed as consumption equivalent variation (CEV) of 9.7, 8.1 and 5.5 percent for low, medium and high skill types, respectively. The removal of bad health states from the model furthermore results in a significant reduction in the wealth gap, measured as the ratio of the 90th to the 50th wealth percentile and the ratio of the 50th to the 25th wealth percentile. We find that the P90/P50 ratio decreases by 44 percent and the P50/P25 ratio decreases by 19 percent. These finding align with prior research by [Hosseini, Kopecky and Zhao](#page-39-0) [\(2021\)](#page-39-0) and [De Nardi, Pashchenko and Porapakkarm](#page-37-1) [\(2024\)](#page-37-1).

Next, we consider another counterfactual scenario in which portfolio choice is eliminated from the model. In this case we only allow for one asset type that pays a certain return that is calculated as the weighted average return of the risk free and risky asset from the two assets version of the model. This single-asset model is comparable to the ones used in prior studies (e.g., [De Nardi, French and Jones](#page-37-2) [2010;](#page-37-2) [Hosseini, Kopecky and](#page-39-0) [Zhao](#page-39-0) [2021;](#page-39-0) [Capatina and Keane](#page-37-0) [2024\)](#page-37-0). In this version of the model wealth accumulates at a slower pace and to lower levels, resulting in significantly reduced wealth inequality among individuals approaching retirement.

We explain the overall larger wealth gap in a model with portfolio choice as follows. Individuals in good health are more likely to participate in the stock market early and hold a riskier asset portfolio with much higher expected rates of return. Meanwhile, exposure to negative health shocks not only introduces immediate and persistent health expenditures but also lowers the labor productivity and the survival probability—which altogether induce sicker individuals to save less and hold more of their investments in the risk free asset that pays a lower rate of return in the long run. This subsequently leads to much higher wealth inequality in the two assets model compared to the one asset model where healthy and sick households invest in the same asset with the same rate of return. The differences observed across the two models highlight that the health-wealth portfolio channel plays an important role in explaining the wealth gaps across groups and over time, especially in the wealth distribution of older individuals, where this effect had time to accumulate via the power of compound interest.

Finally, we examine whether better access to health insurance can reduce wealth inequality at the point of retirement. We investigate the importance of public health insurance in safeguarding the capacity of individuals in poor health to partake in wealth accumulation via risky assets, which in the absence of insurance might be perceived as either too risky or costly. We consider an experiment in which the government extends Medicare to all workers, thereby mitigating the financial repercussions of medical shocks. Doing so aligns the healthy and sick types with respect to their financial investment decisions to some extent. Our findings indicate that the expansion of Medicare reduces wealth inequality by inducing more individuals to commit to riskier investment choices with higher long-term returns. Similarly, an expansion of private health insurance—such as employer sponsored health insurance—to all workers leads to comparable outcomes. The social benefits stemming from the provision of universal health insurance through this channel are absent in models without portfolio choice. Our findings underscore the significance of explicitly incorporating the institutional features of the US health insurance system into a more realistic investment environment for a comprehensive understanding of the wealth inequality dynamics in the U.S. context. These fresh insights suggest that health insurance reforms possess substantial potential to significantly reduce inequality in the U.S.

Our paper is organized as follows. Section [2](#page-6-0) provides empirical evidence on the relationship between health and wealth accumulation. Section [3](#page-10-0) presents the quantitative model. Section [4](#page-16-0) describes our calibration strategy. Section [5](#page-22-0) describes our experiments and quantitative results. Section [6](#page-30-0) presents extensions. Section [7](#page-33-0) concludes. The Online Appendix provides more details about the empirical results, calibration details and simulation results.^{[3](#page-5-0)}

Related literature. Our paper contributes to the growing macro-health literature that studies relationships between health and inequality (e.g., [De Nardi, French and Jones](#page-37-2) [2010;](#page-37-2) [Prados](#page-41-2) [2018;](#page-41-2) [Hosseini, Kopecky and](#page-39-0) [Zhao](#page-39-0) [2021;](#page-39-0) [Jung and Tran](#page-40-2) [2022;](#page-40-2) [Jung and Tran](#page-40-3) [2023;](#page-40-3) [Capatina and Keane](#page-37-0) [2024;](#page-37-0) [Nakajima and Telyukova](#page-41-3) [2024;](#page-41-3) [Chen, Feng and Gu](#page-37-3) [2024;](#page-37-3) [De Nardi, Pashchenko and Porapakkarm](#page-37-1) [2024;](#page-37-1) [Mahler and Yum](#page-40-0) [2024\)](#page-40-0). Existing studies have predominantly focused on medical expenditures, access to health insurance (e.g., [De Nardi, French](#page-37-2) [and Jones](#page-37-2) [2010;](#page-37-2) [Jung and Tran](#page-40-2) [2022;](#page-40-2) [Nakajima and Telyukova](#page-41-3) [2024;](#page-41-3) [Chen, Feng and Gu](#page-37-3) [2024\)](#page-37-3), the effect of health on labor productivity and labor supply (e.g., [Hosseini, Kopecky and Zhao](#page-39-0) [2021\)](#page-39-0), the role of lifestyle behaviors (e.g., [Mahler and Yum](#page-40-0) [2024\)](#page-40-0), and medical treatment (e.g., [Capatina and Keane](#page-37-0) [2024\)](#page-37-0). In contrast, our study identifies a new channel—the health-wealth portfolio channel—that amplifies the effect of health shocks on wealth concentration, primarily via health-induced variations in the rate of return on wealth accumulation.

Furthermore, our work bridges the macro-health literature mentioned above with research emphasizing the contribution of heterogeneous investment returns in driving wealth inequality (e.g., [Benhabib, Bisin and](#page-36-0) [Zhu](#page-36-0) [2015;](#page-36-0) [Gabaix et al.](#page-38-0) [2016;](#page-38-0) [Benhabib, Bisin and Luo](#page-36-1) [2019\)](#page-36-1). Arguably, the rates of return of financial investments are driven by numerous factors including exogenous shocks, ability, knowledge and choices. [Bach,](#page-35-0) [Calvet and Sodini](#page-35-0) [\(2020\)](#page-35-0) and [Fagereng, Guiso, Malacrino and Pistaferri](#page-38-3) [\(2020\)](#page-38-3) provide evidence of substantial heterogeneity in individual returns to wealth. [Lusardi, Michaud and Mitchell](#page-40-4) [\(2017\)](#page-40-4) build a structural model and demonstrate that heterogeneity in rate of return is driven by endogenous differences in financial knowledge. In our framework, the rate of return is stochastic and endogenously determined by exposure to health shocks, access to health insurance and investment portfolio choices. We demonstrate that the heterogeneity in the rate of return is strongly influenced by the health-wealth portfolio channel which can account for up to 50 percent of the wealth gap observed in retirement.

Moreover, our paper aligns with the household finance and lifecycle portfolio choice literature that goes back to [Samuelson](#page-42-0) [\(1969\)](#page-42-0) and [Merton](#page-41-4) [\(1971\)](#page-41-4). Recent surveys of the theoretical and empirical household finance literature are provided in [Gomes](#page-38-4) [\(2020\)](#page-38-4) and [Gomes, Haliassos and Ramadorai](#page-39-1) [\(2021\)](#page-39-1), respectively. The composition of household savings portfolios is widely studied. While some papers identify a positive effect of wealth on the proportion of risky assets (i.e., stocks) held by a household [\(Wachter and Yogo](#page-42-1) [2010\)](#page-42-1), other studies find that wealth changes have only minor effects on the portfolio composition due to inertia [\(Brun](#page-36-3)[nermeier and Nagel](#page-36-3) [2008\)](#page-36-3). Additional channels have been highlighted such as stock market entry/adjustment costs [\(Alan](#page-35-1) [2006;](#page-35-1) [Bonaparte, Cooper and Zhu](#page-36-4) [2012;](#page-36-4) [Fagereng, Gottlieb and Guiso](#page-38-5) [2017\)](#page-38-5), education [\(Cocco,](#page-37-4) [Gomes and Maenhout](#page-37-4) [2005;](#page-37-4) [Ehrlich, Hamlen and Yin](#page-38-6) [2008;](#page-38-6) [Cooper and Zhu](#page-37-5) [2016\)](#page-37-5), unemployment [\(Bagliano,](#page-35-2) [Fugazza and Nicodano](#page-35-2) [2014;](#page-35-2) [Bagliano, Fugazza and Nicodano](#page-35-3) [2019\)](#page-35-3), the introduction of the Pension Protection Act of 2006 [\(Parker, Schoar, Cole and Simester](#page-41-5) [2022\)](#page-41-5), the availability of reverse mortgages [\(Nakajima](#page-41-6) [and Telyukova](#page-41-6) [2017\)](#page-41-6), and the cyclicality of the skewness of income shocks [\(Catherine](#page-37-6) [2022\)](#page-37-6). We extend this literature by highlighting health as a pivotal determinant of portfolio choices and asset composition throughout the lifecycle.

 3 The Technical Appendix provides additional information about the data sources, empirical analysis and computational methods.

Our paper is also related to studies based on estimated structural lifecycle models of portfolio choice and retirement [\(Yogo](#page-42-2) [2016;](#page-42-2) [Fagereng, Gottlieb and Guiso](#page-38-5) [2017;](#page-38-5) [Gomes and Smirnova](#page-39-2) [2021\)](#page-39-2). [Yogo](#page-42-2) [\(2016\)](#page-42-2) investigates the role of health, housing, and the investment portfolio composition of the retired. [Campanale, Fugazza](#page-36-5) [and Gomes](#page-36-5) [\(2015\)](#page-36-5) and [Tischbirek](#page-42-3) [\(2019\)](#page-42-3) use a calibrated lifecycle models to investigate the effects of liquidity costs of stocks and long-term bonds on household investment decisions. Distinguishing our approach from these lifecycle models is our particular emphasis on the significance of accounting for health shocks occurring at younger ages as a pivotal factor in comprehending the composition of wealth portfolios and wealth gaps in retirement.

Lastly, our study relates to an empirical literature that investigates how health-related factors shape the wealth portfolio of households. For instance, [Goldman and Maestas](#page-38-7) [\(2013\)](#page-38-7) and [Ayyagari and He](#page-35-4) [\(2016\)](#page-35-4) offer insights into how spending and health insurance has affected the portfolio choice of the elderly. [Rosen and Wu](#page-41-1) [\(2004\)](#page-41-1), [Edwards](#page-38-2) [\(2008\)](#page-38-2), [Bressan, Pace and Pelizzon](#page-36-2) [\(2014\)](#page-36-2) and [Böckerman, Conlin and Svento](#page-36-6) [\(2021\)](#page-36-6) provide empirical evidence showing that realization of poor health lowers the probability of holding assets in the form or risky stocks. While observing similar contemporaneous effects in the HRS and PSID samples, we focus on the dynamic and long-term effects of poor health on wealth portfolio composition and, by extension, on wealth accumulation over the life cycle. Our contribution goes beyond the mere presentation of empirical observations; instead, we construct a structural framework capable of identifying welfare effects, thereby enhancing our understanding of the intricate relationship between health, wealth portfolios and wealth inequality.

2 Health and wealth portfolio channel: Empirical evidence

In this section we document empirical patterns describing the long-run relationship between health status and the asset composition of wealth portfolios at retirement age. We use wealth data from two representative US household panel surveys, the Health and Retirement Study (RAND-HRS) and the Panel Study of Income Dynamics (PSID). We provide more details about these surveys in our Technical Appendix.

2.1 Data and construction of variables

Data. The Health and Retirement Study (RAND-HRS) is a longitudinal survey that collects data every two years and is available from 1992–2018. New cohorts were added regularly since 1992. We use all 14 waves of available data in this study. The survey covers a broad range of topics, including health, income, assets, employment, retirement, insurance, and family structure. Survey respondents are non-institutionalized individuals and we exclude individuals living in nursing homes from the analysis. The majority of them are between 51 and 61 years old when they enter the survey and it includes information about their spouses of any age. The Panel Study of Income Dynamics (PSID) is a longitudinal survey that collects data annually from 1968–1997 and biennially since then. Wealth data was first available for the years 1984, 1989, 1994 and biennially from 1999 onward. We also limit the sample to heads of households and to the age group of 40–80 year olds and exclude the Latino sample.^{[4](#page-6-1)}

⁴Our Technical Appendix (Sections [A](#page-68-0) and [B\)](#page-94-0) contains more details about the HRS and PSID surveys, respectively. We also provide a discussion about sample selection and present summary statistics.

We limit both samples to heads of households between 40–80 years of age. Since we have panel data we are able to include health status information when these individuals were between the ages of $45-55$ $45-55$ $45-55$.⁵ We only include head of households for whom we have wealth information when they are between 40–80 and health information when they were between 45–55. In the regression analyses that follow we use a reduced sample of 60–70 year old head of households. We use their investment portfolio information and investigate its relationship with the health state of the same individuals when they were 45–55 years old.

Wealth measures. The HRS measures wealth in 20 components at the household level including holdings in checking/savings accounts, CDs, bonds, T-bills, stocks, mutual funds, and IRA/Keogh accounts which provides a good snapshot of a household's asset portfolio.^{[6](#page-7-1)} We collapse financial assets into two classes: (*i*) the safe assets (checking and savings accounts, money market funds, CDs, government savings bonds, T-bills, corporate, municipal and foreign bonds, as well as bond funds) and (*ii*) risky assets (stocks and mutual funds).

The HRS also reports household holdings in retirement accounts such as IRAs and Keogh plans and separately individuals report balances of their (and their spouse's) defined contribution pension plans such as 401(k) plans. Unfortunately, the HRS does not report what kinds of assets are held in these retirement accounts. We follow the procedure in [Tischbirek](#page-42-3) [\(2019\)](#page-42-3) who uses data from the Employee Benefit Research Institute (EBRI) and attributes 45.8 percent of funds held in IRAs to stocks and similarly data from [Agnew, Balduzzi and Sundén](#page-35-5) (2003) to assign 41 percent of funds in defined contribution pension plans to stocks.^{[7](#page-7-2)}

PSID wealth data has similar information but do not contain information about assets in defined contribution plans such as $401(k)$ s. On the plus side, it is a deeper panel with wealth data from year 1984 which is also representative for individuals in their 40s.

We focus on portfolio shares of these two asset types of individuals between ages 60–70 as the dependent variables in the regression analyses below. We then further distinguish between individuals investing in either one of these two asset types and conditional on investing, on the percentage of the asset type in the overall financial portfolio.

Health measures. Both surveys contain health status information that is self reported and recorded as either (*i*) excellent, (*ii*) very good, (*iii*) good, (*iv*) fair, or (*v*) poor or as a binary variable indicating whether an individual has a work limiting health problem. If health state information is missing we interpolate health measures with health state information in the previous and next round of the interview. [Diehr and Patrick](#page-37-7) [\(2001\)](#page-37-7) report that interpolated values tend to be under dispersed and they suggest to add a small random error. Given the two-year observational lags and leads in the HRS, we follow their method and add a small random error after interpolation and then round to the nearest health category. [Engels and Diehr](#page-38-8) [\(2003\)](#page-38-8) report that this method is less biased than other methods. We use these health status variable and construct an indicator variable BAD-HEALTH-45-55 that is set to equal one if an individual ever reports of being in either "fair" or "poor" health between the ages of 45–55. We use unweighted sample data throughout the analysis as individuals who

 $⁵HRS$ observations are predominantly from heads of households between the age of 50–55 as there are only very few households</sup> below the age of 50 in the sample.

⁶The questions are usually formulated as "Do you (or your husband/wife/partner) have any holdings in ..."

⁷The data in [Agnew, Balduzzi and Sundén](#page-35-5) [\(2003\)](#page-35-5) only considers $401(k)$ accounts. See [Copeland and Fronstin](#page-37-8) [\(2011\)](#page-37-8) for details on IRA holdings available at [https://www.ebri.org/content/'ira-asset-allocation'-and-'characteristics-of-the](https://www.ebri.org/content/) [-cdhp-population-2005-2010'-4823](https://www.ebri.org/content/)

are younger than 50 years of age typically are assigned a sampling weight of zero. Since our identification of the long-term effects of bad health requires information of health at ages below 50, we prefer including these individuals (which is only possible if we do not weight the observations). When possible we also include estimation results based on HRS person weights as sensitivity checks.

Alternatively the HRS also asks about whether an individual experiences a work limiting health problem. The survey questions is formulated as: "Now I want to ask how your health affects paid work activities. Do you have any impairment or health problem that limits the kind or amount of paid work you can do?" The answer is coded as yes/no. We use this measure as a robustness check in the regressions that follow.

2.2 Stylized facts

We first document some empirical facts about the relationship between health status and a person's wealth portfolio over the lifecycle. Figure [1](#page-43-0) shows the age profiles of financial assets, including total financial assets, risky financial assets (i.e., stock), stock ratio (i.e., share of risky financial assets relative to safe financial assets), conditional on health status at age 45-55. We distinguish between individuals who report having been in bad health at age 45–55 (sick in red) and individuals who report being healthy throughout age 45–55 (healthy in black). In Figure [1,](#page-43-0) we observe only minor differences in wealth by health status in the early 40s based on our raw PSID data sample. The wealth gap by health status widens around age 45, increases exponentially by retirement time, and then remains relatively stable in the 70s. Interestingly, the stock ratio, i.e. share of risky assets, by health status follows different lifecycle patterns. From the fourth row of Figure [1](#page-43-0) we observe an an increasing trend in the stock ratio for healthy individuals starting from age of 50 while the stock ratio of sick individuals tends to be flat. 8

Figures [3a](#page-45-0) and [3b](#page-45-1) show participation (intensive margin) and portfolio share (extensive margin) over the lifecycle conditional on health status at age 45–55 based on data from PSID and HRS, respectively. The first row of both figures reports averages per age group, not controlled for time or cohort effects. In the top two panels 1.A and 1.B of Figure [3a](#page-45-0) we show the participation age profile of stock investments and conditional on owning stocks, the share of stocks in the wealth portfolio.^{[9](#page-8-1)} In row one of Figure [3a](#page-45-0) we observe a much higher participation rate in risky asset investments of healthy individuals over the entire age range. It ranges between 40–58 percent for healthy individuals and 15–25 percent for sick individuals. Both profiles show a slight hump shape. If we condition on an individual reporting having stock investments and then calculate the average wealth share of risky stock investments in an individuals wealth portfolio, we observe first flat profiles for both healthy and sick types and second only very small differences in the wealth shares of risky assets between the two health types. The risky asset share is around 40 percent.

In Figure [2](#page-44-0) we report the distribution of assets by health and age. We find that individuals that were healthy (i.e. no bad health between 45–55) are able to shift their asset distribution when moving from ages 40–50 to ages 60–70. Conversely, individuals that were sick (i.e., had bad health between 45–55) are not able to climb up the wealth ladder and shift their asset distribution up. As seen in panel 4 of Figure [2,](#page-44-0) the distribution of assets of the sick is virtually unchanged after 20 years. Thus, wealth mobility is low and decreases with age for the sick.

 8 We observe similar trends in HRS data. However, the noise level for observations below age 50 is very large.

 $9A$ similar discussion about the safe asset share is available in Section [B](#page-94-0) in the Technical Appendix.

Controlling for time and cohort effects. The profiles discussed thus far do not distinguish cohort, time, and age effects. We therefore introduce three different methods to control for cohort and time effects. The first method is based on simple regressions of an indicator variable equal to one if an individual reports positive stock holdings and zero otherwise on a set of dummy variables for age, observation year, and birth cohort that we run separately on the sample of sick and healthy individuals. The profiles based on this method are reported in panel 2.A of Figure [3b.](#page-45-1) We then use a similar regression using the wealth share of stock investments as dependent variable and data from the sample of individuals reporting positive stock investments for the figure in panel 2.B. The new profiles flatten out compared to the original "raw" profiles without controls.[10](#page-9-0) For our final two approaches we implement the method in [Deaton and Paxson](#page-37-9) [\(1994\)](#page-37-9) to control for cohort and time effects. In panels 3.A–3.B in Figure [3b](#page-45-1) we use a two-part model and in panels 4.A–4.B we use a selection model to accomplish this.^{[11](#page-9-1)}

Overall we can see that the stock participation profiles lose their hump shape after controlling for time and cohort effects and become slightly increasing for healthy individuals and decreasing for sick individuals. The wealth share of stock investments tends to increase after controlling for time/cohort effects and the distinction between healthy and sick types become more pronounced. The safe asset participation profile are flat after controlling for time/cohort effects. The wealth shares of safe assets are also flat for healthy types but increasing for sick types. Our preferred profiles are the ones in panels 4.A–4.B in Figures [3a](#page-45-0) and [3b](#page-45-1) as they implement the often used [Deaton and Paxson](#page-37-9) [\(1994\)](#page-37-9) method together with a selection model which accounts for the fact that the wealth share in panel 4.B is only observable if the individual participates in the asset market. These estimates are therefore most in line with our computational model and used as a calibration target.

The effects of bad health on the wealth portfolio. We estimate the effects of bad health at age 45–55 on the level and composition of an individual's wealth portfolio at ages 60–70. To do this we regress the risky-assetshare (i.e., the share of the value of stocks in the financial portfolio) on a "sick" indicator variable coded as being in "poor health at age 45–55" and control variables. Specifically, we estimate the following econometric model

$$
y_{i,t} = \beta + \gamma \times 1_{\{\text{Sick } 45-55, i\}} + \delta \times Z_{i,t} + \varepsilon_{i,t},
$$

where $y_{i,t}$ is the share of the value of stocks in the financial portfolio at ages 60–70, $1_{\{\text{Sick }45-55,i\}}$ is an indicator for being in bad health in at least one survey wave between the ages of 45–55, and *Zi*,*^t* is a vector of exogenous control variables including employment, health, health insurance, marital status, gender race, education, income and wealth. Finally, $\varepsilon_{i,t}$ is a random error term. We also interact the sick indicator variable with a lagged unemployment indicator and a lagged uninsured indicator variable to highlight possible pathways of poor health and its effect on the wealth accumulation.

Columns (1) , (3) , (5) , (7) , and (9) in Tables [10](#page-46-0) and [11](#page-47-0) report the results of these regressions for the sick indicator variable using data from the PSID and HRS, respectively. The even numbered columns in the same table show the results for the sick indicator being based on the alternative health measure of reporting a worklimiting health issue in at least one survey wave between the ages of 45–55. Column (3) uses weighted data,

 10 Controlling for age, time, and cohort effects simultaneously is not possible due to perfect multicollinearity. It works here because the cohort effects are assumed to be constant for birth cohorts within a certain amount of years.

¹¹ More details about the methods to control for time and cohort effects are presented in the Technical Appendix (Sub-sections [A.4](#page-79-0) and [B.4\)](#page-106-0). It also includes profiles of safe assets.

column (5) estimates a random effects model, column (7) is a random effects model on a smaller sample that only includes individuals that have positive stock holdings, and column (9) uses again population weights on this smaller sample of stock investors.

We see that having a health issue at ages 45–55 has a significant and negative effect on the level of stock holdings of 60–70 year old individuals in both samples. However, the statistical significance vanishes once we concentrate on the smaller samples of stock holders. This is a first indication that the health effect might work through the extensive margin and not the intensive margin.

We next investigate the extensive and intensive margins by estimating a two-part (see Table [12\)](#page-48-0) and a selection model (see Table [13\)](#page-48-1) that show a participation equation (whether an individual invests or not) and conditional on investing and outcome equation (the level of the asset share). Both types of models show similar results. In the participation equation (the extensive margin) we can see that bad health has a negative effect on participating in risky investments into stocks. However, once an individual has decided to invest into stocks, health has a much weaker effect on the share of stock holdings in the overall financial portfolio. ^{[12](#page-10-1)}

These results remain robust even after excluding individuals who reported poor health at age 40—something only possible with PSID data, as shown in Table [14.](#page-49-0) By focusing on those who were healthy at age 40, we reduce the risk of confounding long-term characteristics that could bias the estimates. Additionally, the results hold steady when we alter the definition of risky assets. Since we lack detailed information on the composition of IRAs in terms of risky and safe assets, we exclude IRAs from our measurement of risky assets and rerun the analysis. Table [15](#page-49-1) shows that although the decrease in stock market participation probability is slightly smaller, it remains highly statistically significant. The effect of health in the outcome equation of the two-part model continues to be insignificant regarding the stock share.

The HRS data also suggests some possible pathways that have been highlighted in the literature. First, while we do not observe any significant difference in risk aversion between sick and healthy individuals, we do observe large differences in their subjective life expectations to either age 75 or age 85. Healthy individuals report much higher subjective survival probabilities than their sick counterparts. This could partially explain why healthy individual are more likely to invest in either stocks or the safe asset class. Furthermore, the data shows that healthy individuals are much more forward looking than their sick counterparts. 13

3 Lifecycle model

In this section we introduce the stochastic lifecycle model with investment portfolio decisions similar to [Cocco,](#page-37-4) [Gomes and Maenhout](#page-37-4) [\(2005\)](#page-37-4) and [Gomes and Michaelides](#page-38-9) [\(2005\)](#page-38-9) and augment it with exogenous shocks to health and health insurance status.

3.1 Demographics

Individuals enter the model in period $j = 1$ (age 40), works until period $j = J_w$ (age 65), and lives in retirement up to a maximum age of *J* (age 94). In each period individuals of age *j* face an exogenous survival probability

¹²The situation is slightly different for safe asset shares. From Tables $12-13$ $12-13$ we see that while the probability of having savings in safe assets decreases with poor health as well, conditionally upon having safe assets, being in poor health increases the proportion of safe asset holdings.

 13 Compare Figures [A.7](#page-88-0) and [A.8](#page-91-0) in the Technical Appendix for more details.

 $\pi_j(\varepsilon^h)$ that depends on their exogenous health state ε^h . Due to the mortality risk, individuals will leave accidental bequests.

3.2 Preferences

The period utility function $u(c_j, \ell_j; \omega_{j, \vartheta}; \bar{n}_j(\vartheta, \varepsilon^h); \bar{u})$ depends on consumption (c) , leisure (ℓ) , and laborforce participation status which is only equal to one if labor supply is positive. The parameter $\omega_{i,\vartheta}$ is an equivalence scale capturing changes in household size by age *j* and permanent income type ϑ while $\bar{n}_j(\vartheta,\pmb{\varepsilon}^h)$ denotes the fixed cost of working which depends on age, income type, and health status. The additive constant $\bar{u} > 0$ ensures that the continuation value of being alive exceeds the utility from dying.^{[14](#page-11-0)} Individuals value leaving bequests via function $u^{beq}(W_j)$ which is increasing in wealth W_j . Individuals use a fixed time discount factor β to discount a future period.

3.3 Health status, health expenditure, and health insurance

The individual's health status ε_j^h evolves exogenously over the lifecycle and follows a Markov process that depends on age and the permanent income group so that conditional transition probabilities are elements of matrix $\Pi^h(j, \vartheta)$. A specific level of health expenditures $m(j, \vartheta, \varepsilon_j^h)$ is linked to health status and fluctuates accordingly. In addition, the permanent income type and age also affect health expenditures.^{[15](#page-11-1)}

For working age households the exogenous private health insurance state $\varepsilon_{j,\vartheta}^{\text{ehi}}$ is defined as

$$
\mathcal{E}_{j,\vartheta}^{\text{ehi}} = \begin{cases} 0 & \text{not privately insulated,} \\ 1 & \text{privately health insurance,} \end{cases} \quad \text{for } j \le J_w.
$$

It depends on age and the permanent skill type and follows a Markov switching process with age and skill type dependent transition probability matrix $\Pi_{j,\vartheta}^{\text{ehi}}$. Transition probabilities to next period's insurance state $\varepsilon_{j+1,\vartheta}^{\text{ehi}}$ depend on the current insurance state $\varepsilon_{j,\vartheta}^{\text{ehi}}$ so that an element of transition matrix $\Pi_{j,\vartheta}^{\text{ehi}}$ is the conditional probability $P\left(\varepsilon_{j+1,\vartheta}^{\text{ehi}}|\varepsilon_{j,\vartheta}^{\text{ehi}}\right)$. The health insurance state evolves exogenously. If the household ends up with private insurance, she only pays a fraction γ^{Ins} of her medical expenses in addition to a premium prem^{ehi} which is paid at the beginning of the period. Finally, households will have Medicare once they reach retirement age $J_w + 1$. The Medicare coinsurance rate is γ^{meare} and households will also pay Medicare Plan B premiums premmcare at the beginning of each period.

In addition, households can qualify for Medicaid insurance if they pass the Medicaid income and asset test. The Medicaid coinsurance rate is $γ^{\text{maid}}$. There is no Medicaid premium. The indicator variable for Medicaid $1_{\text{[maid-yes]}}$ equals one if adjusted gross income is less than the earnings threshold $y_j^{\text{agi}} < y^{\text{maid}}$ and the asset

¹⁴In our model with exogenous health spending and exogenous mortality (that depends on the exogenous health state) this is not crucial to solving the model unlike in endogenous mortality models such as [Hall and Jones](#page-39-3) [\(2007\)](#page-39-3) where it would be optimal to die immediately without positive utility values. However, in a later experiment we calculate the welfare cost of having health issues between ages 45–55—similar to [De Nardi, Pashchenko and Porapakkarm](#page-37-1) [\(2024\)](#page-37-1)—and for this calculation we need to ensure that utilities from better health exceed utilities from poor health. Since in our model health does affect survival, we need to ensure that utility from living exceeds the utility from immediate death as otherwise sicker individuals would have higher welfare.

¹⁵We undertake a similar modeling approach as in [De Nardi, French and Jones](#page-37-2) [\(2010\)](#page-37-2), [Hosseini, Kopecky and Zhao](#page-39-0) [\(2021\)](#page-39-0) and [De Nardi, Pashchenko and Porapakkarm](#page-37-1) [\(2024\)](#page-37-1) and use an exogenous health spending model. There is an alternative modeling approach that uses endogenous medical spending models (e.g., [Jung and Tran](#page-40-5) [2016;](#page-40-5) [Fonseca, Langot, Michaud and Sopraseuth](#page-38-10) [2023\)](#page-38-10).

holdings are below the asset threshold $a_j < a^{\text{maid}}$ and zero otherwise. We assume that individuals that qualify for Medicaid will use it as either their primary insurance (if they have not other insurance) or as secondary insurance in case they already have either private insurance or Medicare.^{[16](#page-12-0)}

The out-of-pocket medical expenditures therefore depend on the exogenous insurance state (i.e., private health insurance or Medicare) as well as the income/asset eligibility for Medicaid. We summarize out-ofpocket medical expenditures as $o_j(m_j, \varepsilon_{j, \vartheta}^{\text{ehi}}, y_j^{\text{agi}})$ $\binom{agi}{j}, a_j$ =

primary HI	working, no private HI		
$1_{\text{[middle-yes]}} \gamma^{\text{middle}}$	if $\epsilon_{j,\vartheta}^{\text{ehi}} = 0 \land j \leq J_w$		
Medical is secondary HI	$1_{\text{[middle-yes]}} \gamma^{\text{mail}}$	$\times \left(\gamma^{\text{ehi}} \times m(j, \vartheta, \varepsilon_j^h) \right)$	working, with private HI
$1_{\text{[middle-yes]}} \gamma^{\text{mail}}$	$\times \left(\gamma^{\text{ehi}} \times m(j, \vartheta, \varepsilon_j^h) \right)$	it $\epsilon_{j,\vartheta}^{\text{ehi}} = 1 \land j \leq J_w$	
Medical is secondary HI	$1_{\text{[middle-yes]}} \gamma^{\text{main}}$	$\times \gamma^{\text{meare}} \times m(j, \vartheta, \varepsilon_j^h)$	retired, with Medicine

3.4 Endowments

In each period households are endowed with one unit of time that can be used for work ℓ or leisure. Conditional on labor force participation, a household earns before-tax wage income $y_j = w \times e_j(\theta, \varepsilon^{\text{incP}}, \varepsilon^h) \times n_j$ at age *j*, where w is the wage rate, and e_j is a labor productivity endowment that depends on age j , a permanent income group ϑ , an idiosyncratic persistent productivity shock ε^{incP} , and idiosyncratic health state ε^h . Labor shocks follow a Markov process with transition probability matrix $\Pi^{\text{incP}}(j, \vartheta)$.

3.5 Financial markets

The household can invest in two types of assets: a risk-free bond *b* which pays a fixed real return of r^b and a risky asset which pays a stochastic real return of \tilde{r}^s . Similar to [Gomes, Michaelides and Polkovnichenko](#page-39-4) [\(2009\)](#page-39-4) asset returns are taxed and taxes are paid on nominal returns. The nominal returns are taxed at rate τ*d*. Assuming a constant rate of inflation π , the after-tax real returns on the risk free assets are:

$$
\bar{r}_{\text{net}}^b = \frac{1 + \left[\left(r^b + 1 \right) \left(1 + \pi \right) - 1 \right] \left(1 - \tau^d \right)}{1 + \pi} - 1.
$$

The risky stock *s* pays a real return of

$$
\tilde{r}^s = r^b + \mu^s + \varepsilon^s,\tag{1}
$$

^{16"}Dual eligibles" are households that qualify for both private health insurance and Medicaid before retirement or Medicare and Medicaid after retirement. In this case Medicaid is typically the secondary insurance or the payer of last resort. Given this setup the private insurance company or Medicare would pay $(1 - \gamma^{\text{chi}}) m_j$ or $(1 - \gamma^{\text{macro}}) m_j$, respectively and Medicaid as secondary insurance would pay a fraction $(1 - \gamma^{\text{maid}}) \gamma^{\text{ehi}} m$ or $(1 - \gamma^{\text{maid}}) \gamma^{\text{mcare}} m$ of the residual out-of-pocket amount. In order to not complicate the model, we do not allow for "triple eligibles" where typically private health insurance would be the primary insurance, Medicare the secondary, and Medicaid the tertiary insurance. See [Bagchi and Jung](#page-35-6) [\(2023\)](#page-35-6) for a setup with "triple eligibles."

where $\mu^s > 0$ is a risk premium and ε^s is a stochastic rate of return and follows $\varepsilon^s \sim N(0, \sigma_{\varepsilon^s}^2)$. We assume that this random return comprises a constant nominal dividend yield d and a stochastic nominal capital gain \tilde{g} , deflated by the inflation rate π

$$
\tilde{r}^s = \frac{1 + \tilde{g} + d}{1 + \pi} - 1.
$$
\n(2)

We can use expression [\(1\)](#page-12-1) and [\(2\)](#page-13-0) to solve for the stochastic capital gain \tilde{g} . Similar to [Gomes, Michaelides and](#page-39-4) [Polkovnichenko](#page-39-4) [\(2009\)](#page-39-4) we impose that asset return taxes are paid on nominal returns at two different rates, τ*^g* is the capital gains tax and τ_d is the dividends tax. Assuming a constant rate of inflation π , the after-tax real return of the risky asset is:

$$
\tilde{r}_{\text{net}}^s = \frac{1 + \tilde{g}(1 - \tau^g) + d\left(1 - \tau^d\right)}{1 + \pi} - 1. \tag{3}
$$

Workers save for insuring themselves against shocks to income, health expenditure shocks, uncertainty related to their health insurance status, and for retirement. We allow workers to borrow using the risk-free bond with a borrowing limit so that $b_{i+1} \geq b$ and stock holdings cannot be negative $s_{i+1} \geq 0$. When households trade in the risky asset they incur a fixed transaction cost $q_j(\vartheta,\varepsilon^h)$ that can vary by age, permanent education status, and health status.^{[17](#page-13-1)}

3.6 Taxes and transfers

The government collects the following taxes: a progressive labor income tax on taxable income y_j^{tax} denoted tax^{*y*}(y_j^{tax}), payroll taxes tax^{ss} $(y_j^{\text{ss}}; \bar{y}^{\text{ss}})$ and tax^{mcare} (y_j^{ss}) for Social Security and Medicare respectively collected on eligible labor income y_j^{ss} , and a consumption tax τ^c . Payroll tax eligible labor income y_j^{ss} is essentially labor income minus employer HI premiums which are income and payroll tax deductible. In addition, the payroll tax for Social Security is proportional only up to the maximum taxable earnings of \bar{y}^{ss} .

With these tax revenues, the government runs the following spending programs: Social Security, Medicare, Medicaid, lump-sum transfers tr^{si} to low income earners that guarantee a minimum consumption level c_{\min} , and residual (unproductive) government consumption.

Households with sufficiently low income qualify are eligible for a transfer that guarantees a minimum consumption level *c*min. Households are eligible for Medicaid payments if they pass the income and asset tests $y_j < \bar{y}^{\text{maid}}$ and $a_j < \bar{a}^{\text{maid}}$, respectively. Similar to [Hubbard, Skinner and Zeldes](#page-39-5) [\(1995\)](#page-39-5), low-skill and sick households in our model have an incentive to accumulate less assets to maintain eligibility for means-tested Medicaid.

Households receive Social Security benefits $tr_j^{ss}(\bar{y}^{\theta})$ after the eligibility age $(j > J_w)$. The amount of benefits paid depends on the average earnings history of a permanent income type \bar{y}^{ϑ} .^{[18](#page-13-2)} In addition, households become eligible for Medicare after age $j > J_w$ at which point they also start paying a Medicare premium premmcare every period.

 17 [Ehrlich, Hamlen and Yin](#page-38-6) [\(2008\)](#page-38-6) propose a theory of asset management as a quest for information signals that improve the precision of the forecast of the risky asset's return. This precision is a function of asset management time, information gathering technology, education, and a fixed cost. Our type dependent transaction cost is a simplified version of this process.

¹⁸In reality the government calculates an average of past earnings (up to the maximum taxable earnings), referred to as the Average Indexed Monthly Earnings (AIME). The Social Security benefit amount, also called the Primary Insurance Amount (PIA), *bss*, *^j*(AIME) is then a function of AIME.

Finally, we assume that Social Security, Medicare, and Medicaid are part of the overall budget constraint.

3.7 Household optimization problem

3.7.1 Working households

Following [Campanale, Fugazza and Gomes](#page-36-5) [\(2015\)](#page-36-5) we cast the problem of stock and bond state variables into an equivalent variable pair consisting of current wealth *a* and current share α invested in stock. This method allows us to reduce the state space as α is simply a choice variable and does not need to be tracked over time.

The state vector of the working household is $x_j = \left\{\vartheta, a_j, \varepsilon_j^{\text{incP}}, \varepsilon_j^h, \varepsilon_j^{\text{ehi}}\right\} \in \{1, 2, 3\} \times R \times \{1, 2, 3, 4\} \times R$ $\{1,2,3,4,5\} \times \{0,1\}$, where ϑ denotes the permanent income group, a_j denotes current wealth, $\varepsilon_j^{\text{incP}}$ denotes the persistent labor shock, ε^h denotes the exogenous health state, and $\varepsilon_j^{\text{ehi}}$ is the private insurance state. After the realization of the state variables, agents simultaneously chose from their choice set

$$
\mathscr{C}_j \equiv \left\{ (c_j, \ell_j, \alpha_j) \in R^{++} \times [0, 1] \times [0, 1] \right\}
$$

where c_j is consumption, ℓ_j is leisure and α_j is the fraction of stock holdings in the investment portfolio for the next period in order to maximize their lifetime expected utility. All choice variables in the optimization problem are functions of the state vector but we suppress this notation in order to not clutter the exposition. The household problem of the working household can be recursively written as

$$
V(x_j) = \max_{\mathcal{C}_j} \left\{ u(c_j, \ell_j) + \beta \mathbb{E}_{\varepsilon_{j+1}^{\text{incP}}, \varepsilon_{j+1}^h, \varepsilon_{j+1}^{\text{ch}}} \left[\pi_j \left(\varepsilon_j^h \right) V(x_{j+1}) + \left(1 - \pi_j \left(\varepsilon_j^h \right) \right) u^{\text{beq}}(a_{j+1}) \right] \right\}
$$
(4)
s.t.

$$
a_{j+1} = \tilde{R}_{j+1} \left(a_j + y_j \left(\ell_j, \vartheta, \varepsilon_j^h, \varepsilon_j^{\text{incP}} \right) + \operatorname{tr}_j^{\text{si}} - o_j \left(m_j, \varepsilon_{j, \vartheta}^{\text{ehi}}, y_j^{\text{agi}}, a_j \right) - 1_{\left[\varepsilon_j^{\text{ehi}} = 1 \right]} \operatorname{prem}_j^{\text{ehi}} - \operatorname{tax}_j - (1 + \tau^c) c_j - 1_{\left[\alpha_j > 0 \right]} q_j \left(\vartheta, \varepsilon_j^h \right) \right)
$$

$$
\tilde{R}_{j+1} = \alpha_j \left(1 + \tilde{r}_{net,j+1}^s \right) + (1 - \alpha_j) \left(1 + \bar{r}_{net}^b \right),
$$

$$
\underline{b} \leq b_{j+1},
$$

$$
0 \leq s_{j+1},
$$

where β is a time preference factor, $\pi_j(\varepsilon^h)$ is the age and health state dependent survival probability, *r* is the interest rate, $o(m_i)$ is out-of-pocket medical spending, prem^{ehi} is the insurance premium paid. The indicator functions are defined as $1_{[true]} = 1$ and $1_{[false]} = 0$. Labor income y_j , total taxable income y_j^{tax} , and payroll tax eligible income y_j^{ss} are defined as

$$
y_j = \widehat{w} \times e_j \left(\vartheta, \varepsilon_j^{\text{incP}}, \varepsilon^h \right) \times (1 - \ell_j),
$$

\n
$$
y_j^{\text{tax}} = y_j - 1_{\left[\text{in}_{j+1} = 2 \right]} \text{prem}_j^{\text{chi}} - \max \left[0, o_j \left(m_j, \varepsilon_{j, \vartheta}^{\text{chi}}, y_j^{\text{agi}}, a_j \right) - 0.075 \times (y_j + r_b \times b_j + r_s \times s_j) \right],
$$
\n(5)
\n
$$
y_j^{\text{ss}} = y_j - 1_{\left[\text{in}_{j+1} = 2 \right]} \text{prem}_j^{\text{chi}},
$$
\n(6)

where private HI premiums are tax deductible as are out-of-pocket health expenses that exceed 7.5 percent of

adjusted gross income.^{[19](#page-15-0)} For simplicity we assume that, adjusted gross income y_i^{agi} j_j^{ag} is equal to earnings y_j as we do not explicitly model many of the additional income categories—such as cancellation of debt, stock options, etc. or deductible categories such as educator expenses, IRA deductions, student loan deductions, etc.—that enter the calculation of adjusted gross income.

Consumption is taxed with rate τ^c and the remaining taxes are defined as

$$
tax_j = tax^y (y_j^{tax}) + tax^{ss} (y_j^{ss}; \bar{y}^{ss}) + tax^{mcare} (y_j^{ss}),
$$

$$
tax^{ss} (y_j^{ss}; \bar{y}^{ss}) = \tau^{ss} \times \min [y_j^{ss}; \bar{y}^{ss}],
$$

$$
tax^{mcare} (y_j^{ss}) = \tau^{mcare} \times y_j^{ss},
$$

where tax^{*y*} is a progressive income tax function of taxable household income $y_j^{\text{tax}}, \tau^{\text{ss}}$ is the social security payroll tax levied on "social security wages"—essentially wages minus GHI premiums—and an upper contribution limit of \bar{y}^{ss} , and tax^{mcare} is a Medicare payroll function with the same tax base but without an upper limit.^{[20](#page-15-1)} Social transfers are defined as

$$
tr_j^{si} = max [0, c_{min} + o(m_j) - y_j^{at} - a_j],
$$

\n $y_j^{at} = y_j - tax_j,$

and ensure a minimum consumption floor *c*min after medical expenses and taxes are paid for. A household consuming at the lower bound cannot save into the next period or purchase private insurance.

Average past labor earnings for each permanent income group ϑ follow

$$
\bar{y}^{\vartheta} = \int_{j \le J_w} y_j(x(\vartheta)) d\Lambda(x(\vartheta))
$$

where $x(\theta)$ is the mass of households belonging to permanent income group ϑ .

3.7.2 Fully retired households.

Households stop working at age 65, or $j > J_w$. They then receive Social Security benefits and qualify for Medicare starting. The state vector of a retired household at a particular age is defined as $x_j = \left\{\vartheta, a_j, \varepsilon_j^h\right\} \in$

¹⁹Compare Schedule A (Form 1040), Itemized Deductions at: [https://www.irs.gov/forms-pubs/about-schedule-a-form](https://www.irs.gov/forms-pubs/about-schedule-a-form-1040) [-1040](https://www.irs.gov/forms-pubs/about-schedule-a-form-1040)

 20 Employers contribute 50 percent of Medicare and Social Security taxes. For simplicity, we assume that employees pay 100 percent of all payroll taxes.

 ${1,2,3} \times R \times {1,2,3,4,5}$. The household optimization problem reduces to

$$
V(x_j) = \max_{\{c_j, \alpha_j\}} \left\{ u(c_j) + \beta \mathbb{E}_{\varepsilon_{j+1}^h, \varepsilon_{j+1}^s | \varepsilon_j^h} \left[\pi_j \left(\varepsilon_j^h \right) V(x_{j+1}) + \left(1 - \pi_j \left(\varepsilon_j^h \right) \right) u^{\text{beq}}(a_{j+1}) \right] \right\}
$$
(7)
s.t.

$$
a_{j+1} = \tilde{R}_{j+1} \left(a_j + \text{tr}_j^{\text{ss}} \left(\bar{y}^{\vartheta} \right) + \text{tr}_j^{\text{si}} - o_j \left(m_j, \varepsilon_{j,\vartheta}^{\text{ehi}}, y_j^{\text{agi}}, a_j \right) - \text{prem}^{\text{mcare}} - \text{tax}^y \left(y_j^{\text{tax}} \right) - (1 + \tau^c) c_j - 1_{\{\alpha_j > 0\}} q_j \left(\vartheta, \varepsilon_j^h \right) \right)
$$
(8)

$$
\tilde{R}_{j+1} = \left(\alpha_j \left(1 + \tilde{r}_{net,j+1}^s \right) + (1 - \alpha_j) \left(1 + \bar{r}^b \right) \right)
$$

$$
\underline{b} \leq b_{j+1},
$$

$$
0 \leq s_{j+1},
$$

where taxable income y_j^{tax} is defined as

$$
y_j^{\text{tax}} = \text{tr}_j^{\text{ss}} \left(\bar{y}^{\vartheta} \right) - \max \left[0, \left(o_j \left(m_j \right) + \text{prem}^{\text{mcare}} \right) - 0.075 \times \left(r_b \times b_j + r_s \times s_j + \text{tr}_j^{\text{ss}} \right) \right].
$$

For retirees out-of-pocket expenses plus Medicare premiums that exceed 7.5 percent of gross income are tax deductible.^{[21](#page-16-1)} Social insurance transfers are defined as

$$
\text{tr}_{j}^{\text{si}} = \max\left[0, \, c_{\min} + o_j\left(m_j\right) + \text{prem}^{\text{mcare}} + \text{tax}^{\text{y}}\left(y_j^{\text{tax}}\right) - a_j - \text{tr}_{j}^{\text{ss}}\right].
$$

Since we force every retired individual into the combined Medicare/Medicaid program, the social insurance transfers include the Medicare premium.

4 Mapping the model to data

In this section we follow a two-step procedure to map the model to data. In the first step, we pick parameter values by either using established estimates from the previous literature or estimating them directly from the data. These calibrated parameters include medical expense shocks, health state transition matrices, productivity profiles, labor market shocks, risky asset return shocks, and survival probabilities. In the second step, we use a moment matching method to calibrate the remaining parameters, including the fixed cost of work by skill and health state, a utility constant, a tax scaling parameter, thresholds for Medicaid asset and income tests, a consumption floor, a time preference parameter, the weight on consumption, the strength of the bequest motive and stock market participation costs by skill and health status.^{[22](#page-16-2)} We first describe the set of parameters that were estimated externally without using our model and report them in Tables [16](#page-53-0) and [17.](#page-54-0)

²¹ Details about the tax deductibility of out-of-pocket expenses and Medicare premiums can be found in [IRS](#page-39-6) [\(2010\)](#page-39-6).

 22 Income data is based on MEPS as this survey contains observations of the 40–65 age cohorts at annual frequencies. Medical expense shocks and health state transition matrices are estimated with data from MEPS 1996–2018. While asset data is also available in MEPS, it is not publicly available. Therefore we base the financial assets information on data from the PSID 1984–2019. The Technical Appendix provides details about sample selection and contains summary statistics for the HRS, PSID and MEPS survey data.

4.1 Demographics and preferences

One model period is defined as one year. Households have a life span from age 40 to age 94 which results in $J = 55$ periods. Once the individual enters age 65, i.e., period $J_{w+1} = 26$, she is forced to retire. We take the age and health specific survival probabilities from Imrohoroglu and Kitao [\(2012\)](#page-39-7). For the purpose of survival probabilities $\pi\left(h\left(\mathcal{E}^h\right)\right)$ we distinguish between healthy and sick individuals. We specify period utility as

$$
u\left(c_j,\ell_j;\omega_{j,\vartheta};\bar{n}_j\left(\vartheta,\varepsilon^h\right);\bar{u}\right)=\frac{\left(\left(\frac{c_j}{\omega_{j,\vartheta}}\right)^{\eta}\times\left[\ell_j-1_{\left[0
$$

The equivalence weight is calculated using data from the HRS as $\omega_{j,\vartheta} = (a\text{dults}_j + 0.7 \times \text{children}_j)^{0.7}$ following [Scholz, Seshadri and Khitatrakun](#page-42-4) [\(2006\)](#page-42-4), where adults*^j* and children*^j* are the number of adults and children (respectively) in the household associated with a household head of age *j*. We set the relative risk aversion parameter σ to 3. The warm-glow bequest function is $u^{\text{beq}}(a) = \theta_1 \frac{(a+\theta_2)^{(1-\sigma)\eta}}{1-\sigma}$ $\frac{\theta_2}{1-\sigma}$, where parameter θ_1 determines the strength of the bequest motive, while parameter θ_2 is the threshold of wealth at which a household finds it valuable to leave a bequest. Similar to [French](#page-38-11) [\(2005\)](#page-38-11) we set the bequest parameter θ_2 to 500,000.^{[23](#page-17-0)} The remaining parameters will be calibrated from within the model as described in Section [4.6.](#page-20-0)

4.2 Health status, health expenditures, and private health insurance

We use data from MEPS 1996–2018 to estimate the magnitude of the age dependent health expenditure shocks $m(j, \vartheta, \varepsilon^h)$ as well as the Markov transition probability matrix Pr $(\varepsilon_{j+1}^h | \varepsilon_j^h)$. We group individuals into five health groups ε^h \in $\{1,2,3,4,5\}$ by self-reported health status: 1. excellent health, 2. very good health, 3. good health, 4. fair health, and 5. poor health. We then calculate average medical spending of each health group by age and education level to determine the magnitude of the health spending shocks $m(j, \vartheta, \varepsilon^h)$. Since MEPS only accounts for about 65–70 percent of health care spending in the national accounts (see [Sing, Banthing,](#page-42-5) [Selden, Cowan and Keehan](#page-42-5) [2006;](#page-42-5) [Bernard, Cowan, Selden, Cai, Catling and Heffler](#page-36-7) [2012\)](#page-36-7) we scale up the medical spending profiles for individuals older than 65 similar to [Pashchenko and Porapakkarm](#page-41-7) [\(2013\)](#page-41-7). The resulting spending profiles are shown in Panels [1]–[3] of Figure [4.](#page-50-0) Next, we estimate an ordered logit model to determine the conditional probability of moving to a specific health group $\varepsilon_{j+1,t+1}^h$ in year $t+1$ conditional on being a member of health group $\varepsilon_{j,t}^h$ at time *t* and age *j* using a fourth order age polynomial.^{[24](#page-17-1)} Finally, we use MEPS 1996–2018 data and estimate that the fraction of 40 year old households with private health insurance, $\varepsilon_j^{\text{ehi}} = 1$ is 75 percent.

 23 This functional form is similar to the one in [French](#page-38-11) [\(2005\)](#page-38-11). This warm-glow type bequest motive was first introduced by [Andreoni](#page-35-7) [\(1989\)](#page-35-7) and used in a general equilibrium model in [De Nardi](#page-37-10) [\(2004\)](#page-37-10). A more sophisticated form of altruism would require an additional state variable and increase the computational complexity.

 24 The Technical Appendix provides detailed information on the distribution of health groups by age and the associated distribution of medical spending shocks by health group and age, and the conditional transition probabilities between the health states by age.

4.3 Endowments

To calibrate the labor income process, we first assume that labor productivity at age *j* can be decomposed as

$$
e_j\left(\vartheta,\varepsilon^h,\varepsilon^{\text{incP}}\right)=\bar{e}_j\left(\vartheta,h\left(\varepsilon^h\right)\right)\times\varepsilon^{\text{incP}},\tag{9}
$$

where $\bar{e}_j(\theta, h(\epsilon^h))$ depends on age *j*, education level θ , and health state ϵ^h . The education level is permanent and fixed at age 40.

Using 1996–2018 MEPS data we construct cohort adjusted and bias corrected wage profiles for each education-health subgroup $(\vartheta, h(\varepsilon^h))$ limiting the sample to heads of households with labor incomes larger than $$400.²⁵$ $$400.²⁵$ $$400.²⁵$ We distinguish between three permanent educational groups

$$
\vartheta = \begin{cases} 1 & \text{if less than high school,} \\ 2 & \text{if high school,} \\ 3 & \text{if college graduate or higher,} \end{cases}
$$

and two health states

$$
h\left(\varepsilon^{h}\right) = \begin{cases} \text{ healthy} & \text{if } \varepsilon^{h} \in \{\text{excellent, very good, good}\},\\ \text{sick} & \text{if } \varepsilon^{h} \in \{\text{fair, poor}\}. \end{cases}
$$

These are standard definitions for healthy and sick in the health macro literature. Panel [4] in Figure [11](#page-57-0) depicts the fraction of healthy individuals and Table [17](#page-54-0) shows the relative cohort sizes of healthy/sick types by permanent income group.

We deflate hourly wage observations with the urban CPI and remove cohort effects. We then follow the procedure in [Rupert and Zanella](#page-41-8) [\(2015\)](#page-41-8) and [Casanova](#page-37-11) [\(2013\)](#page-37-11) and estimate a selection model to remove the selection bias that is typically associated with wage observations to get an average wage offer rate for each $(\theta, h(\varepsilon^h))$ subgroup. We finally smooth the wage profiles with a second degree polynomial in age.^{[26](#page-18-1)} The income shock component is modeled as an auto-regressive process so that

$$
\ln\left(\varepsilon_j^{\text{incP}}\right) = \rho \times \ln\left(\varepsilon_{j-1}^{\text{incP}}\right) + \varepsilon,\tag{10}
$$

with persistence parameter ρ and a white-noise disturbance $\varepsilon \sim N(0, \sigma_{\rm pl}^2)$ $\epsilon_{\text{e}^{\text{incp}}}^{2}$). To calibrate the stochastic component ε^n , we use $\rho = 0.977$ and σ_{ε}^2 t_{g}^{2} = 0.0141 based on estimates in [French](#page-38-11) [\(2005\)](#page-38-11) who uses PSID data and controls for cohort effects and health states. We approximate the joint distribution of the persistent and transitory shocks using a five-state first-order discrete Markov process following [Tauchen and Hussey](#page-42-6) [\(1991\)](#page-42-6).

Initial asset holdings are based on wealth holdings of individuals between ages 40–44 in the HRS and include all assets except for housing and real estate wealth as discussed in Section [2.1](#page-6-2) and shown in the first panel of Figure [12.](#page-58-0) We drop individuals with assets exceeding 1 million USD and set negative assets equal to

 25 Labor income follows the definition in PSID and comprises wage income (variable WAGEP) and 75 percent of business income (variable BUSNP).

 26 The online appendix contains more details about the procedures to remove cohort effects and wage biases.

zero as the model does not allow borrowing.

4.4 Financial markets

Stock market returns are standard estimates from the literature. We assume that the risk premium is $\mu^s = 0.04$ and $\sigma_{\varepsilon^s} = 0.157$ (e.g., [Athreya, Ionescu and Neelakantan](#page-35-8) [2023;](#page-35-8) [Cocco](#page-37-12) [2005;](#page-37-12) [Mehra and Prescott](#page-40-6) [1985\)](#page-40-6). The nominal dividend yield *d* in expression [2](#page-13-0) is set at 3.2 percent following [Gomes, Michaelides and Polkovnichenko](#page-39-4) [\(2009\)](#page-39-4). The inflation rate is set at 2.8 percent. The risk free rate is $r^b = 0.02$ [\(McGrattan and Prescott,](#page-40-7) [2000\)](#page-40-7). This results in an average risky stock return of 6 percent. The stock market participation costs by age, skill and health status, $q_j(\theta, \varepsilon^h)$, will be calibrated from within the model as described in Section [4.6.](#page-20-0)

4.5 Taxes and transfers

Taxes and transfers are calibrated to mimic the US fiscal policy settings. Following [Gomes, Michaelides and](#page-39-4) [Polkovnichenko](#page-39-4) [\(2009\)](#page-39-4) we set the proportional dividend tax $\tau^d = 25$ percent and the tax on capital gains $\tau^g = 20$ percent. The progressive income tax function has the following specification

$$
\tan^y(y^{\tan x}) = \max\left[0, y - \tau_0^i \times y^{(1-\tau_1^i)}\right],
$$

where $\text{tax}^y(y)$ denotes net tax revenues as a function of pre-tax income *y*, τ_1^i is the progressivity parameter, and τ_0^i is a scaling factor.^{[27](#page-19-0)} We impose a non-negative tax payment restriction in the benchmark model, tax^{*y*}(*y*) \ge 0. This restriction excludes all government transfers embedded in the progressive tax function. Government transfers are explicitly modeled in government spending programs. We chose the tax curvature parameter $\tau_1 = 0.053$ following [Guner, Lopez-Daneri and Ventura](#page-39-8) [\(2016\)](#page-39-8).^{[28](#page-19-1)} The consumption tax rate τ^c is set to 5 percent. The Social Security system is partly financed via a payroll tax with a contribution limit. The Social Security payroll tax is $\tau^{ss} = 10.6$ percent. The Social Security payroll tax is collected on labor income up to a maximum of $$106,800.²⁹$ $$106,800.²⁹$ $$106,800.²⁹$ The government collects a Medicare payroll tax from workers and Medicare premium payments of individuals older than 65. The Medicare payroll tax is $\tau^{meare} = 2.9$ percent. It is not restricted by an upper limit (see [SSA,](#page-42-7) [2007\)](#page-42-7).

In the model, social security transfers are defined as a function of average labor income per skill type \bar{y}^{ϑ} . Let tax^{ss} (ϑ) = Ψ^{ϑ} × \bar{y}^{ϑ} be type specific pension payments where $\Psi^{\vartheta} = \{0.66, 0.47, 0.39\}$ is a skill type dependent replacement rate that determines the size of the pension payments.^{[30](#page-19-3)}

We fix the Medicare coinsurance rate at $\gamma^{\text{mcare}} = 0.30$ is calculated directly from MEPS data and the Medicare premium at USD 1,140 which is close to 2.1. percent of per capita GDP a value used in [Jeske and Kitao,](#page-39-9) [2009.](#page-39-9) The Medicare tax τ^{mcare} is set to 2.9 percent.^{[31](#page-19-4)} The Medicaid coinsurance rate $\gamma^{\text{maid}} = 0.11$ is calculated directly from MEPS data. The income test for Medicaid varies greatly across states. According to [Kaiser](#page-40-8)

²⁷This tax function is fairly general and captures the common cases of (*i*) full redistribution if $\tau_1 = 1$, (*ii*) progressive taxes if $0 < \tau_1 < 1$, *(iii)* proportional taxes if $\tau_1 = 0$, and *(iv)* regressive taxes if $\tau_1 < 0$.

 28 This tax function was implemented into a dynamic setting by [Benabou](#page-36-8) [\(2002\)](#page-36-8) and more recently in [Heathcote, Storesletten and](#page-39-10) [Violante](#page-39-10) [\(2017\)](#page-39-10). These authors do not model transfers explicitly and therefore allow income taxes to become negative for low income groups.

²⁹Compare contribution bases for Social Security contributions at: <https://www.ssa.gov/oact/cola/cbb.html>

³⁰These replacement rates are based on wage indexed average earnings presented in Table 1 in [Biggs and Springstead](#page-36-9) [\(2008\)](#page-36-9).

³¹ Medicare payroll taxes are 2×1.45 percent on all earnings split in employer and employee contributions (e.g., see [SSA,](#page-42-7) [2007\)](#page-42-7).

[\(2013\)](#page-40-8), 16 states have Medicaid eligibility thresholds below 50 percent of the FPL, 17 states have eligibility levels between 50 and 99 percent, and 18 states have eligibility levels that exceed 100 percent of the FPL. In ad-dition, state regulations also vary greatly with respect to the asset test of Medicaid.^{[32](#page-20-1)} The remaining parameters are calibrated from within the model as described in the next section.

4.6 Calibration of internal parameters

As previously mentioned in the preceding sections, in the second step we apply a moment matching method to calibrate the remaining parameters within the model, including fixed cost of work by skill and health state, a utility constant, a tax scaling parameter, thresholds for Medicaid asset and income tests, a consumption floor, a time preference parameter, the weight on consumption, the strength of the bequest motive and stock market participation costs by skill and health status

$$
\Theta = \left\{ \bar{n}_j\left(\vartheta,\varepsilon^h\right), \bar{u}, \tau_0^i, \bar{a}^{\text{maid}}, \bar{y}^{\text{maid}}, c_{\text{min}}, \beta, \eta, \theta_1, q(\text{age-group}, \vartheta, \varepsilon^h) \right\}.
$$

These internally calibrated parameters are jointly chosen to minimize the (weighted) distance between target moments estimated in the data and the corresponding moments simulated by the model, taking the externally determined parameter values from the first step as given. Specifically, we use asset data from PSID 1984–2019 and labor hours as well as labor market participation data from MEPS 1996–2018 to construct the data moments. The structural model provides a mapping from a set of parameters Θ to the model-simulated moments. We simulate the model to construct the simulated counterpart of the empirical target moments. We then calculate the difference between the data moments and the simulated-model-data moments and use the moment matching method to jointly discipline these structural parameters.

The fixed cost of working $\bar{n}_j(\vartheta, \varepsilon^h)$ is effective if the individual works (i.e., $n_j = (1 - \ell_j) > 0$) and is set to match the average work participation rate by age, permanent education type, and health status from MEPS as shown in Figure [8.](#page-52-0) The constant \bar{u} is set at 10 to match a value of statistical life of 2.5 million for the working age population of 40–65 year olds.^{[33](#page-20-2)} The consumption intensity parameter η is chosen to match the average labor hours of the working age population.

We calibrate the scaling factor τ_0^i to match average U.S. income taxes of 40 year olds. The government makes lump-sum transfers to maintain a minimum level of consumption c_{min} of \$4,000. Similarly to [Jeske and](#page-39-9) [Kitao](#page-39-9) [\(2009\)](#page-39-9) this floor is calibrated to target the 20 percent share of households with net asset worth of less than \$5,000 based on estimates in [Kennickell](#page-40-9) [\(2003\)](#page-40-9).

In the model we therefore calibrate the Medicaid income eligibility level to $\bar{y}^{\text{maid}} = 5,500 \text{ USD}$ in order to target the Medicaid eligible working age population between ages 40–50. Similarly we calibrate the asset eligibility level to $\bar{a}^{\text{maid}} = 75,000 \text{ USD}$ in order to match the fraction of workers between ages 51–64 insured via Medicaid. Panel [4] of Figure [7](#page-52-1) shows the Medicaid coverage by age group in the model vs. MEPS data.

We target the behavior of households over the lifecycle with respect to wealth accumulation and risky assets participation. While time preferences β can influence various model-generated moments, it has a particularly strong effect on wealth accumulation. Therefore, we use the wealth-to-income ratio as a targeted moment.

³²Compare [Remler and Glied](#page-41-9) [\(2001\)](#page-41-9) and [Aizer](#page-35-9) [\(2003\)](#page-35-9) for additional discussions of Medicaid take-up rates.

 33 The estimates range from 1 million to 16 million based on a review by [Viscusi](#page-42-8) [\(1993\)](#page-42-8). [De Nardi, Pashchenko and Porapakkarm](#page-37-1) [\(2024\)](#page-37-1) target a value of 2 million but working age in their model is lower and starts at the age of 20.

Parameter η , the weight on consumption vs. leisure will strongly influence labor supply of the households. In order to estimate the strength of the bequest motive θ_1 we target moments of assets holdings at age 80 and higher. Finally, to estimate the age-group, education, and health state dependent stock market participation costs, we rely on moments of stock market participation rates by three age groups (40-59, 60-64, 65-80), three education levels (low, medium and high), and two health states (sick and healthy). We report the internally calibrated parameter values in Tables [18](#page-54-1) and [19.](#page-55-0)

4.7 Model performance

Our benchmark model is capable of matching important lifecycle patterns observed from the data. Figure [5](#page-51-0) shows the targeted stock market participation rates by health status while Figure [9](#page-53-1) shows the associated stock market participation costs. Participation costs depend on permanent income type as well as health. Individuals with low education have the lowest participation costs, around USD 2,000. These costs decrease with age for both sick and healthy types, but they decrease more for healthier individuals. A similar pattern can be observed for individuals with a high school education, however, overall their participation cost is higher and ranges between USD 3,800–5,800. Finally, individuals with college degrees have the highest participation costs. Our calibrated values range between USD 6,300–16,300. The estimates in the literature show a wide range of estimates of participation costs that range from a few hundred dollars per year such as [Fagereng, Gottlieb and](#page-38-5) [Guiso](#page-38-5) [\(2017\)](#page-38-5) and [Catherine](#page-37-6) [\(2022\)](#page-37-6) who both require coefficients of relative risk aversion beyond a value of 4, to a few thousand dollars.^{[34](#page-21-0)} For instance, [Vissing-Jorgensen](#page-42-9) [\(2003\)](#page-42-9) estimates that per-period stock-market participation costs range from \$890–\$1,930 (in 2018 dollars). These estimates does not include first time investment costs, a fixed cost of trading stocks, nor variable (proportional) cost of brokerage commissions and should therefore be interpreted as lower bound estimates. More recently [Daminato and Pistaferri](#page-37-13) [\(2024\)](#page-37-13) use a lifecycle model similar to ours (but without health shocks for working age individuals and without labor supply decisions) and estimate participation costs of \$1,300 for highly educated and \$2,100 (in 2018 dollars) for lower educated workers. This does not seem to be in line with the structural estimation results of [Khorunzhina](#page-40-10) [\(2013\)](#page-40-10) who models income based stock market participation costs and finds that stock market participation costs range between 4–6 percent of labor income. This result suggests that the overall cost is higher for individuals with better education which is in line with our results. Finally, Figures [8–](#page-52-0)[7](#page-52-1) show additional targeted moments of the calibration, including labor force participation, work hours and asset holdings over the lifecycle.

Figures [10–](#page-56-0)[14](#page-60-0) and Tables [20](#page-56-1)[–23](#page-63-0) report not-targeted data moments. Figures [10](#page-56-0) shows the stock market participation rates by health at age 45–55. These are the very profiles we already discussed in the empirical section. We can now see that the model replicates this long-term correlation and shows the distinctive gap in stock participation between the two health-types.

Figure [11](#page-57-0) shows that the model reproduces the overall shape of the labor income and the health expenditure distribution. The model tracks the lifecycle profiles of medical spending as fraction of income and the overall fraction of healthy individuals. Figure [12](#page-58-0) shows the close fit of the financial wealth distribution by health type based on PSID data. The wealth Gini coefficient is 0.73 in the model, which is close to 0.76 calculated from PSID.

³⁴A more recent contribution by [Velásquez-Giraldo](#page-42-10) [\(2023\)](#page-42-10) finds similarly low participation costs with a much lower risk aversion factor of 1.6 via introducing heterogeneity in expectations of stock returns.

Figure [13](#page-59-0) shows how the financial wealth distributions of sick and healthy individuals shift as individuals age from the 40–50 age group into the 60–70 age group. The model replicates the pattern discussed in section [2](#page-6-0) that shows a rightward shift in the financial asset distribution of healthy individuals as they age, but not for sick individuals who seem to be "stuck" and have limited ability to "move" the financial wealth distribution to the right.^{[35](#page-22-1)} The model also tracks the average wealth to average income ratio by age, health type, and education level fairly well as shown in Figure [14.](#page-60-0)

Finally, Table [21](#page-61-0) uses model generated data to estimate a selection model of stock market participation similar to the regressions in Section [2](#page-6-0) and illustrate how the strong correlation of health-at-age 45–55 with stock market participation rates at age 60–70 is replicated in the model. Finally, Table [22](#page-62-0) present estimates of the same selection model for the simulated subsample of individuals who report being healthy at age 40, in order to abstract from differences in initial health conditions. These estimates using model generated data show similarly strong correlations of health status when young and stock participation as well as stock shares in the wealth portfolios of older individuals. In Table [23](#page-63-0) we estimate the selection model separately by education group and find that while stock market participation is negatively affected by poor health at younger ages across all three education groups, the null effect of poor health on the stock share of the elderly is driven by college graduates. Individuals with lower levels of education do seem to be negatively affected by poor health with respect to their stock market participation rate and the fraction of assets held in risky assets.

5 Quantitative analysis

In this section we use the model to assess the impact of health dynamics on lifetime earnings and wealth inequality via the health-wealth portfolio channel.

5.1 The benefits of good health

We first quantify the monetary benefit of good health in the two financial assets version of the model. In our framework the monetary benefit of being in good health arises from lower out-of-pocket health expenditure, higher labor income resulting from higher labor productivity and longer work hours, and higher capital income due to holding more of the financial wealth in stocks that pay a higher return in the long-run. In addition, the survival channel adds an incentive to increase earnings in order to accumulate more wealth. By adding up these benefits we can measure the accumulated gains due to good health that an individual experiences over the lifecycle.

In order to accomplish this we follow [De Nardi, Pashchenko and Porapakkarm](#page-37-1) [\(2024\)](#page-37-1) and place individuals into a counterfactual situation where they only draw "good health states" (by surprise) while all the other exogenous variables evolve identically as in the original benchmark economy. This type of experiment does not require a resolving of the policy functions. When we simulate the choices of an individual over her lifecycle, we simply use the benchmark policy functions but "surprise" the individual with only good health state draws throughout her lifetime. We use the following notation to differentiate benchmark outcomes from outcomes based on "good health surprises." An individual i in the benchmark economy has income y_{ij}^* in period j while

 35 Tables [E.1](#page-124-0) and [E.2](#page-124-1) in the Technical Appendix present the close fit of the model with respect to the wealth mobility index based on [Shorrocks](#page-42-11) [\(1978\)](#page-42-11).

	All	By skill level		
		Low	Medium	High
In good health between 45–55 \bullet % of time in bad health eliminated • Medical cost \downarrow + income \uparrow \bullet Welfare (CEV)	8.89% \$3,278	12.56% \$3,815 $+9.72%$	8.10% \$3,070 $+8.11\%$	5.64% \$3,032 $+5.55\%$
In good health between 40-death \bullet % of time in bad health eliminated • Medical cost \downarrow + income \uparrow \bullet Welfare (CEV)	16.27% \$7,913	23.19% \$9,256 $+21.45%$	15.17% \$7,534 $+20.01%$	10.125% \$6,971 $+13.68%$

Table 1: The benefit of good health

Notes: Good health conditions are defined as health states of excellent for this counterfactual experiment. Skill types include: Low (No high school), Medium (High school) and High (College).

an individual in the hypothetical alternative scenario has income y_{ij}^{**} .^{[36](#page-23-0)} We then compare their lifetime income (net out-of-pocket health spending) and calculate the average monetary benefit as:

$$
\overline{\text{benefit}}_i = \frac{\sum_{j=1}^J 1_{\text{alive}_j} \times \left(\left(y_{ij}^{**} - oop_{ij}^{**} \right) - \left(y_{ij}^* - oop_{ij}^* \right) \right)}{\sum_{j=1}^J 1_{\text{alive}_j}},
$$

where oop_{ij}^* is out-out-pocket health expenditure of the individual in the benchmark economy and oop_{ij}^{**} is out-out-pocket health expenditure of the same individual who only draws good health states. The difference in available income between the benchmark and the counterfactual world with only good health draws presents a measure of the monetary benefit of good health (or the average cost of falling into poor health if one were to switch the sign of the expression).

We next calculate a measure of welfare which is a more comprehensive measure as health shocks additionally influence the disutility from work and life expectancy. We therefore implement a similar procedure to measure welfare gains/losses in terms of compensating equivalent consumption variation (CEV).^{[37](#page-23-1)}

We focus on two counterfactuals: (*i*) good health during the peak of the earnings capacity between ages 45–55; and good health (*ii*) from age 40 to death. We display the main results in Table [1.](#page-23-2) We also report the stock market participation profile changes as well as changes in asset profiles, labor market profiles, and insurance take-up profiles in Figures [15–](#page-64-0)[18](#page-66-0) for the first counterfactual experiment with good health draws between the ages of 45–55.

We begin with the case where individuals are switched to excellent health during the peak of their earnings capacity between ages 45–55. This experiment eliminates about 9 percent of time spent in bad health and therefore decreases health expenditure while it increases labor productivity simultaneously for individuals who experienced bad health states in the benchmark economy. The average monetary benefit of staying in best health (i.e., a health status of excellent) is around \$3,280 per year. The monetary benefits differ across skill types as the lower skill types are more likely to transition into bad health states. As a result, they have significantly higher benefits of around \$3,800 if they are able to remain in good health between the ages of 45–55. Importantly, we

³⁶Variable *y* refers to gross income from earnings and transfers but excludes dividends, capital gains, and interest income.

 37 More technical details about the CEV welfare calculations are provided in Section [G](#page-132-0) in the Technical Appendix.

calculate large welfare gains for all individuals across all skill types. Specifically, the welfare gains in terms of CEV are 9.7, 7.8 and 5.2 percent for low, medium and high skill types, respectively.

Figure [15](#page-64-0) shows that the stock participation rate increases for both health types. The group of individuals with poor health who were classified as being sick in the benchmark economy ceases to exist for the ages of 45–55 as can be seen from panel 1, but then show much higher participation rates starting at age 56 and up when individuals belonging to this group are hit with bad health shocks again. The absence of bad health shocks during the age of 45–55 allows these individuals (who were classified as sick in the benchmark) to participate in the stock market at much higher rates as they have more funds available to invest and pay the participation cost. A potentially surprising effect is that the same is true for individuals in good health who also participate at higher rates. The reason is that individuals considered to be healthy have health states of either (*i*) excellent, (*ii*) very good or (*iii*) good. Since we "surprise" everybody with excellent health, individuals in very good health and good health also experience a productivity boost and a decrease in their out-of-pocket health spending. From panel 2 we see that the stock shares also follow a very similar pattern across the healthy and sick types. The reason for why panel 2 almost mirrors panel 1 is the fact that in out model without liquidity costs, a household who ends up joining the stock market does so with close to 100 percent of her assets as can be seen from panel 3. Panels 4–6 show the stock participation, stock share, and stock share conditional on participating in the stock market by health-at-45–55. We again see that the healthy group also benefits from the good health surprise and increases its stock market participation. The sick-at-45–55 group does, of course, not exist in this context as we "surprise" everybody with good health draws when they are between 45–55 in this experiment.

From Figure [16](#page-65-0) we see that the overall financial asset level increases for all age group starting with age 45 (panel 1) while wealth inequality—measured here as the ratio of the 90th percentile over the 50th percentile of financial wealth—decreases across all age groups (panel 6). In terms of labor market effects we observe in Figure [17](#page-65-1) an increase in labor participation of workers between age 45–55 (panel 1) and an increase in hours worked (panel 2) with subsequent increases in labor income (panels 3 and 4). These are primarily the results of increased productivity due to better health. Panel 5 shows that the expected reduction in out-of-pocket medical spending and panel 6. the overall increase in consumption across all age groups. Overall these effects lead to welfare gains that we have already highlighted above in Table [1.](#page-23-2) Finally, from Figure [18](#page-66-0) we see that the good health surprise draws lead to increases in private employer provided health insurance as more people join the labor market (panels 1.A, 2.A) and decreases in the fraction of individuals on Medicaid (panels 1.B and 2.B).

In a follow up experiment we use the model to calculate the treatment effect on the treated (ATET). In the above experiment the treated were defined as households who reported being in poor health in at least one year between the age of 45–55. We now focus the analysis on just this group and remove everybody else from the simulated sample. We then take these individuals and surprise them with excellent health between the age of 45–55 and let them adjust (according to their policy functions) to this new information. This results in counterfactual outcomes of the treatment group, had they NOT been treated. Figure [19a](#page-67-0) shows the age profiles of stock participation, stock levels, safe asset levels, total assets, labor income and consumption. The gap in the curves is a measure of the average treatment effect of the treated or ATET and is shown in Figure [19b.](#page-67-1) From the respective panel 1 in Figures [19a](#page-67-0) and [19b](#page-67-1) we see that had this group of individuals not suffered from poor health in their 40s and early 50s, then their participation rate in risky assets at age 65 would have been 17

percentage points higher (an increase from 30 percent to 47 percent). From panel 4 we see that this amounts to an asset gap of 40,000 USD by age 65. This asset gap at retirement then translates into a persistent gap in consumption levels post retirement.

Next, we turn to the case where individuals are surprised with excellent health from age 40 until death. Unsurprisingly the monetary benefits of good health over the entire lifetime more than double to around \$7,900 on average. Similarly we observe larger welfare gains, between 13 and 21 percent of annual consumption across the different skill groups.^{[38](#page-25-0)} These findings are consistent with the results in [De Nardi, Pashchenko and](#page-37-1) [Porapakkarm](#page-37-1) [\(2024\)](#page-37-1) that are based on a single asset model.

5.2 The health-wealth portfolio channel

As discussed before, there are four pathways through which health can affect wealth inequality in our model: (*i*) health-longevity channel, (*ii*) health-labor productivity/income channel, (*iii*) health-medical expenditure channel, and (*iv*) health-wealth portfolio channel. In this section, we evaluate the relative importance of the health-wealth portfolio channel and implications for wealth inequality.

We start from the benchmark model [A.1] and consider three counterfactual experiments: [A.2] Excellent health "surprise" for all individuals from age 40 until death, [A.3] No portfolio choice where households can only invest in one asset which pays a risk free return without any participation costs, and [A.4] Excellent health and no portfolio choice which is essentially the combination of simulation A.2 and simulation A.3. We report the simulation results in Table [3.](#page-27-0)

	Two assets economy		Single asset economy		
	A.1 Bench.	A.2 Good health $(40$ -death)	A.3 Single asset $A.4=A.2+A.3$		
Stock participation					
• Age 40: sick $45-55$	12%	n/a	n/a	n/a	
• Age 40: healthy $45-55$	15%	14%	n/a	n/a	
• Age 65: sick $45 - 55$	34%	n/a	n/a	n/a	
• Age 65: healthy $45-55$	47%	55%	n/a	n/a	
Assets	100	122.11	70.77	81.94	
Labor participation	51.4%	68.8%	51.89%	68.42%	
Hours (workers)	100	101.98	98.02	102.12	
Consumption	100	104.70	98.62	102.15	
Wealth-to-income (W/I)					
\bullet W/I at 40: all	1.09	1.09	1.12	1.12	
\bullet W/I at 65: all	4.41	5.42	2.79	3.19	
• W/I at 65: sick $45-55$	3.12	n/a	2.06	n/a	
• W/I at 65: healthy $45-55$	5.29	5.42	3.29	3.19	

Table 2: Importance of the health-wealth portfolio channel

Notes: Both safe and risky assets are present in the two asset economy [A.1]. The bad health states are removed in [A.2]. Portfolio choice is eliminated in [A.3]. The health-wealth portfolio channel is completely eliminated in [A.4].

 38 We also calculate the value of statistical life (VSL) and find that there are large differences in the VSL between sick and healthy individuals over the lifecycle, varying between 0.6–0.8 million. We present the detailed calculation of the VSL in Section [H](#page-132-1) in the Technical Appendix.

Labor supply, income, consumption and assets. The first two columns [A.1] and [A.[2](#page-25-1)] of Table 2 highlight the economic benefits of always being in good health. Eliminating bad health states induces more individuals to participate in the stock and labor markets. Overall, the value of asset holdings increases by 22 percent.

When the risky asset choice is removed from the model, only the first three health channels are in play. Individuals in the single asset economy are poorer as shown in column A.3 of Table [2.](#page-25-1) The benefits of removing bad health states in the single asset economy are still positive but slightly smaller than in the benchmark (2 assets) economy. To see this, compare the change in consumption levels across the last two columns [A.3] and [A.4] of Table [2](#page-25-1) to the change in consumption levels across the first two columns [A.1] and [A.2]. The removal of bad health states in the 2 assets economy increases aggregate consumption by almost 5 percent whereas the increase in consumption in the one asset economy is smaller at around 4 percent.

Not surprisingly, the wealth-to-income (W/I) ratios are quite similar at age 40 with and without portfolio choice, as all models are started from the same initial asset distribution based on PSID data of 40–44 year old individuals and the model tracks labor income fairly. However, the W/I ratios at 65 are much higher in the two asset economy, 4.41 in [A.1] compared to 2.79 in [A.3]. The main reason is that interest compounding is more forceful in the two assets model where individuals can invest in risky high return assets. This increases the W/I ratios more forceful over time in the two assets economy [A.1]. Removing bad health states from the two assets economy also drives up the W/I ratios to higher levels than removing bad health states from the single asset economy (5.42 in column [A.2] compared to 3.19 in column [A.4]). These differences underscore the quantitative importance of the health-wealth portfolio channel.

Wealth inequality. We next decompose the effects of the health-wealth portfolio channel on wealth inequality. We measure wealth inequality in terms of the gap between the 90th and the 50th wealth percentile as well as the gap between the 50th and the 25th wealth percentile. These wealth gaps are expressed as ratios, P90/P50 and P50/P25 respectively. In addition we also calculate the wealth Gini coefficient and report all measures in Table [3.](#page-27-0) For direct comparison, we do not recalibrate the model for each counterfactual experiment.

	Two assets economy		Single asset economy			
	A.1 Bench.	A.2 Excellent health $(40-Death)$	A.3 Single asset $A.4 = A.2 + A.3$			
Wealth gap All age groups						
\bullet P90/P50 \bullet P50/P25	14.47 6.58	$8.12 \, (\downarrow 43.9\%)$ 5.35 (18.7%)	8.92 $(\downarrow$ 38.4%) 6.08 (17.6%)	$6.37 \ (\text{\textsterling}56.0\%) \ (\text{\textsterling}28.6\%)$ 3.44 $(\sqrt{47.7\%})(\sqrt{43.4\%})$		
Age 65						
\bullet P90/P50 \bullet P50/P25	15.96 7.08	7.72 $(\sqrt{51.6\%})$ 6.62 (16.5%)	$9.34 \, (\downarrow 41.5\%)$ 7.59 (17.2%)	5.98 $(\text{\textbackslash}62.5\%)$ $(\text{\textbackslash}36.0\%)$ 3.73 (147.3%) (150.9%)		
Wealth Gini	0.73	0.74	0.69	0.71		

Table 3: Wealth inequality

Notes: Both safe and risky assets are present in the two asset economy [A.1]. The bad health shocks are removed in [A.2]. The wealth portfolio channel is eliminated in [A.3]. The health-wealth portfolio channel is completely eliminated in [A.4]. The bold numbers in column A.2 indicate the percentage change compared to column A.1, whereas the bold numbers in column A.4 indicate the percentage change to column A.3. As such, the bold numbers indicate the effect of removing bad health on the financial wealth gap in the two assets economy and the one asset economy, respectively. Removing bad health from the two asset economy reduces the P90/P50 wealth gap by 43.9 percent, whereas removing bad health from the one asset economy reduces the P90/P50 wealth gap by "only" 28.6 percent.

In the two assets economy, the two measured wealth gaps are large at 14.47 and 6.58, respectively. Removing bad health states from the model results in a significant reduction in the wealth gap measures as shown in column A.2 of Table [3.](#page-27-0) The P90/50 and P50/P25 wealth gaps decrease by 43.9 percent and 18.7 percent in the counterfactual economy, respectively. The wealth gaps over the lifecycle are also much lower. The P90/50 and P50/P25 wealth gaps at 65 decrease by 51.6 percent and 6.5 percent, respectively. Hence, the wealth gap between the top P90 and middle P50 wealth groups decreases relatively more.

In the single asset economy where the health-portfolio channel is not operational (column A.3 of Table [3\)](#page-27-0), we observe a similar pattern of wealth gap reduction. However, the decline of the overall P90 to P50 wealth gap is smaller at around 38 percent, while the reduction of the P50 to P25 financial wealth gap is around 7.6 percent. Fr 65 year old individuals we observe a much smaller reduction in the P90/P50 wealth gap (41.5 percent) than in the two assets model where the reduction was 51.6 percent. For the P50/P25 wealth gap we even observe a slight increase in the one asset economy. This result indicates that the presence of wealth/investment portfolio choice and heterogeneity in the rate of return can results in a large variation in wealth disparity over the lifecycle between modeling environments that allow for 2 assets and modeling environments that enforce a single asset with a fixed return.

In the final experiment where both bad health and portfolio choice are eliminated (column A.4 of Table [3\)](#page-27-0), the wealth gaps for P90/P50 and P50/P25 are reduced further by 56 percent and 48 percent, respectively. The P90/P50 wealth gap at 65 declines even more by 62.5 percent. This result implies that the interaction between health heterogeneity and portfolio choice amplifies wealth disparity across groups and over the lifecycle.

Finally, it is interesting to point out that the lowering of the P90/P50 wealth gap due to the "good health surprise" is much larger in the model with two assets at 43.9 percent for all age groups and 51.6 percent for the 65 year olds. In the single asset model, the removal of bad health states only leads to decreases in the P90/P50

wealth gap of 28.6 percent for all age groups and 36 percent for 65 year old (see the bold numbers in the final column of Table [3\)](#page-27-0). Thus, our counterfactual analysis implies that the health-wealth portfolio channel plays an important role in explaining variations in wealth gaps.

5.3 Relative importance of four health channels

In this section we quantify the relative importance of each of the four channels through which health affects households and their capacity to accumulate wealth. We begin with the benchmark model in which all four channels of health effects are in play: (*i*) health-longevity channel, (*ii*) health-labor productivity/income channel, (*iii*) health-medical expenditure channel, and (*iv*) health-wealth portfolio channel.

We then consider four counterfactual experiments: [A.1-1] Turning off the health-longevity channel by assigning everyone the survival rates of healthy agents; [A.1-2] Turning off the health-labor productivity/income channel by assigning everyone the labor productivity of healthy agents; [A.1-3] Turning off the health-medical expenditure channel by assigning everyone the medical expenditures associated with an excellent health state; and [A.1-4] Turning off the health-wealth portfolio channel by assuming a uniform rate of return of 4% for both assets. We report the simulation results in Table [4.](#page-28-0)

	Two assets economy						
	A.1 Bench.	$A.1-1$ $H \neq$ Longev.	$A.1-2$ $H \neq$ LaborProd.	$A.1-3$ $H \neq Med.Exp.$	$A.1-4$ $H \neq$ Portfolio		
Stock participation • Age 65: sick $45-55$ • Age 65: healthy $45-55$	34% 47%	37% 51%	38% 47%	32% 45%	0% 0%		
Assets	100	104.36	102.57	100.5	78.53		
Wealth-gap • All age: P90/P50 • At $65: P90/P50$	14.47 15.96	13.80 14.22	13.80 14.22	13.46 17.16	7.93 8.32		

Table 4: The decomposition of four health-wealth channels

Notes: [A.1]. The benchmark mode where all four channels are in play. [A.1-1] Turning off the health-longevity channel by assigning everyone the survival rates of healthy agents; [A.1-2] Turning off the health-labor productivity/income channel by assigning everyone the labor productivity of healthy agents; [A.1-3] Turning off the health-medical expenditure/income channel by assigning everyone the medical expenditures associated with an excellent health state; and [A.1-4] Turning off the health-wealth portfolio channel by assuming a uniform rate of return of 4 percent for both assets

The results of this decomposition exercise confirm that the health-wealth portfolio channel is the most important channel through which health heterogeneity affects variations in the wealth gaps between P90 and P50.

5.4 The value of health insurance

Our results so far indicate that health is an important source of wealth inequality and even more so in the two assets economy that allows for asset type choice. The participation of individuals in poor health in the risky asset market with its higher long-term returns is significantly lower than the participation of healthy individuals.

This suggests that one way to reduce wealth inequality is to expand access to health insurance. In this section we assess the effect of alternate (counterfactual) health insurance arrangements.

To that end, we consider two counterfactual health insurance reforms: (*i*) the expansion of public health insurance (i.e., Medicare for all workers and retirees) and (*ii*) the expansion of private health insurance (i.e., employer-sponsored health insurance (EHI) for all workers). We report the effects of these insurance expansions in Table [5.](#page-29-0)

	A.1 Benchmark	A.5 Medicare for all + No EHI / Medicaid	A.6 EHI for all workers + Medicaid & Medicare
Assets Stock participation	100	104.3	103.8
• At 65: sick $45-55$	34%	39%	38%
• At 65: healthy $45-55$	47%	51%	51%
Wealth gap			
• All age: P90/P50	14.47	$10.53 \ (\downarrow 27.2\%)$	11.23 $(\downarrow$ 22.4%)
\bullet All age: P50/P25	6.58	7.94 $($ \uparrow 20.7%)	7.47 $($ 13.52%)
• At $65: P90/P50$	15.96	11.43 $(\downarrow 28.4\%)$	$12.18 \ (\downarrow 23.68\%)$
• At $65: P50/P25$	7.08	5.66 (\downarrow 20.1%)	6.91 $(\downarrow 2.4\%)$
Welfare (CEV) Low Inc.	$\overline{0}$	$+1.97$	$+1.93$
$\overline{\bullet}$ sick 45–55	$\boldsymbol{0}$	$+3.08$	$+2.98$
\bullet healthy 45–55	θ	$+3.12$	$+2.97$
Mid Inc.			
\bullet sick 45–55	$\boldsymbol{0}$	$+1.99$	$+2.27$
\bullet healthy 45–55	$\boldsymbol{0}$	$+1.86$	$+1.89$
High Inc.			
$\overline{\bullet}$ sick 45–55	$\boldsymbol{0}$	$+0.81$	$+0.65$
\bullet healthy 45–55	$\boldsymbol{0}$	$+0.62$	$+0.51$

Table 5: Public and private health insurance expansion

Notes: The health-wealth portfolio channel is in play in the two asset economy model. Two experiments: [A.5] Medicare for all expansion of Medicare for all workers and retirees; and [A.6] EHI for all workers - expansion of EHI for all workers while maintaining Medicare and Medicaid.

Universal Medicare. In our benchmark model, sick workers are more likely to have lower income as health shocks correlate with labor productivity in addition to higher health expenditures; meanwhile, low income workers are also more likely to be uninsured—as long as they do not qualify for Medicaid—as they are less likely to be matched with an employer that offers EHI. The expansion of Medicare reduces the exposure to medical expenditure shocks for these workers. Individuals are now not only more able but also more willing to invest into risky assets. First, according to the background risk theory, individuals facing undesirable risk (such as medical expenditure risk) are less willing to take on other types of risk and therefore less likely to investment in the risky stock market (e.g., see [Pratt and Zeckhauser](#page-41-0) [1987;](#page-41-0) [Kimball](#page-40-11) [1993;](#page-40-11) [Gollier and Pratt](#page-38-1) [1996\)](#page-38-1). Second, similar to [Hubbard, Skinner and Zeldes](#page-39-5) [\(1995\)](#page-39-5), removing the income and asset tests for Medicaid eligibility induces low-skill and sick workers to accumulate more assets in this environment.

Overall, we find that a Medicare expansion induces more households to participate in the risky asset market

and hold riskier wealth portfolios with higher long-term returns.^{[39](#page-30-1)} As shown in column [A.5], the expansion of Medicare leads to an increase in the stock market participation rates, wealth accumulation and a reduction in the wealth gap across all wealth gap measures and age groups. Specifically, the P90/P50 wealth gap across all age groups declines by 27.2 percent and for 65 year olds it is slightly larger at 28.4 percent. The relatively larger reduction in the wealth gap between the top P90-P50 and middle P50-P25 groups implies a larger impact of universal Medicare on wealth accumulation at the middle or lower end of the wealth distribution–since more of the lower income groups now participate in the stock market, the wealth gap reduction between them is smaller.

EHI for all workers. The expansion of private health insurance via EHI to all workers has also a significant effects on wealth inequality. However, the reductions in the wealth gaps are is slightly smaller than under the more comprehensive expansion of Medicare (compare column [A.6]). These smaller changes can be explained by the overall higher coinsurance rate of EHI contracts.

Interestingly, we observe smaller changes in the P50/P25 wealth gap under both health insurance reforms. This result implies that these insurance reforms mainly affect workers at both the middle and lower end of the income distribution, i.e., P50 and P25, who are more likely to be uninsured in the benchmark model. Finally, these two health insurance reforms result in large welfare gains (between 1.9 and 2.0 percent of CEV) a bulk of which can be attributed to gains of low and middle income individuals.

Our results emphasize that health insurance, in addition to its traditional role of mitigating exposure to health expenditure shocks, plays a vital role in encouraging investments into stocks. Reforming Medicare and employer-sponsored health insurance programs can have large impacts on health-wealth inequality in our multi-asset environment with health risk. These new findings highlight the importance of accounting for the institutional features of the US health insurance system when studying wealth inequality in the US context. Health insurance reforms that do expand the coverage to a wider population can be an important tool in the fight to reduce inequality in the US.

6 Extensions

In this section we investigate whether the health-wealth portfolio channel discussed in the previous section is robust under different counterfactual considerations, including other policy reforms and different preferences.

6.1 Risky asset returns and the health-wealth portfolio channel

We next investigate to what extent stock returns affect the strength of the health-wealth portfolio channel.

Risk premium. We first consider alternative experiments in which we reduce the risk premium μ^s in expression [1,](#page-12-1) holding all other parameters unchanged. After reoptimizing household decisions, we report the results in Table [6.](#page-31-0)

 39 Figures [F.5–](#page-129-0)[F.7](#page-131-0) in the Technical Appendix show the changes in the age profiles of stock market participation, assets and labor market participation.

	A.1 Benchmark.		B.1 $\mu^s = 0.03$ B.2 $\mu^s = 0.02$ B.3 $\mu^s = 0.01$	
Assets	100	71.09	52.59	43.53
Stock participation				
• At $65:$ sick $45-55$	34%	20%	17%	$~10\%$
• At 65 : healthy $45-55$	47%	30%	10%	$~10\%$
Wealth gap				
• At 65: P90/P50	15.96	16.53	11.61	11.47
• At 65: P50/P25	7.08	4.76	4.35	3.69
Welfare (CEV)	0.0	-1.38	-2.19	-2.52

Table 6: B - Risk premium

Notes: The risk premium is 4 percent in the benchmark model, i.e., $\mu = 0.04$.

We find that lowering the risky asset premium reduces the incentive to invest in stocks, leading to lower stock market participation and asset holdings overall as can be seen from columns [B.1]–[B.3] in Table [6.](#page-31-0) Once the risk premium is sufficiently low, individuals stop investing in risky stocks because the expected returns no longer justify the additional risk and the participation costs associated with stock investments. As a result, the wealth gap narrows due to the weakened health-portfolio channel.

Low vs. high realizations of stock returns. We next investigate to what extent stock returns affect the strength of the health-wealth portfolio channel. We use the policy functions from the benchmark economy where agents expect a risky asset premium of 4 percent but "surprise" individuals with low risky asset returns throughout their life from age 40–94. In order to do this we set the net stock returns in expression [3](#page-13-3) equal to the lowest realization of stock returns in the benchmark model throughout the lifetime of all individuals. These low surprise returns measure to what extent a poor performing stock market would affect the buildup of the wealth gap at the age of retirement. We show the results of this experiment in column [C.1] in Table [7.](#page-31-1) We then consider the other extreme where individuals are surprised with the highest risky asset return level throughout their lifetime. The results for this highly performant stock market are shown in column [C.2] in Table [7.](#page-31-1) These two experiments present the lower and upper bound of the risky asset's potential contribution to the wealth gap at retirement through the health-wealth portfolio channel.

	A.1 Benchmark	Two assets C.1 Low \tilde{r}_{net}^s	C.2 High \tilde{r}_{net}^s	Single Asset A.3 No stocks
Assets	100	70.82	109.58	70.77
Stock participation • At $6\bar{5}$: sick $45-55$ • At 65 : healthy $45-55$	34% 47%	29% 40%	37% 51%	n/a n/a
Wealth gap				
• At 65: P90/P50 • At $65: P50/P25$	15.96 7.08	13.64 6.65	12.26 9.88	9.34 7.59
Welfare (CEV)	0.0	-5.77	$+2.26$	-2.52

Table 7: C - Low and high shocks to risky asset returns

Notes: The risk premium is 4 percent in the benchmark model, i.e., $\mu = 0.04$.

If the stock market performs consistently poorly throughout the lifetime of the agents (and households do not re-optimize their investment strategy) we find that the stock market participation drops and large welfare losses of 5.8 percent of CEV are realized as shown in column [C.1]. This experiment is different from the single asset economy in column [A.3] where households optimized their investment strategy under a single, risk free asset regime. Column [C.1] shows that even with consistent low stock market returns, households still participate in the stock market as they form expectations based on a 4 percent risky asset premium. The drop in participation is therefore a reflection of lower income levels from stock returns and not updated expectations about the stock market. Finally, since all households experience the same low risky asset returns, the wealth gap decreases slightly.

If, on the other hand, the stock market performs very well and household reap the high returns from their stock investments throughout their lifetime, stock market participation increases and welfare gains of 2.3 percent of CEV are realized compared to the benchmark economy where stock return realizations are volatile.

6.2 Expansion of private health insurance

We next consider two additional reforms that both expand private health insurance further: (*i*) the extension of EHI to all workers while removing Medicaid for the poor; and (*ii*) the extension of EHI to all workers and retirees while removing Medicaid for the poor as well as Medicare for retirees. We summarize the results from these two experiments in Table [8.](#page-32-0)

	A.1 Benchmark	A.7 EHI for All Workers + No Medicaid	A.8 EHI for All + No Medicaid/No Medicare
Assets Stock participation	100	104.05	149.08
• At $6\bar{5}$: sick $45-55$	34%	39%	73%
• At 65: healthy 45-55	47%	51%	80%
Wealth gap			
• At $65: P90/P50$	15.96	12.18 (\downarrow 23.68%)	3.69 (\downarrow 76.87%)
• At 65: P50/P25	7.08	6.04 (\downarrow 14.69%)	3.19 $(\downarrow 54.94\%)$
Welfare (CEV)	0.0	$+1.80$	-6.54

Table 8: A Health insurance reforms

Notes: We consider two other health insurance reforms: [A.6] EHI for all workers + No Medicaid - expansion of EHI for all workers, while removing Medicaid; and [A8] Extending EHI to all workers and retirees, while removing both Medicaid and Medicare.

Our results reported in column [A.7] of Table [8](#page-32-0) show the value of employer-sponsored health insurance (EHI) in reducing health inequality. Interestingly, a more radical reform that replaces the entire Medicare and Medicaid system with universal EHI for all (workers and retirees) results in a large reduction in wealth inequality; however, there are large welfare costs of 13 percent of CEV (see column [A.8]) as it replaces the generous public health insurance. This highlights the social benefit of social health insurance programs.

6.3 Health-in-utility (HIU) preferences

We next model health status as a consumption good which introduces a utility-health channel into the model. In this setting, there are now two channels through which the exogenous health states affect household welfare: (*i*) via the household budget constraint (as in our benchmark model) and (*ii*) via a preference shifter that depends on health status *h*, which is a function of the exogenous health states ε^h . We follow the approach in [De Nardi,](#page-37-2) [French and Jones](#page-37-2) [\(2010\)](#page-37-2) and assume that each period the individual's utility depends on consumption, leisure and health status, *h*, according to

$$
u(c_j, \ell_j; \bar{n}_j) = \theta(h) \frac{\left(c_j^{\eta} \times \left[\ell_j - \bar{n}_j \cdot 1_{\left[0 \le n_j\right]}\right]^{1-\eta}\right)^{1-\sigma}}{1-\sigma},\tag{11}
$$

where $\theta(h) = \theta(h(\varepsilon^h))$ is a preference shifter and health state $h(\varepsilon^h)$ is restricted to either either healthy $(h = 1)$ or sick $(h = 0)$ based on health status ε^h . Following [De Nardi, French and Jones](#page-37-2) [\(2010\)](#page-37-2), we specify the preference shifter as $\theta(h) = 1 + \theta_h \times h$ and set parameter $\theta_h = -0.21$. Given our parameterization this results in $u_c > 0$, $u_h > 0$ and $u_{c,h} < 0$. In other words, if an individual moves from healthy ($h = 1$) to sick ($h = 0$), her consumption spending *c* is going to increase. We keep all other components of the benchmark model unchanged when we re-estimate the benchmark model using the method of simulated moments as discussed above.

	A.1 Bench.		A.2 Good health (40–Death)		A.3 No portfolio		$A.4 = A.2 + A.3$	
	Regular	HIU	Regular	HIU	Regular	HIU	Regular	HIU
Assets Stock participation	100	100.00	122.19	121.05	61.26	62.51	71.18	71.63
• At $65:$ sick $45-55$ • At 65 : healthy $45-55$	34% 47%	31% 44%	55%	NA 53%	0.0% 0.0%	0.0% 0.0%	0.0% 0.0%	0.0% 0.0%
Wealth gap • P90/P50 at 65 • $P50/P25$ at 65	15.96 7.08	16.39 7.8	7.72 6.62	$8.72 \, (\downarrow 46.8\%)$ 5.98 $(\downarrow 23.3\%)$	9.34 7.59	$9.31 \ (1.43.2\%)$ 6.58 (\downarrow 15.6%)	5.98 3.73	$6.19 \, (\downarrow 61.2\%)$ 3.81 $(\downarrow 51.2\%)$
Welfare (CEV)	0.0	0.0	$+17.08$	$+18.28$	NA	NA	$+17.25$	$+19.97$

Table 9: Wealth inequality with HIU preferences

Notes: Both safe and risky assets are present in the two asset economy [A.1]. The bad health shocks are removed in [A.2]. The wealth portfolio channel is eliminated in [A.3]. The health-wealth portfolio channel is completely eliminated in [A.4]

We use the new benchmark model to run similar experiments as in section [5.](#page-22-0) We summarize the main results in Table [9.](#page-33-1) Overall, we find the main conclusions established in section [5](#page-22-0) carry over to the model with health in the utility function.

7 Conclusion

In this paper we study the dynamic effects of health shocks on savings, portfolio choice, wealth accumulation and wealth inequality over the lifecycle. We argue that when there are multiple forms of savings with different payoff patterns available to households, then the early exposure to health shocks has strong and long-lasting impacts on the portfolio choice of households and the observed wealth gap among households at retirement age. This observed wealth gap due to early health issues is much wider in a multi-asset model than in standard

household consumption-savings models with a single-asset. Intuitively, the presence of both safe and risky assets creates an environment with heterogeneous asset returns that contribute to the observed wealth gap between sick and healthy individuals, especially as sicker individuals often forgo investing in risky assets that pay higher returns in the long-run. This health-wealth portfolio channel amplifies wealth concentration across groups and over the lifecycle.

In order to investigate this mechanism we first use PSID and HRS data and show that the exposure to negative health shocks at prime earnings ages shifts investment toward less risky assets. Individuals in bad health are either not able to or simply chose not to invest in high return, but risky, assets. This leaves them with low-risk wealth portfolios that accumulate wealth much slower over time due to lower (but much safer) investment returns. Differences in asset portfolio composition subsequently accumulate to large differences in wealth levels across the sick and healthy types at retirement age.

Next, we develop a structural lifecycle model of portfolio choice with household heterogeneity in terms of health status, health expenditure, health insurance, education and labor productivity. We calibrate the model to match US data and conduct a series of counterfactual experiments to demonstrate that this new healthwealth channel significantly amplifies the effects of health shocks on wealth inequality. In the absence of the health-wealth portfolio channel, the observed wealth gap at retirement is 40–50 percent smaller. In addition, we provide new insights into the social benefit of health insurance. The expansion of public or private health insurance in the US can reduce wealth inequality via mitigating exposure to health expenditure shocks and thereby allow households to make riskier investment choices with higher long-term returns.

While our structural partial equilibrium lifecycle model is able to highlight the strength of the health-wealth portfolio channel, it is limited in addressing broader policy questions that involve systemic policy reforms and their implications on wealth inequality and public finance. We leave the investigation of such questions in dynamic general equilibrium macro-health models with multiple assets and portfolio choice for future research. In addition, issues of human capital accumulation in the context of a multi-asset model with either exogenous or endogenous health processes is beyond the analysis presented in this paper. Finally, we leave the investigation of other demographic factors such as race, ethnicity, gender and health type that might drive health heterogeneity (e.g., [Russo, McGee, DeNardi, Borella and Abram](#page-42-12) [2024;](#page-42-12) [Borella, Bullano, DeNardi, Krueger and Manresa](#page-36-10) [2024\)](#page-36-10) for future research.

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Appendix

Empirical results

Figure 1: Raw financial asset profiles conditional on health at age 45–55

Notes: TA is total asset; RA is risky asset; TFA is total financial asset. We distinguish between individuals who do not report having bad health (or alternatively work limiting health issues) between ages 45–55 and individuals who do. We refer to these two groups as Healthy 45–55 vs. Sick 45–55. We use unweighted data. Total assets includes all assets including IRAs but excluding housing wealth and assets in defined benefit pension plans such as 401Ks. Total financial assets includes assets held in defined benefit pension plans. The stock ratio in the bottom row is calculated as the average ratio of stock value over total financial assets per age group. Data source: Heads of households in PSID 1984–2019.

Figure 2: Asset distribution by age group and health state between ages 45–55

Notes: We distinguish between individuals who do not report having bad health (or alternatively work limiting health issues) between ages 45–55 and individuals who do. We refer to these two groups as Healthy vs. Unhealthy. The graph shows asset distributions based on unweighted "raw" data per age and health group. Assets are corrected for cohort and time effects. Data source: Heads of households in **PSID 1984–2019**.

(b) HRS

Figure 3: Stocks profiles by health state between ages 45–55

Notes: We distinguish between individuals who do not report having bad health (or alternatively work limiting health issues) between ages 45–55 and individuals who do. Panel 2.A is based on a linear probability model whereas Panels 3.A and 4.A are based on Probit models. We refer to these two groups as Healthy vs. Unhealthy. We use unweighted data. Data sources: Heads of households in PSID 1984–2019 (left two columns) and heads of households in HRS 1992–2018 (right two columns).

Standard errors in parentheses

[∗] *p* < 0.10, ^{∗∗} *p* < 0.05, ^{∗∗∗} *p* < 0.01

Notes: The dependent variable is the detrended ratio of stocks in the financial portfolio at ages 60–70 including individuals with zero stock holdings. The independent variables of interest are indicator variables for whether an individual has reported being in bad health at ages 45–55 or whether an individual has reported to ever having a work limiting health problem at ages 45–55. Column (7) and (8) are estimated on the subsample of individuals with positive stock holdings. The regressions also include controls for age, an indicator for Hispanic, size of outstanding mortgage and size of other home loans. Data source: Heads of households in the PSID 1984–2019.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Sick at 45_55	$-0.025***$ (0.007)		$-0.030***$ (0.009)		$-0.038***$ (0.010)		0.003 (0.015)		-0.002 (0.012)	
Health Lim. Wrk at 45 55		$-0.020***$ (0.007)		$-0.023**$ (0.009)		$-0.026**$ (0.010)		0.000 (0.014)		-0.003 (0.011)
Unemployed at 45_55	$-0.026***$	$-0.024***$	$-0.027***$	$-0.026***$	$-0.029***$	$-0.028***$	0.005	0.005	-0.003	-0.003
	(0.007)	(0.007)	(0.009)	(0.009)	(0.010)	(0.011)	(0.014)	(0.015)	(0.012)	(0.012)
Uninsured at 45_55	$-0.024***$	$-0.023***$	-0.013	-0.013	$-0.029***$	$-0.028***$	0.006	0.006	$0.020*$	$0.020*$
	(0.007)	(0.007)	(0.009)	(0.009)	(0.009)	(0.010)	(0.014)	(0.014)	(0.012)	(0.012)
Healthy	$0.037***$	$0.043***$	$0.046***$	$0.053***$	$0.021***$	$0.025***$	0.007	0.007	0.007	0.008
	(0.007)	(0.007)	(0.009)	(0.008)	(0.007)	(0.007)	(0.012)	(0.011)	(0.012)	(0.012)
Insured	$0.035***$	$0.036***$	$0.036***$	$0.036***$	0.013	0.013	0.002	0.002	0.010	0.010
	(0.009)	(0.009)	(0.012)	(0.012)	(0.008)	(0.008)	(0.014)	(0.014)	(0.017)	(0.017)
Smoker	$-0.021***$	$-0.021***$	$-0.021**$	$-0.021**$	-0.011	-0.011	0.002	0.002	0.020	0.020
	(0.007)	(0.007)	(0.010)	(0.010)	(0.009)	(0.009)	(0.013)	(0.013)	(0.014)	(0.014)
Female	0.000	0.000	0.010	0.010	-0.008	-0.008	-0.017	-0.018	0.021	0.021
	(0.009)	(0.009)	(0.012)	(0.012)	(0.012)	(0.012)	(0.018)	(0.018)	(0.019)	(0.019)
Married/Partnered	$0.045***$	$0.044***$	$0.059***$	$0.059***$	$0.037***$	$0.037***$	$-0.031**$	$-0.031**$	-0.002	-0.002
	(0.009)	(0.009)	(0.011)	(0.011)	(0.010)	(0.010)	(0.016)	(0.016)	(0.017)	(0.017)
Black	$-0.074***$	$-0.075***$	$-0.057***$	$-0.058***$	$-0.075***$	$-0.076***$	-0.019	-0.019	$-0.029**$	$-0.030**$
	(0.008)	(0.008)	(0.008)	(0.008)	(0.012)	(0.012)	(0.019)	(0.019)	(0.014)	(0.014)
High school degree	$0.043***$	$0.045***$	$0.051***$	$0.053***$	$0.042***$	$0.047***$	0.006	0.005	$0.033**$	$0.033**$
	(0.008)	(0.008)	(0.008)	(0.008)	(0.011)	(0.011)	(0.019)	(0.019)	(0.014)	(0.014)
College or higher	$0.095***$	$0.098***$	$0.110***$	$0.113***$	$0.096***$	$0.102***$	0.016	0.016	$0.036**$	$0.036**$
	(0.010)	(0.010)	(0.011)	(0.011)	(0.014)	(0.014)	(0.021)	(0.021)	(0.015)	(0.015)
tanh(preGovIncHH)	0.012	0.012	$0.055**$	$0.053**$	0.014	0.013	-0.048	-0.048	-0.032	-0.032
	(0.021)	(0.021)	(0.025)	(0.025)	(0.019)	(0.019)	(0.038)	(0.038)	(0.034)	(0.034)
tanh(assets)	$0.046***$	$0.046***$	$0.054***$	$0.054***$	$0.025***$	$0.026***$	-0.004	-0.004	0.008	0.008
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.015)	(0.015)	(0.013)	(0.013)
Initial (mean) Stock-Ratio 40-51	$0.258***$	$0.260***$	$0.259***$	$0.259***$	$0.264***$	$0.267***$	$0.188***$	$0.188***$	$0.198***$	$0.198***$
	(0.013)	(0.013)	(0.018)	(0.018)	(0.019)	(0.019)	(0.023)	(0.023)	(0.021)	(0.021)
Debt (\$1,000)	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations R^2 Conditional P(Y>0) Random Effects Weighted	6144 0.290 $\rm No$ No No	6143 0.289 $\rm No$ No No	6111 0.284 $\rm No$ No Yes	6110 0.283 $\rm No$ No Yes	6144 No Yes No	6143 No Yes No	3072 Yes Yes No	3072 Yes Yes No	3065 0.080 Yes No Yes	3065 0.080 Yes No Yes

Table 11: Risky asset share and poor health status (HRS sample)

Standard errors in parentheses

^{*} $p < 0.10$, ^{**} $p < 0.05$, *** $p < 0.01$

Notes: The dependent variable is the detrended ratio of stocks in the financial portfolio at ages 60–70 including individuals with zero stock holdings. The independent variables of interest are indicator variables for whether an individual has reported being in bad health at ages 45–55 or whether an individual has reported to ever having a work limiting health problem at ages 45–55. Column (7) and (8) are estimated on the subsample of individuals with positive stock holdings. The regressions also include controls for age, an indicator for Hispanic, size of outstanding mortgage and size of other home loans. Data source: Heads of households in the HRS 1992-2018.

	Stock Share	P(Stocks)	Safe A. Share	P(Safe A.)	Stock Share	P(Stocks)	Safe A. Share	P(Safe A.)
Sick at 45 55	0.000 (0.015)	$-0.095***$ (0.018)	$0.040***$ (0.011)	$-0.039***$ (0.013)				
Health Lim. Wrk at 45 55					-0.003 (0.010)	0.001 (0.012)	0.002 (0.008)	$-0.016*$ (0.010)
Unemployed at 45 55	$0.035***$ (0.013)	$-0.035**$ (0.016)	-0.006 (0.010)	$-0.039***$ (0.011)	$0.033***$ (0.011)	$-0.056***$ (0.012)	0.006 (0.008)	$-0.055***$ (0.010)
Uninsured at 45 55	-0.003 (0.027)	$-0.122***$ (0.019)	$0.052***$ (0.012)	$-0.097***$ (0.021)	-0.019 (0.023)	$-0.077***$ (0.017)	$0.038***$ (0.012)	$-0.054***$ (0.013)
Initial (median) Stock-Ratio 35-45	$0.113***$ (0.018)	$0.338***$ (0.028)	$-0.211***$ (0.017)	$0.066***$ (0.015)	$0.099***$ (0.016)	$0.350***$ (0.022)	$-0.211***$ (0.013)	$0.053***$ (0.017)
Observations	2335	5625	4746	5625	2346	5671	4783	5671

Table 12: Two-Part model: Risky and safe asset share

Standard errors in parentheses

[∗] *p* < 0.10, ∗∗ *p* < 0.05, ∗∗∗ *p* < 0.01

Notes: The dependent variables are: (i) an indicator variable for whether an individual has investments in risky assets (participation equation); (ii) the detrended risky asset share conditional on having investments in risky assets (outcome equation); (iii) an indicator variable for whether an individual has investments in safe assets (participation equation) and (iv) the safe asset share conditional on having such investments (outcome equation). All four variables refer to the financial wealth portfolio at ages 60–70. The independent variables of interest are indicator variables for whether an individual has reported being in bad health at ages 45–55 or whether an individual has reported to ever having a work limiting health problem at ages 45–55. Additional control variables not shown in the table include: age, health status, insurance status, smoking status, gender, marriage status, number of children, race, education indicator for college or higher, debt, mortgage, overall asset level, cohort controls, time trend controls, region controls, as well as initial health at age 0–16. The participation equations are based on a linear probability model and are indicated as P(). They additionally include controls for high school status and time year indicators. Data source: Heads of households in the PSID 1984–2019. Estimates based on family unit sampling weights.

Table 13: Selection model: Risky and safe asset share

Standard errors in parentheses

[∗] *p* < 0.10, ∗∗ *p* < 0.05, ∗∗∗ *p* < 0.01

Notes: The dependent variables are: (i) an indicator variable for whether an individual has investments in risky assets (participation equation); (ii) the detrended risky asset share conditional on having investments in risky assets (outcome equation); (iii) an indicator variable for whether an individual has investments in safe assets (participation equation) and (iv) the safe asset share conditional on having such investments (outcome equation). All four variables refer to the financial wealth portfolio at age 60–70. The independent variables of interest are indicator variables for whether an individual has reported being in bad health at ages 45–55 or whether an individual has reported to ever having a work limiting health problem at ages 45–55. Additional control variables not shown in the table include: age, health status, insurance status, smoking status, gender, marriage status, number of children, race, education indicator for college or higher, debt, mortgage, overall asset level, cohort controls, time trend controls, region controls. The participation equations, indicated as P(), are based on a Probit model and additionally include controls for high school status and time year indicators. Data source: Heads of households in the **PSID 1984–2019**. Estimates based on unweighted data.

Standard errors in parentheses

[∗] *p* < 0.10, ^{∗∗} *p* < 0.05, ^{∗∗∗} *p* < 0.01

Notes: The dependent variables are: (i) an indicator variable for whether an individual has investments in risky assets (participation equation); (ii) the detrended risky asset share conditional on having investments in risky assets (outcome equation); (iii) an indicator variable for whether an individual has investments in safe assets (participation equation) and (iv) the safe asset share conditional on having such investments (outcome equation). All four variables refer to the financial wealth portfolio at ages 60–70. The independent variables of interest are indicator variables for whether an individual has reported being in bad health at ages 45–55 or whether an individual has reported to ever having a work limiting health problem at ages 45–55. Additional control variables not shown in the table include: age, health status, insurance status, smoking status, gender, marriage status, number of children, race, education indicator for college or higher, debt, mortgage, overall asset level, cohort controls, time trend controls, region controls, as well as initial health at age 0–16. The participation equations are based on a linear probability model and are indicated as P(). They additionally include controls for high school status and time year indicators. Data source: Heads of households in the PSID 1984–2019. Estimates based on family unit sampling weights.

	Stock Share	P(Stocks)	Safe A. Share	P(Safe A.)	Stock Share	P(Stocks)	Safe A. Share	P(Safe A.)
Sick at 45 55	0.019 (0.036)	$-0.043***$ (0.014)	$0.022*$ (0.012)	$-0.037***$ (0.014)				
Health Lim. Wrk at 45 55					0.011 (0.023)	-0.013 (0.011)	$0.016*$ (0.009)	$-0.021**$ (0.010)
Unemployed at 45 55	0.017 (0.026)	$0.057***$ (0.014)	$-0.040***$ (0.011)	$-0.037***$ (0.012)	0.016 (0.024)	$0.031***$ (0.011)	$-0.029***$ (0.010)	$-0.049***$ (0.010)
Uninsured at 45 55	0.018 (0.050)	-0.006 (0.014)	-0.002 (0.012)	$-0.090***$ (0.021)	-0.045 (0.055)	-0.004 (0.015)	0.001 (0.014)	$-0.050***$ (0.014)
stockNew3 ratio Age35 45								
Observations	1025	5625	4682	5625	1031	5671	4718	5671

Table 15: Two-Part model: Risky and safe asset share (w/o IRAs)

Standard errors in parentheses

[∗] *p* < 0.10, ∗∗ *p* < 0.05, ∗∗∗ *p* < 0.01

Notes: The dependent variables are: (i) an indicator variable for whether an individual has investments in risky assets (participation equation); (ii) the detrended risky asset share conditional on having investments in risky assets (outcome equation); (iii) an indicator variable for whether an individual has investments in safe assets (participation equation) and (iv) the safe asset share conditional on having such investments (outcome equation). All four variables refer to the financial wealth portfolio at ages 60–70. The independent variables of interest are indicator variables for whether an individual has reported being in bad health at ages 45–55 or whether an individual has reported to ever having a work limiting health problem at ages 45–55. Additional control variables not shown in the table include: age, health status, insurance status, smoking status, gender, marriage status, number of children, race, education indicator for college or higher, debt, mortgage, overall asset level, cohort controls, time trend controls, region controls, as well as initial health at age 0–16. The participation equations are based on a linear probability model and are indicated as P(). They additionally include controls for high school status and time year indicators. Data source: Heads of households in the PSID 1984–2019. Estimates based on family unit sampling weights.

Model calibration

Figure 4: Exogenous data input

Notes: Healthy is defined as an individual reporting either Excellent, Very Good, or Good health. Sick is defined as Fair or Poor health. Data source is MEPS 1999–2018. The observational unit is the head of a Health Insurance Eligibility Unit (HIEU) which is a subset of a household. We apply population weights.

The survival probabilities in panel [6] are from Imrohoroğlu and Kitao [\(2012\)](#page-39-0) who base their estimates on data from the Health and Retirement Study and life table estimates in [Bell and Miller](#page-36-0) [\(2005\)](#page-36-0).

Calibration targets

Figure 5: Estimation target: Risky asset participation rate by current health and education

Notes: We target stock market participation by permanent education status of individuals in good respectively bad current health. We use risky asset market access cost as parameters. These costs differ by age, education status, and current health status: $q_j(\vartheta,\pmb{\varepsilon}^h)$. Data source is **PSID 1984–2019**, heads of households.

Figure 6: Calibration target: Labor supply and overall assets

Notes: Data source for Panel [1] is MEPS 1996–2018, heads of households. Data sources for Panel [2] are heads of households in HRS 1992–2018 and heads of households in PSID 1984–2019.

Figure 7: Calibration target: Insurance type (only Medicaid is a calibration target)

Notes: We target Medicaid take-up of 40–50 year olds and 55–65 year olds in panel 2. Data source is **MEPS 1996–2018**, heads of households.

Figure 8: Calibration target: Labor force participation by education and health

Notes: Cohort adjusted labor participation profiles by permanent income group and health state. Data source is MEPS 1996–2018, heads of households, population weighted.

Parameter values

Figure 9: The estimated costs of risky asset market participation

Notes: We target stock market participation rates by current health status as shown in Figure [5.](#page-51-0)

Table 16: External parameters

Notes: These parameters are based on our own estimates from MEPS and CMS data as well as other studies.

Notes: Weighted data from MEPS 1996–2018. Sick are individuals who report having fair or poor health. Healthy are individuals who report excellent, very good, and good health.

Table 18: Internal calibrated parameters

Notes: We choose internal parameters so that model generated data matches data from MEPS, CMS, and NIPA. The average tax rate of 40 year olds is based on the TaxSim software at: <https://taxsim.nber.org/byage/>

Table 19: Internal calibrated parameters

Notes: The estimates are obtained using a minimum distance approach. We minimize the distance between moments of actual and simulated data. Data moments include measures of wealth-to-income ratios, labor hours, stock market participation rates by age-group, education level, and health status at 45–55. Figure [5](#page-51-0) shows the estimation target of stock participation rates by age, education and health state together with the model generated moments. Figure [9](#page-53-1) shows the associated participation cost by age, education and health state.

Model performance

Table 20: Benchmark model performance

Notes: These are not calibration targets. (*) We do not distinguish between Medicare and Medicaid for the population older than 65. We therefore compare the size of Medicare in the model to the spending of Medicare plus Medicaid on individuals older than 65 to capture the out-of-pocket spending of the older generation more realistically without explicitly modeling Medicaid past the age of 65. According to NHEA (2010) aggregate Medicare spending in 2010 was approximately 3.47 percent of GDP. More details are provided in Section [4.](#page-16-1) (**) Medicaid in the model refers to the portion of Medicaid that targets the working age population. According to NHEA (2010) aggregate Medicaid payments for individuals younger than 65 in 2010 was approximately 1.7 percent of GDP. More details are provided in Section [4.](#page-16-1)

Figure 10: Performance Check: Risky asset participation rate by health-at-45–55 and education

Notes: This is not a target. The lines distinguish between individuals in good respectively bad health when 45–55 years old. Data source is PSID 1984–2019, heads of households.

Figure 11: Model performance: medical spending and health states

Notes: These are not calibration targets. Data sources is MEPS 1996–2018, heads of HIEU, population weighted.

Figure 12: Model performance: financial asset distribution by age group and health type *Notes:* These are not calibration targets. Data source: head of households in PSID 1984–2019.

Figure 13: Model performance: financial asset distribution of 40–50 vs 60–70 year olds by health type at ages 45–55

Notes: These are not calibration targets.

Figure 14: Model performance: wealth to income ratio by age group and health type

Notes: These are not calibration targets. For asset data we use information from heads of households in HRS 1992–2016 and PSID 1984–2019. Income is labor income plus government transfers.

	Model		PSID		Model		PSID	
	Stock Share	P(Stocks)	Stock Share	P(Stocks)	Safe A. Share	P(Safe A.)	Safe A. Share	P(Safe A.)
Sick at 45 55	$0.006***$	$-0.246***$	0.003	$-0.271***$	$0.030***$	$0.253***$	$0.036***$	$-0.198***$
	(0.001)	(0.003)	(0.015)	(0.051)	(0.000)	(0.003)	(0.009)	(0.058)
Unemployed at 45_55	$0.017***$	$-0.480***$	$0.034***$	$-0.175***$	$0.063***$	$0.474***$	0.003	$-0.232***$
	(0.002)	(0.003)	(0.012)	(0.047)	(0.001)	(0.003)	(0.008)	(0.053)
Uninsured at 45 55	-0.001	$-0.074***$	-0.027	$-0.382***$	$0.012***$	$0.078***$	$0.044***$	$-0.170***$
	(0.001)	(0.003)	(0.026)	(0.076)	(0.000)	(0.003)	(0.012)	(0.064)
Age	$0.007***$	$-0.046***$	$0.003***$	0.012	$0.015***$	$0.043***$	$0.002**$	0.023
	(0.000)	(0.000)	(0.001)	(0.014)	(0.000)	(0.000)	(0.001)	(0.017)
Healthy	0.001	$0.713***$	$0.058***$	$0.283***$	$-0.054***$	$-0.768***$	$-0.055***$	$0.154***$
	(0.003)	(0.004)	(0.017)	(0.055)	(0.001)	(0.005)	(0.009)	(0.058)
Insured	$-0.015***$	$0.364***$	0.037	$0.377***$	$-0.050***$	$-0.355***$	$-0.046**$	$0.308***$
	(0.002)	(0.005)	(0.039)	(0.133)	(0.001)	(0.005)	(0.021)	(0.100)
High school degree		$0.111***$ (0.004)		$0.421***$ (0.091)		$-0.171***$ (0.004)		$0.469***$ (0.069)
College or higher	$0.003*$	$0.589***$	0.009	$0.910***$	$-0.060***$	$-0.692***$	$-0.078***$	$0.723***$
	(0.002)	(0.005)	(0.015)	(0.096)	(0.001)	(0.005)	(0.008)	(0.092)
tanh(preGovIncHH)	$0.040***$	$-0.759***$	0.011	-0.158	$0.091***$	$0.655***$	0.047	$0.628***$
	(0.002)	(0.005)	(0.058)	(0.296)	(0.001)	(0.004)	(0.049)	(0.213)
$tanh($ assets $)$	$0.590***$	$2.659***$	0.017	$0.620***$	$-0.153***$	$-2.210***$	$-0.067***$	$0.305***$
	(0.008)	(0.018)	(0.028)	(0.060)	(0.001)	(0.016)	(0.008)	(0.043)
Observations	945861		5625		945861		5625	

Table 21: Selection model: Risky and safe asset share simulated model data

Standard errors in parentheses

[∗] *p* < 0.10, ∗∗ *p* < 0.05, ∗∗∗ *p* < 0.01

Notes: The dependent variables are the ratio of risky investments, an indicator variable for having any investments in risky stocks, the ratio of investments in safe assets, and an indicator variable for having any investments in safe assets as part of the financial wealth portfolio at ages 60–70. The independent variables of interest are indicator variables for whether an individual has reported being in bad health at ages 45–55. The first four columns are based on data of head of households from the PSID 1984–2019 and the last four columns are based on simulated data from our lifecycle model with 150,000 individuals that are observed from ages 40–94. Additional control variables used in the regressions based on PSID data (which are omitted from the table) include: gender, race indicators, marriage status, number of children, smoking status, debt, mortgage, other home loans, cohort controls, time trends, and states.

	All			Healthy-at-40		All	Healthy-at-40		
	Stock Share	P(Stocks)	Stock Share	P(Stocks)	Safe A. Share	P(Safe A.)	Safe A. Share	P(Safe A.)	
Sick at 45_55	$0.006***$	$-0.246***$	$0.005***$	$-0.233***$	$0.030***$	$0.253***$	$0.030***$	$0.239***$	
	(0.001)	(0.003)	(0.001)	(0.003)	(0.000)	(0.003)	(0.001)	(0.003)	
Unemployed at 45_55	$0.017***$	$-0.480***$	$0.014***$	$-0.469***$	$0.063***$	$0.474***$	$0.064***$	$0.463***$	
	(0.002)	(0.003)	(0.002)	(0.003)	(0.001)	(0.003)	(0.001)	(0.003)	
Uninsured at 45_55	-0.001	$-0.074***$	-0.001	$-0.078***$	$0.012***$	$0.078***$	$0.013***$	$0.081***$	
	(0.001)	(0.003)	(0.001)	(0.003)	(0.000)	(0.003)	(0.001)	(0.003)	
Age	$0.007***$	$-0.046***$	$0.006***$	$-0.045***$	$0.015***$	$0.043***$	$0.015***$	$0.043***$	
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	
Healthy	0.001	$0.713***$	$0.005*$	$0.706***$	$-0.054***$	$-0.768***$	$-0.057***$	$-0.762***$	
	(0.003)	(0.004)	(0.003)	(0.005)	(0.001)	(0.005)	(0.001)	(0.005)	
Insured	$-0.015***$	$0.364***$	$-0.013***$	$0.374***$	$-0.050***$	$-0.355***$	$-0.053***$	$-0.363***$	
	(0.002)	(0.005)	(0.002)	(0.005)	(0.001)	(0.005)	(0.001)	(0.005)	
High school degree		$0.111***$ (0.004)		$0.109***$ (0.004)		$-0.171***$ (0.004)		$-0.169***$ (0.004)	
College or higher	$0.003*$	$0.589***$	$0.005***$	$0.570***$	$-0.060***$	$-0.692***$	$-0.061***$	$-0.674***$	
	(0.002)	(0.005)	(0.002)	(0.005)	(0.001)	(0.005)	(0.001)	(0.005)	
tanh(preGovIncHH)	$0.040***$	$-0.759***$	$0.036***$	$-0.773***$	$0.091***$	$0.655***$	$0.099***$	$0.670***$	
	(0.002)	(0.005)	(0.002)	(0.005)	(0.001)	(0.004)	(0.001)	(0.005)	
tanh(assets)	$0.590***$	$2.659***$	$0.614***$	$2.628***$	$-0.153***$	$-2.210***$	$-0.162***$	$-2.191***$	
	(0.008)	(0.018)	(0.008)	(0.018)	(0.001)	(0.016)	(0.002)	(0.017)	
Observations	945861		845142		945861		845142		

Table 22: Selection model: Risky and safe asset share w/ simulated model data of only healthy at 40 individuals

Standard errors in parentheses

[∗] *p* < 0.10, ∗∗ *p* < 0.05, ∗∗∗ *p* < 0.01

Notes: The dependent variables are the ratio of risky investments, an indicator variable for having any investments in risky stocks, the ratio of investments in safe assets, and an indicator variable for having any investments in safe assets as part of the financial wealth portfolio at ages 60–70. The independent variables of interest are indicator variables for whether an individual has reported being in bad health at ages 45–55. The first four columns are based on data of head of households from the PSID 1984–2019 and the last four columns are based on simulated data from our lifecycle model with 150,000 individuals that are observed from ages 40–94. Additional control variables used in the regressions based on PSID data (which are omitted from the table) include: gender, race indicators, marriage status, number of children, smoking status, debt, mortgage, other home loans, cohort controls, time trends, and states.

Table 23: Selection model: Risky and safe asset share w/ simulated model data of only healthy at 40 individuals by education

Standard errors in parentheses

[∗] *p* < 0.10, ∗∗ *p* < 0.05, ∗∗∗ *p* < 0.01

Notes: The dependent variables are the ratio of risky investments, an indicator variable for having any investments in risky stocks, the ratio of investments in safe assets, and an indicator variable for having any investments in safe assets as part of the financial wealth portfolio at ages 60–70. The independent variables of interest are indicator variables for whether an individual has reported being in bad health at ages 45–55. The first four columns are based on data of head of households from the PSID 1984–2019 and the last four columns are based on simulated data from our lifecycle model with 150,000 individuals that are observed from ages 40–94. Additional control variables used in the regressions based on PSID data (which are omitted from the table) include: gender, race indicators, marriage status, number of children, smoking status, debt, mortgage, other home loans, cohort controls, time trends, and states.

Experiment results

Figure 15: Experiment: Surprise excellent health shocks at age 45–55 – Stock market activities *Notes:* Benchmark vs. experiment.

Figure 16: Experiment: Surprise excellent health shocks at age 45–55 – Asset profiles *Notes:* Benchmark vs. experiment.

Figure 17: Experiment: Surprise excellent health shocks at age 45–55 – Labor market comparison *Notes:* Benchmark vs. experiment.

Figure 18: Experiment: Surprise excellent health shocks at age 45–55 – Change of insurance by education *Notes:* Benchmark vs. experiment.

(a) Treatment group outcomes when treated vs. not-treated

(b) Average treatment effect of the treated

Figure 19: Simulation of individuals in poor health at 45–55 and their counterfactual outcome with excellent health at 45–55

Notes: In this experiment we compare a subsample of individuals that reports being sick in at least one year between age 45–55 in the Benchmark simulation. We call this the treatment group. We show averages of key outcome variables by age in "blue" in Panel (a). We then construct a counterfactual for this group and surprise the same individuals with excellent health between the age of 45–55—this is the outcome of the treated group had they NOT been treated (with poor health). The gap in the profile curves from Panel (a) are shown in Panel (b). These are the **average treatment effects** (of being sick at least once during age 45–55) **of the treated (ATET) by age**.

Technical Appendix for "Health Heterogeneity, Portfolio Choice and Wealth Inequality"

Juergen Jung and Chung Tran

A Health and Retirement Study (HRS)

The [HRS](#page-39-5) [\(2022\)](#page-39-5) (Health and Retirement Study) is sponsored by the National Institute on Aging (grant number NIA U01AG009740) and is conducted by the University of Michigan. The [RAND-HRS](#page-41-0) [\(2022\)](#page-41-0) is developed from the HRS and comprises a cross-wave file with variables derived consistently across waves. It is a composite data set over 14 waves (including 16 years of survey years) that combines seven cohorts to construct a nationally representative panel of the older population in the U.S. The cohorts comprise the AHEAD cohorts born before 1924, the CODA cohorts born between 1924–1930, the HRS cohorts born between 1931–1941 and the War Baby cohorts born between 1942–1947, Early Baby Boomer cohort born between 1948–1953, Mid Baby Boomer cohort born between 1954–1959, and most recently the Late Baby Boomer cohort born between 1960–1965. The RAND-HRS is maintained by the RAND Center of Aging. ^{[40](#page-68-0)}[Juster and Suzman](#page-40-2) [\(1995\)](#page-40-2) present a general overview of the HRS, [Wallace and Herzog](#page-42-2) [\(1995\)](#page-42-2) review the health measures, [Hurd,](#page-39-6) [Meijer, Moldoff and Rohwedder](#page-39-6) [\(2016\)](#page-39-6) review the often imputed wealth measures, and [Fisher and Ryan](#page-38-3) [\(2017\)](#page-38-3) provide a more recently published summary.

A.1 Sample selection

We primarily use data from the Health and Retirement Study from the years 1992–2018. Sample selection proceeds as follows. After cleaning the data (i.e., removing individuals who do not report their age or have other critical information missing) we drop individuals younger than 40 and older than 80 and are thus left with an unbalanced panel with 147,171 head of households observations. These individual observations are relatively evenly split across the 14 waves with the exception of the first wave that contains "only" 7,501 observations as can be seen from Table [A.1a.](#page-72-0) The top panel of Figure [A.1](#page-70-0) shows the age distribution of this sample. HRS observations are only available every other year. The average (unweighted) age in the HRS sample is 56.7 in 1992 and then increases to around 67 in wave 2008 and then drops down to 64.2 in wave 2018. This means that despite the fact that the HRS is a true panel in the sense that a household can be tracked over multiple years, entering new households in specific waves ensure that the sample remains representative of the older population with an average age of around 64.5 years.

We next drop outliers with respect to income and wealth. We drop individual observations if their reported total asset holdings (excluding housing) is larger than 2 million USD. We also drop individuals whose We next only keep individuals who report their health status at least once when they are between ages 45–55 so that we can assign them into treated (i.e., report to have poor health or work limiting health problems when aged 45–55) and untreated groups. Since not all individuals report their health status and since some individuals first entered the survey when they where older than 55, we lose about half the observations and are left with

⁴⁰More information is available at:

<https://www.rand.org/well-being/social-and-behavioral-policy/centers/aging/dataprod/hrs-data.html>

a sample of 73,466 head of household observations as shown in Table [A.1b.](#page-72-1) Out of the 73,466 head of household observations, 22,2243 report that they were in poor health at least once when aged 45–55 (compare second column in Table [A.2\)](#page-76-0). This is the sample used to make the risky and safe asset profile graphs in Figures [3b–](#page-45-0)[B.7.](#page-107-0)

The second panel of Figure [A.1](#page-70-0) shows the age distribution of this sample. Figure [A.3](#page-71-0) shows the stock participation profile, the wealth portfolio share of stocks conditional on owning stocks, the safe asset participation profile, and the wealth portfolio share of safe assets for the sample of individuals who report their health state when they were 45–55 years old compared to the full sample of 40–80 year olds. We can see that the sample with individuals that reports the relevant health information has very similar lifecycle profiles of risky and safe assets. Only the oldest individuals between 77–80 report statistically significantly lower participation rates in safe assets and lower portfolio shares of safe assets compared to the full sample. This is not necessarily a problem for our analysis, as our regressions focus on the 60–70 year olds and for those groups we do not observe a significant difference in asset profiles between the two samples.

Out of the 73,466 individuals aged 40–80, 59,262 were still alive at ages 60–70. Finally, the sample of 60–70 year olds that report health status information when they were 45–55 year old (and are still alive in at least one wave when they are 60–70 year old) contains 24,773 individuals. This is the base sample that is used in the regressions shown in Tables [11](#page-47-0)[–A.6.](#page-78-0) The age distribution of this sample is shown in the third panel of Figure [A.1.](#page-70-0) Finally, Figure [A.4](#page-74-0) shows the age distribution of this sample for individuals reporting to being "sick" when they were 45–55 years old and individuals who reported being "healthy".

Depending on which control variables are added the sample further decreases in sample size. The age distribution, staring age, and year of first appearance in the sample of the "smallest" sample used in regression Tables [11,](#page-47-0) [A.5,](#page-78-1) and [A.6](#page-78-0) are shown in Figure [A.2.](#page-71-1)

Figures

Empirical results

Figure A.1: Age distribution of full and restricted sample

Notes: Sample selection. The top panel shows the full sample with heads of households aged 40–80. The middle panel shows heads of households aged 40–80 who report their health when they are between 45–55 and who are still in the sample when they are between 60–70 years old. The third panel are heads of households between ages 60–70 who reported their health status when they were between 45–50. The bottom panel are heads of households and their spouse between ages 60–70 who reported their health status when they were between 45–50. Since we limit the data to heads of households, the last two histograms are identical. All information is from HRS waves 1992–2018, unweighted.

Figure A.3: Asset profiles in full sample vs. sample with health status info at age 45–55

Notes: We distinguish between the full sample of 40–80 year olds and individuals between 40–80 year olds who report their health status at least once while they are 45-55 years old. We use *unweighted* data. Data source: Heads of households in HRS 1992–2018.

Figure A.2: Distribution of individual/time observations of 60–70 year old main sample

Notes: Sample selection. The panel shows frequency counts of individual/year observations of 60–70 year old heads of households in HRS. This is the main sample used in the regression analyses of Tables [11,](#page-47-0) [A.5,](#page-78-1) and [A.6.](#page-78-0) These individuals reported their health status when they were between 45–55, their current wealth composition, and important control variables as shown in Table [11.](#page-47-0) All information is from HRS waves 1992–2018, unweighted.

Table A.1: HRS Sample Selection

Notes: Panel (a) shows unweighted counts and average age of the sample of 40–80 year old heads of households in each wave. Panel (b) shows 40–80 year old heads of households who repor^t their health status when they are between ages 45–55. Panel (c) shows 40–80 year old heads of households who repor^t their health status when between ages 45–55 and who are still in the sample in at least one waves when they are between 60–70 years old., Panel (d) shows 60–70 year old heads of households who repor^t their health status when between 45–55.This is the sample used in the regression analysis. Source: HRS 1992–2018.

A.2 Summary statistics

Unweighted summary statistics of the dependent and control variables of the different samples are presented in Table [A.2.](#page-76-0)^{[41](#page-73-0)} Our core sample of 40–80 year old individuals who report health information in at least one wave when they were 45–55 year old comprises 73,471 individual/year observations. About 30 percent of these report that they were in poor health in at least one wave when they were 45–55 year old. Summary statistics of this group are shown in column (2) of Table [A.2.](#page-76-0)

The group reporting bad health when 45–55 has a smaller fraction investing in financial assets (only 26 percent invest in risky assets compared to 49 percent in the full sample and 63 percent invest in the safe assets compared to 80 percent in the full sample), has lower levels of financial assets (USD 19,000 vs. USD 61,000 in risky assets and USD 30,000 vs. USD 80,000 in safe assets), and has lower shares of investments in both assets (10 percent vs. 20 percent in risky assets and 52 vs. 60 percent in safe assets). Note that these shares do not sum to one as they include individuals who report to have zero holdings in either asset. The "sick" group has slightly higher debt (USD 7,220 vs. USD 6,960) but lower mortgages. In addition, this group is also slightly younger (age 58.6 vs. 59.9), has more females (39 percent vs. 31 percent), is less likely to be married (47 percent vs. 58 percent), has a higher fraction of minorities (51 percent compared to 35 percent), is less educated and has less income, is in worse current health, has a higher fraction of smokers (31 percent vs. 23 percent), has higher out-of-pocket medical expenditures and is less likely to have health insurance.

Table [A.4](#page-77-0) shows a tabulation of individuals between ages 45–55 by whether they have ever reported being in bad health—defined as a health status of either "fair" or "poor". If they have, we call them the "Sick". First, we observe a strong correlation between an individual reporting being in bad health and having work limiting health problems. Furthermore, respondents in bad health are more likely to be unemployed. Therefore, not surprisingly, individuals in bad health are also more likely to be uninsured than individuals who report better health states. Sick individuals are less likely to have a college degree. Sick individuals have slightly higher levels of risk aversion and their planning horizon for financial savings are much shorter.

⁴¹All dollar values are denominated in 2018 USD using the OECD-CPI for the U.S. from OECD (2022), "Inflation (CPI)" (indicator) at: <https://doi.org/10.1787/eee82e6e-en> (accessed on 09 November 2022).

Figure A.4: Age distribution of 60–70 year old individuals by health status between ages 45–55 *Notes:* Heads of households in HRS 1992–2018, unweighted.

Figure A.5: Raw financial asset profiles conditional on health at age 45–55

Notes: TA is total asset; RA is risky asset; TFA is total financial asset. We distinguish between individuals who do not report having bad health (or alternatively work limiting health issues) between ages 45–55 and individuals who do. We refer to these two groups as Healthy 45–55 vs. Sick 45–55. We use unweighted data. Total assets includes all assets including IRAs but excluding housing wealth and assets in defined benefit pension plans such as 401Ks. Total financial assets includes assets held in defined benefit pension plans. The stock ratio in the bottom row is calculated as the average ratio of stock value over total financial assets per age group. Data source: Heads of households in HRS 1992–2018.

Table A.2: HRS Summary Statistics

Notes: Core samples unweighted summary statistics of heads of households in the HRS 1992–2018. The first column shows the sample of 40–80 year olds who report their health status in at least one wave when they were between 45–55 years old. Column (2) shows individuals who reported a poor health status in at least one year when they were between 45–55 years old. Column (3) show individuals who are between 40–80 years old and alive in at least one year when they are between 60–70 years old. Column (4) are individuals who are between 60–70 years old and column (5) shows a smaller sample of only those 60–70 year olds who reported a health status when they were younger at ages 45–55. Columns (6)–(10) reports subsamples of the 60–70 year olds with information from their 45–55 age period and includes only individuals who reported at ages 45–55 to be either sick, having a work limiting health problem, being unemployed, being sick and unemployed, and being sick and uninsured, respectively.

Notes: Tabulation is based on HRS 1992–2018 data of heads of households between ages 45–55.

A.3 Additional empirical results

	Stock Share	P(Stocks)	Safe A. Share	P(Safe A.)	Stock Share	P(Stocks)	Safe A. Share	P(Safe A.)
Sick at 45 55	-0.003 (0.012)	$-0.077***$ (0.018)	$0.031***$ (0.010)	$-0.055***$ (0.014)				
Health Lim. Wrk at 45 55					-0.001 (0.010)	$-0.050***$ (0.013)	$0.020**$ (0.008)	$-0.024**$ (0.010)
Unemployed at 45_55	-0.003 (0.012)	$-0.070***$ (0.016)	$0.036***$ (0.010)	-0.011 (0.012)	0.000 (0.010)	$-0.065***$ (0.013)	$0.031***$ (0.008)	$-0.025**$ (0.010)
Uninsured at 45 55	0.018 (0.012)	$-0.061***$ (0.015)	0.010 (0.010)	$-0.046***$ (0.012)	0.007 (0.010)	$-0.067***$ (0.012)	$0.020***$ (0.008)	$-0.062***$ (0.010)
Initial (mean) Stock-Ratio 40-51	$0.201***$ (0.020)	$0.352***$ (0.031)	$-0.272***$ (0.019)	$0.051***$ (0.018)	$0.200***$ (0.016)	$0.374***$ (0.023)	$-0.270***$ (0.014)	$0.062***$ (0.018)
Observations	3065	6111	5111	6111	3072	6143	5126	6143

Table A.5: Two-Part model: Risky and safe asset share

Standard errors in parentheses

[∗] *p* < 0.10, ∗∗ *p* < 0.05, ∗∗∗ *p* < 0.01

Notes: The dependent variables are: (i) an indicator variable for whether an individual has investments in risky assets (participation equation); (ii) the detrended risky asset share conditional on having investments in risky assets (outcome equation); (iii) an indicator variable for whether an individual has investments in safe assets (participation equation) and (iv) the safe asset share conditional on having such investments (outcome equation). All four variables refer to the financial wealth portfolio at ages 60–70. The independent variables of interest are indicator variables for whether an individual has reported being in bad health at ages 45–55 or whether an individual has reported to ever having a work limiting health problem at ages 45–55. Additional control variables not shown in the table include: age, health status, insurance status, smoking status, gender, marriage status, number of children, race, education indicator for college or higher, debt, mortgage, overall asset level, cohort controls, time trend controls, region controls. The participation equations are based on a linear probability model and are indicated as P(). They additionally include controls for high school status and time year indicators. Data source: Heads of households in the HRS 1992–2018. Estimates based on family unit sampling weights.

Table A.6: Selection model: Risky and safe asset share

Standard errors in parentheses

[∗] *p* < 0.10, ∗∗ *p* < 0.05, ∗∗∗ *p* < 0.01

Notes: The dependent variables are: (i) an indicator variable for whether an individual has investments in risky assets (participation equation); (ii) the detrended risky asset share conditional on having investments in risky assets (outcome equation); (iii) an indicator variable for whether an individual has investments in safe assets (participation equation) and (iv) the safe asset share conditional on having such investments (outcome equation). All four variables refer to the financial wealth portfolio at age 60–70. The independent variables of interest are indicator variables for whether an individual has reported being in bad health at ages 45–55 or whether an individual has reported to ever having a work limiting health problem at ages 45–55. Additional control variables not shown in the table include: age, health status, insurance status, smoking status, gender, marriage status, number of children, race, education indicator for college or higher, debt, mortgage, overall asset level, cohort controls, time trend controls, region controls. The participation equations, indicated as P(), are based on a Probit model and additionally include controls for high school status and time year indicators. Data source: Heads of households in the HRS 1992-2018. Estimates based on unweighted data.

A.4 Year, time and cohort effects

We use two-part models based on [Athreya, Ionescu and Neelakantan](#page-35-0) [\(2023\)](#page-35-0) based on methods in [Ameriks and](#page-35-1) [Zeldes](#page-35-1) [\(2004\)](#page-35-1) and [Poterba and Samwick](#page-41-0) [\(2001\)](#page-41-0) to control for either time or cohort effects and selection models similar to [Tischbirek](#page-42-0) [\(2019\)](#page-42-0) based on methods in [Deaton and Paxson](#page-37-0) [\(1994\)](#page-37-0) to control for both time and cohort effects simultaneously.

Figure A.6: Asset profiles by year

Notes: We distinguish between the full sample of 40–80 year olds and individuals between 40–80 year olds who report their health status at least once while they are 45–55 years old. Data source: Heads of households in HRS 1992–2018.

Figure A.7: Stocks: Cohort and time effects

Notes: Predictions are based on a Heckman selection model with controls for cohort and time effects similar to [Deaton and Paxson](#page-37-0)
[\(1994\)](#page-37-0). We distinguish between individuals who do not report having bad health (or alternat ages 45–55 and individuals who do. We refer to these two groups as Healthy vs. Unhealthy. The graph shows predictions for participation a market for a specific asset class as well as predictions for the share of this asset in the overall financial portfolio conditional on holding the particular asset. The base cohort (omitted category) when controlling for cohort effects is the HRS cohort born between 1931–41. The base year (omitted category) when controlling for time (year) effects is 1992. Data source: Heads of households in HRS 1992–2018.

Figure A.8: Safe Assets: Cohort and time effects

Notes: Predictions are based on a Heckman selection model with controls for cohort and time effects similar to [Deaton and Paxson](#page-37-0)
[\(1994\)](#page-37-0). We distinguish between individuals who do not report having bad health (or alternat ages 45–55 and individuals who do. We refer to these two groups as Healthy vs. Unhealthy. The graph shows predictions for participation a market for a specific asset class as well as predictions for the share of this asset in the overall financial portfolio conditional on holding the particular asset. The base cohort (omitted category) when controlling for cohort effects is the HRS cohort born between 1931–41. The base year (omitted category) when controlling for time (year) effects is 1992. Data source: Heads of households in HRS 1992–2018.

A.5 Population Weights

While using population weights in the regressions does not significantly change our results, we can see from Figure [A.9](#page-82-0) that including population weights into the asset profiles adds a large amount of noise to the younger age groups between 40–50 as the HRS often assigns a zero population weight to spouses. In order to not lose too much statistical power for the estimation of asset profiles that are controlled for cohort and time effects we therefore prefer to work with the unweighted (and therefore larger) sample.

Figure A.9: Weighted Asset ratios with/without health shock between age 45–55

Notes: Asset ratios by health status at ages 45–55. We distinguish between individuals who do not report having bad health (or alternatively work limiting health issues) between ages 45–55 and individuals who do. We refer to these two groups as Healthy vs. Unhealthy. The graph shows the unweighted average per age group compared to the population weighted average per age group. These profiles confound age, cohort, and time effects. Data source: Heads of households in HRS 1992–2018.

A.6 Other Asset Classes

Figure A.10: Asset profiles decomposition by health status

Notes: Asset profiles decomposition by health status at ages 45–55. We distinguish between individuals who do not report having bad health (or alternatively work limiting health issues) between ages 45–55 and individuals who do. We refer to these two groups as Healthy vs. Sick. We present cumulative sums of unweighted averages of each asset class per age group. All dollar values are expressed in 2018 USD using the OECD-CPI for the US. These profiles confound age, cohort, and time effects. We dropped outlier observations with total asset holdings (excl. housing) of more than 2 million USD as well as households with defined benefit pension balances exceeding 2 million USD. Data source: Heads of households in HRS 1992–2018, unweighted.

Figure A.11: Asset ratios with/without health shock between age 45–55

Notes: Asset ratios by health status at ages 45–55. We distinguish between individuals who do not report having bad health (or alternatively work limiting health issues) between ages 45–55 and individuals who do. We refer to these two groups as Healthy vs. Unhealthy. The graph shows the *unweighted* average per age group. These profiles confound age, cohort, and time effects. We drop observations with asset holdings larger than 2 million USD. Data source: Heads of households in HRS 1992–2018.

Figure A.12: Asset type by current health status

Notes: Asset holdings by current health status of individuals between ages 60–70. We distinguish between individuals who do not report having bad health (or alternatively work limiting health issues) between ages 45–55 and individuals who do. We refer to these two groups as Healthy vs. Unhealthy. We drop observations with asset holdings larger than 2 million USD. Data source: Heads of households in HRS 1992–2018, unweighted.

Figure A.13: Asset ratios by current health status

Notes: Asset ratios by current health status of individuals 60–70. We distinguish between individuals who experienced work limiting health issues between ages 45–55 and individuals who did not. We refer to these two groups as H-Shock vs. No-H-Shock. We drop observations with asset holdings larger than 2 million USD. Data source: Heads of households in HRS 1992–2018, unweighted.

Figure A.14: Asset Type by Gender

Notes: Asset holdings by gender of individuals between ages 60–70. We distinguish between individuals who experienced work limiting health issues between ages 45–55 and individuals who did not. We refer to these two groups as healthy vs. unhealthy. We drop observations with asset holdings larger than 2 million USD. Data source: Heads of households in HRS 1992–2018, unweighted.

A.7 Risk Aversion, life expectations, and health status

Notes: We distinguish between individuals who do not report having bad health (or alternatively work limiting health issues) between age 45–55 and individuals who do. We refer to these two groups as Healthy vs. Sick. The graph shows the **unweighted "raw" average** per age group. The variable Risk Aversion is a categorical variable with four categories coded as integers (1) least risk averse, (2) third most risk averse, (3) second most risk averse, and (4) most risk averse. Data source: Heads of households in HRS 1992–2018.

Figure A.16: Preference/belief differences with/without health shock between ages 45–55

Notes: We distinguish between individuals who do not report having bad health (or alternatively work limiting health issues) between ages 45–55 and individuals who do. We refer to these two groups as Healthy vs. Unhealthy. The graph shows the **population weighted** average per age group. Data source: Heads of households in HRS 1992–2018.

	(1)	(2)	(3)	(4)	(5)				
main									
Health Deterioration	0.008 (0.031)	-0.069 (0.061)	-0.098 (0.112)						
Unhealthy in (t)				-0.016					
				(0.058)					
Unhealthy in $(t-1)$					-0.066				
					(0.102)				
Insured	0.022	0.056	0.101	$0.189***$	$0.190***$				
	(0.037)	(0.072)	(0.133)	(0.058)	(0.058)				
Smoker	0.011	-0.003	-0.019	-0.049	-0.048				
	(0.033)	(0.062)	(0.114)	(0.052)	(0.051)				
Female	-0.022	$0.199**$	$0.363**$	$0.300***$	$0.300***$				
	(0.041)	(0.080)	(0.146)	(0.067)	(0.067)				
Married/Partnered	0.002	0.077	0.116	$0.202***$	$0.201***$				
	(0.041)	(0.079)	(0.144)	(0.066)	(0.066)				
Black	0.017	-0.024	-0.034	0.083	0.083				
	(0.038)	(0.072)	(0.131)	(0.063)	(0.063)				
High school degree	0.029	-0.031	-0.113	-0.060	-0.059				
	(0.041)	(0.075)	(0.143)	(0.063)	(0.062)				
College or higher	0.069	$-0.210**$	$-0.475***$	$-0.491***$	$-0.490***$				
	(0.049)	(0.092)	(0.168)	(0.078)	(0.077)				
Debt (\$1,000)	0.001	0.000	-0.000	$-0.001*$	$-0.001*$				
	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)				
Mortgage (\$1,000)	-0.000	-0.000	-0.000	$-0.001**$	$-0.001**$				
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)				
Other home loans (\$1,000)	0.000	-0.002	$-0.004*$	$-0.003**$	$-0.003**$				
	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)				
Healthy									
tanh(preGovIncHH)									
tanh(assets)									
Initial (mean) Stock-Ratio 40-51									
Observations	1024	1685	1685	7639	7639				
R^2									
Standard errors in parentheses $p < 0.10,$ ** $p < 0.05,$ *** $p < 0.01$									

Table A.7: Risk Aversion and Health Status

Notes: The dependent variable is increase in risk aversion in the first column and an ordinary measure of risk aversion in all other columns. The independent variables of interest are indicator variables for whether an individual has reported being in bad health at ages 45–55 or whether an individual has reported to ever having a work limiting health problem at ages 45–55. Unweighted summary statistics of individuals based on HRS 1992–2018.

A.8 Financial Planning Horizon

Figure A.17: Financial planning horizon differences of 45–55 year old individuals by health state

Notes: We distinguish between individuals who do not report having bad health (or alternatively work limiting health issues) between age 45–55 and individuals who do. We refer to these two groups as Healthy vs. Sick. The graph shows frequency charts of unweighted data. Data source: Heads of households in HRS 1992–2018.

A.9 Sample Attrition

Sample attrition in longitudinal surveys can lead to selective samples which introduce attrition bias into estimates of parametric models. For the following discussion we distinguish between three types of attrition: (*i*) passive attrition due to death, (*ii*) active attrition due to non-reporting of health status, and (*iii*) active attrition due to non-response to the survey in a given year. Table [A.8](#page-93-0) shows the frequencies of the attrition types.

The HRS includes information about people who died either through exit interviews or the regular core interview if a spouse still responds to the survey. We are therefore able to assess passive attrition due to death.

The second type of attrition due to not reporting health state information is very rare. If individuals respond to the survey, they typically report their health state. In HRS, which is a deeper panel in which individuals are followed until they either die or become otherwise non-responsive, it is possible to have partial attrition for some periods. After implementing the interpolation routine described in Section [2.1](#page-6-0) we are left with only three observations with missing health information out of 204,492 person/year observations in years following the initial entry into the survey.

This leaves us with the issue of possible attrition bias generated by complete non-response to the survey. We do not know whether these individuals died or stopped responding for other reasons. After generating an attrition indicator for this type of attrition and running the attrition probit test described in [Fitzgerald, Gottschalk](#page-38-0) [and Moffitt](#page-38-0) [\(1998\)](#page-38-0) as well as the attrition pooling test described in [Becketti, Gould, Lillard and Welch](#page-36-0) [\(1988\)](#page-36-0), we are not able to reject attrition bias in the $HRS⁴²$ $HRS⁴²$ $HRS⁴²$

In order to minimize the estimation bias in our econometric specifications in Section [2.2,](#page-8-0) we implement three strategies. First, we limit the upper age range of the HRS sample in the regression analysis to 70 years. (Some lifecycle profile graphs included individuals up to age 80). By limiting our sample to relatively younger individuals, the issue of death attrition is partly mitigated as can be seen from the relatively low death rates in Figure [A.18.](#page-92-1)

For the HRS, [Kapteyn, Michaud, Smith and Soest](#page-40-0) [\(2006\)](#page-40-0) find very little evidence of attrition bias from selection on observables that would warrant the use of more complicated weights than the HRS weights which do condition on race, ethnicity, gender, and age, the main drivers of attrition from observables. A similar result is demonstrated in [Cao and Hill](#page-36-1) [\(2005\)](#page-36-1) who further distinguish between passive (through death) and active (non-death) attrition. [Kapteyn et al.](#page-40-0) [\(2006\)](#page-40-0) recommend the use of the unbalanced panel that includes individuals that have attrited in the past but have subsequently been recruited back into he survey. We follow their advice and use the unbalanced panel with HRS weights for estimation. While using sampling weights or inverse probability weights can account for attrition on observables, attrition on unobservables would require selection models and exclusion restrictions which are often impossible to find.^{[43](#page-92-2)} Many studies, however, point to very mild attrition effects even in longitudinal surveys with high attrition rates [\(Alderman, Behrman, Kohler,](#page-35-2) [Maluccio and Watkins](#page-35-2) [2001;](#page-35-2) [Fitzgerald, Gottschalk and Moffitt](#page-38-0) [1998;](#page-38-0) [Lillard and Panis](#page-40-1) [1998\)](#page-40-1).

Figure A.18: Head of households who are alive or reported dead by age

Note: Statistics are based on unweighted observations of head of households aged 40–80 in RAND-HRS 1992–2018.

⁴²[Baulch and Quisumbing](#page-35-3) [\(2010\)](#page-35-3) contains detailed descriptions including Stata codes for these type of tests.

⁴³ Attrition on observables occurs when the dependent variable is independent of the attrition process conditional on the explanatory variables. Attrition on unobservables occurs when this conditional independence does not hold. A sample selection model can account for attrition on unobservables but requires an exclusion restriction for identification, that is, an instrumental variable that affects attrition only but not the dependent variable [Hausman and Wise](#page-39-0) [1979;](#page-39-0) [Ridder](#page-41-1) [1992.](#page-41-1) [Fitzgerald, Gottschalk and Moffitt](#page-38-0) [\(1998\)](#page-38-0) point out that it is almost impossible to find plausible exclusion restrictions.

Table A.8: Attrition Rates

Note: Statistics are based on unweighted observations of head of households aged 40–80 in RAND-HRS 1992–2018.

B Panel Study of Income Dynamics (PSID)

The Panel Study of Income Dynamics (PSID) is available in waves from 1968–2021. From 1968–1997 the survey was conducted every year and from 1999 onward every other year. Wealth data was first available through survey supplements for the years 1984, 1989, 1994, 1999, 2001, 2003, 2005, and 2007. Since wave 2009 the wealth questionnaire is part of the main survey and wealth data is available biennially. We primarily use data from the years 1984–2019. We use the PSID_SHELF version [\(Pfeffer, Daumler and Friedman,](#page-41-2) [2023\)](#page-41-2).^{[44](#page-94-0)} We then use the main PSID [\(PSID,](#page-41-3) [2024\)](#page-41-3) for health status information, health expenditure and health insurance information as well as labor hours and wages as those variables are not yet part of PSID_SHELF.

B.1 Sample selection

Sample selection proceeds as follows. After cleaning the data (i.e., removing individuals who do not report their age or have other critical information missing) we drop individuals younger than 40 and older than 80 and are thus left with an unbalanced panel with 107,994 head of household/year observations. These individual/year observations increase by wave, starting with 2,922 in 1984 to 5,263 in 2019 as can be seen from Table [B.1a.](#page-97-0)

The top panel of Figure [B.1](#page-95-0) shows the age distribution of this sample. The average (unweighted) age in this PSID sample is 57.1 in 1984 and it stays relatively stable throughout the remaining waves.

We next drop outliers with respect to income and wealth. We drop individual observations if their reported total asset holdings (excluding housing) is larger than 2 million USD. We also drop individuals whose We next only keep individuals who report their health status at least once when they are between ages 45–55 so that we can assign them into treated (i.e., report to have poor health or work limiting health problems when aged 45–55) and untreated groups. Since not all individuals report their health status and since some individuals first entered the survey when they where older than 55, we lose about 10,000 observations and are left with a sample of 95,244 head of household observations as shown in Table [B.1b.](#page-97-1) Out of the 95,244 head of household observations, 29,356 report that they were in poor health at least once when aged 45–55 (compare second column in Table [B.2\)](#page-102-0). This is the sample used to make the risky and safe asset profile graphs in Figures [3b–](#page-45-0)[B.7.](#page-107-0)

The second panel of Figure [B.1](#page-95-0) shows the age distribution of this sample. Figure [B.3](#page-98-0) shows the stock participation profile, the wealth portfolio share of stocks conditional on owning stocks, the safe asset participation profile, and the wealth portfolio share of safe assets for the sample of individuals who report their health state when they were 45–55 years old compared to the full sample of 40–80 year olds. We can see that the sample with individuals that reports the relevant health information has very similar lifecycle profiles of risky and safe assets.

Out of the 95,244 individuals aged 40–80 with health information, 62,103 are still alive at ages 60–70. Finally, the sample of 60–70 year olds that report health status information when they were 45–55 year old (and are still alive in at least one wave when they are 60–70 year old) contains 20,521 individual/time observations. This sample was used in the regressions shown in Tables [10](#page-46-0)[–13.](#page-48-0) The age distribution of this sample is shown in the third panel of Figure [B.1.](#page-95-0) Finally, Figure [B.4](#page-100-0) shows the age distribution of this sample for individuals reporting to being "sick" when they were 45–55 years old and individuals who reported being "healthy".

Depending on which control variables are added the sample further decreases in sample size. The age

⁴⁴PSID_SHELF is available at: <https://www.openicpsr.org/openicpsr/project/194322/version/V1/view>

distribution, staring age, and year of first appearance in the sample of the "smallest" sample used in regression Tables [10,](#page-46-0) [12,](#page-48-1) and [13](#page-48-0) are shown in Figure [B.2.](#page-96-0)

Figure B.1: Age distribution of full and restricted sample

Notes: Sample selection. The top panel shows the full sample with heads of households aged 40–80. The middle panel shows heads of households aged 40–80 who report their health when they are between 45–55 and who are still in the sample when they are between 60–70 years old. The third panel are heads of households between ages 60–70 who reported their health status when they were between 45–50. The bottom panel are heads of households and their spouse between ages 60–70 who reported their health status when they were between 45–50. Since we limit the data to heads of households, the last two histograms are identical. All information is from PSID waves 1984–2019, unweighted.

Figure B.2: Distribution of individual/time observations of 60–70 year old main sample

Notes: Sample selection. The panel shows frequency counts of individual/year observations of 60–70 year old heads of households in PSID. This is the main sample used in the regression analyses of Tables [10,](#page-46-0) [12,](#page-48-1) and [13.](#page-48-0) These individuals reported their health status when they were between 45–55, their current wealth composition, and important control variables as shown in Table [10.](#page-46-0) All information is from PSID waves 1984–2019, unweighted.

Table B.1: PSID Sample Selection

Notes: Panel (a) shows unweighted counts and average age of the sample of 40–80 year old heads of households in each wave. Panel (b) shows 40–80 year old heads of households who report their health status when hey are be This is the sample used in the regression analysis. Source: PSID 1984–2019.

Figure B.3: Asset profiles in full sample vs. sample with health status info at age 45–55

Notes: We distinguish between the full sample of 40–80 year olds and individuals between 40–80 year olds who report their health status at least once while they are 45-55 years old. We use *unweighted* data. Data source: Heads of households in HRS 1992–2018.

B.2 Summary statistics

Unweighted summary statistics of the dependent and control variables of the different samples are presented in Table [B.2.](#page-102-0)

Our core sample of 40–80 year old individuals who report health information in at least one wave when they were 45–55 year old comprises 92,244 individual/year observations. About 30 percent of these report that they were in poor health in at least one wave when they were 45–55 year old. Summary statistics of this group are shown in column (2) of Table [B.2.](#page-102-0)

The group reporting bad health when 45–55 has a smaller fraction investing in financial assets (only 17 percent invest in risky assets compared to 35 percent in the full sample and 61 percent invest in the safe assets compared to 71 percent in the full sample), has lower levels of financial assets (USD 16,000 vs. USD 49,000 in risky assets and USD 18,000 vs. USD 45,000 in safe assets), and has lower shares of investments in both assets (8 percent vs. 16 percent in risky assets and 55 vs. 61 percent in safe assets). Note that these shares do not sum to one as they include individuals who report to have zero holdings in either asset. The "sick" group has slightly higher debt (USD 10,170 vs. USD 13,350) but lower mortgages. In addition, this group is also slightly younger (age 52.4 vs. 54.7), has more females (38 percent vs. 30 percent), is less likely to be married (48 percent vs. 58 percent), has a higher fraction of minorities, is less educated and has less income, is in worse current health, has a higher fraction of smokers, has similar out-of-pocket medical expenditures but is less likely to have health insurance, and if they have health insurance it is more likely to be public health insurance.

Table [B.6](#page-104-0) shows a tabulation of individuals between ages 45–55 by whether they have ever reported being in bad health—defined as a health status of either "fair" or "poor". If they have, we call them the "Sick". First, we observe a strong correlation between an individual reporting being in bad health and having work limiting health problems. Furthermore, respondents in bad health are more likely to be unemployed. Therefore, not surprisingly, individuals in bad health are also more likely to be uninsured than individuals who report better health states. Sick individuals are less likely to have a college degree. ^{[45](#page-99-0)} Our core sample of 40–80 year old individuals who report health information in at least one wave when they

⁴⁵All dollar values are denominated in 2018 USD using the OECD-CPI for the U.S. from OECD (2022), "Inflation (CPI)" (indicator) at: <https://doi.org/10.1787/eee82e6e-en> (accessed on 09 November 2022).

Figure B.4: Age distribution of 60–70 year old individuals by health status between ages 45–55 *Notes:* Heads of households in PSID 1984–2019, unweighted.

Figure B.5: Stocks profiles by health state between ages 45–55

Notes: We distinguish between individuals who do not report having bad health (or alternatively work limiting health issues) between ages 45–55 and individuals who do. Panel 2.A is based on a linear probability model whereas Panels 3.A and 4.A are based on Probit models. We refer to these two groups as Healthy vs. Unhealthy. We use weighted data. Data source: Heads of households in PSID 1984–2019.

Table B.2: PSID Summary Statistics

Notes: Core samples unweighted summary statistics of heads of households in the PSID 1984–2019. The first column shows the sample of 40–80 year olds who report their health status in at least one wave when they were between 45–55 years old. Column (2) shows individuals who reported a poor health status in at least one year when they were between 45–55 years old. Column (3) show individuals who are between 40–80 years old and alive in at least one year when they are between 60–70 years old. Column (4) are individuals who are between 60–70 years old and column (5) shows a smaller sample of only those 60–70 year olds who reported a health status when they were younger at ages 45–55. Columns (6)–(10) reports subsamples of the 60–70 year olds with information from their 45–55 age period and includes only individuals who reported at ages 45–55 to be either sick, having a work limiting health problem, being unemployed, being sick and unemployed, and being sick and uninsured, respectively.

Table B.4: PSID Summary Statistics (weighted)

Notes: Core samples weighted summary statistics of heads of households in the PSID 1984–2019. This is the sample without the Latino sample. The first column shows the sample of 40–80 year olds who report their health status in at least one wave when they were between 45–55 years old. Column (2) shows individuals who reported a poor health status in at least one year when they were between 45–55 years old. Column (3) show individuals who are between 40–80 years old and alive in at least one year when they are between 60–70 years old. Column (4) are individuals who are between 60–70 years old and column (5) shows a smaller sample of only those 60–70 year olds who reported a health status when they were younger at ages 45–55. Columns (6)–(10) reports subsamples of the 60–70 year olds with information from their 45–55 age period and includes only individuals who reported at ages 45–55 to be either sick, having a work limiting health problem, being unemployed, being sick and unemployed, and being sick and uninsured, respectively.

Table B.6: Summary statistics by health state between ages 45–55

Notes: Tabulation is based on PSID 1984–2019 data of heads of households between ages 45–55.

B.3 Additional empirical results

Table B.7: Risky asset share and poor health status (sample of healthy-at-40 individuals)

Standard errors in parentheses

[∗] *p* < 0.10, ∗∗ *p* < 0.05, ∗∗∗ *p* < 0.01

Notes: The dependent variable is the detrended ratio of stocks in the financial portfolio at ages 60–70 including individuals with zero stock holdings. The independent variables of interest are indicator variables for whether an individual has reported being in bad health at ages 45–55 or whether an individual has reported to ever having a work limiting health problem at ages 45–55. Column (7) and (8) are estimated on the subsample of individuals with positive stock holdings. The regressions also include controls for age, an indicator for Hispanic, size of outstanding mortgage and size of other home loans, Insurance status, smoking status, gender, marriage status, race dummies, high school and college indicators, gross household income, debt excl. primary home, and controls for initial health at age 0–16 and initial median stock ratio in the wealth portfolio at age 35–45. Data source: Heads of households in the PSID 1984–2019.

Table B.8: Selection model: Risky and safe asset share (w/o IRAs)

Standard errors in parentheses

[∗] *p* < 0.10, ∗∗ *p* < 0.05, ∗∗∗ *p* < 0.01

Notes: The dependent variables are: (i) an indicator variable for whether an individual has investments in risky assets (participation equation); (ii) the detrended risky asset share conditional on having investments in risky assets (outcome equation); (iii) an indicator variable for whether an individual has investments in safe assets (participation equation) and (iv) the safe asset share conditional on having such investments (outcome equation). All four variables refer to the financial wealth portfolio at age 60–70. The independent variables of interest are indicator variables for whether an individual has reported being in bad health at ages 45–55 or whether an individual has reported to ever having a work limiting health problem at ages 45–55. Additional control variables not shown in the table include: age, health status, insurance status, smoking status, gender, marriage status, number of children, race, education indicator for college or higher, debt, mortgage, overall asset level, cohort controls, time trend controls, region controls. The participation equations, indicated as P(), are based on a Probit model and additionally include controls for high school status and time year indicators. Data source: Heads of households in the **PSID 1984–2019**. Estimates based on unweighted data.

B.4 Year, time and cohort effects

We use two-part models based on [Athreya, Ionescu and Neelakantan](#page-35-0) [\(2023\)](#page-35-0) based on methods in [Ameriks and](#page-35-1) [Zeldes](#page-35-1) [\(2004\)](#page-35-1) and [Poterba and Samwick](#page-41-0) [\(2001\)](#page-41-0) to control for either time or cohort effects and selection models similar to [Tischbirek](#page-42-0) [\(2019\)](#page-42-0) based on methods in [Deaton and Paxson](#page-37-0) [\(1994\)](#page-37-0) to control for both time and cohort effects simultaneously.

Figure B.6: Asset profiles by year

Notes: We distinguish between the full sample of 40–80 year olds and individuals between 40–80 year olds who report their health status at least once while they are 45–55 years old. We use weighted data. Data source: Heads of households in PSID 1984–2019.

In panel 1.A of Figure [B.7](#page-107-0) we observe the pattern for the participation rates in safe asset investments. We observe higher overall participation rates of healthy individuals and a slight hump shape in the profiles of both health types. However, the participation rates in safe asset investments are much higher than in risky stocks investments and range between 70–90 percent for healthy types and 60–80 percent for sick types. The safe asset shares in the wealth portfolio differ significantly between health types and are higher at about 90 percent for the sick types and about 75 percent for the healthy types. Similar to the risky asset share profiles in Figure [3b,](#page-45-0) the safe asset share profiles become flat and are actually decreasing for the healthy types.

Figure B.7: Safe assets profiles by health state between ages 45–55

Notes: We distinguish between individuals who do not repor^t having bad health (or alternatively work limiting health issues) between ages 45–55 and individuals who do. We refer tothese two groups as Healthy vs. Unhealthy. The graph shows the **unweighted "raw" average** per age group. These profiles confound age, cohort, and time effects. Data sources: Heads of households in HRS 1992–2018 (left two columns) and heads of households in PSID 1984–2019 (right two columns).

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B.5 Other Asset Classes

Figure B.8: Asset profiles decomposition by health status

Notes: Asset profiles decomposition by health status at ages 45–55. We distinguish between individuals who do not report having bad health (or alternatively work limiting health issues) between ages 45–55 and individuals who do. We refer to these two groups as Healthy vs. Sick. We present cumulative sums of unweighted averages of each asset class per age group. All dollar values are expressed in 2018 USD using the OECD-CPI for the US. These profiles confound age, cohort, and time effects. We dropped outlier observations with total asset holdings (excl. housing) of more than 2 million USD as well as households with defined benefit pension balances exceeding 2 million USD. Data source: Heads of households in PSID 1984-2019, weighted.

C Medical Expenditure Panel Survey (MEPS)

C.1 Sample selection

We primarily use data from the Medical Expenditure Panel Survey (MEPS) from the years 1996–2018 for our estimation and calibration. MEPS provides a nationally representative survey about health care use, health expenditures, health insurance coverage as well as demographic data on income, health status, and other socioeconomic characteristics. The original household component of MEPS was initiated in 1996. Each year about 15,000 households are selected and interviewed five times over two full calendar years. MEPS groups individuals into families similar to the CPS (Current Population Survey) as well as Health Insurance Eligibility Units (HIEU) which are subsets of households that typically include individuals covered under the same health insurance—usually a couple and their children. We do abstract from family size effects and concentrate on adult head of households aged 40–80.

A variable in a MEPS survey of year *t* is typically represented three times as either VARNAME13, VAR-NAME24, and VARNAME35, where 13 indicates that this variable is either a response of a first round interview of an individual who entered the survey in year *t* or the third round interview of an individual who entered the survey in year $t - 1$. Similarly 24 indicates that this response is the second interview response of the individual who entered in year *t* or the fourth round response of the individual who entered the previous year $t - 1$. Finally, 35 indicates that this variable is the response from the third interview of an individual who entered in year *t* or the final fifth round interview response from an individual who entered in the prior year *t* −1 and then subsequently exits the survey.

We drop outlier observations from individuals whose gross household income exceeds 1 million USD, whose labor income exceeds 400,000 USD, and whose medical spending exceeds 100,000 USD.

C.2 Summary statistics

Summary statistics of the unweighted sample are presented in Table [C.1](#page-111-0) and a histogram of the age distribution is presented in Figure [C.1.](#page-110-0) 46

⁴⁶All dollar values are denominated in 2018 USD using the OECD-CPI for the U.S. from OECD (2022), "Inflation (CPI)" (indicator) at: <https://doi.org/10.1787/eee82e6e-en> (accessed on 09 November 2022).

Source: MEPS 1996-2018, Head of HIEU

Figure C.1: Age distribution

Notes: Data source is MEPS 1996–2018, heads of households, unweighted.

Table C.1: MEPS Summary Statistics

Notes: Unweighted summary statistics of heads of households based on MEPS 1996–2018.

C.3 Cohort effects

Panel data variables over the lifecycle of an individual are determined by age, time and cohort effects. Since our model only explicitly accounts for age effects, we should ideally remove time and cohort effects from the data in order to make lifecycle observations from the data consistent with lifecycle statistics generated by the model. Since age, time and cohort effects are perfectly collinear it is difficult to estimate all three simultaneously (e.g., [Jung and Tran](#page-40-0) [\(2014\)](#page-40-0)). The literature (e.g., [Kaplan](#page-40-1) [\(2012\)](#page-40-1)) suggests to conduct separate analyses once controlling for the cohort effect and in a repeat exercise controlling for the time effect in order to assess modeling implications. In this work we explicitly control for cohort effects of wages, income, wealth and health expenditures by regressing the log of the output variable on a set of age and cohort dummies. We focus on controlling of cohort effects because [Jung and Tran](#page-40-0) [\(2014\)](#page-40-0) show that they seem to be large in health expenditure data and time effects can be somewhat mitigated by deflating with the CPI index. We then use predictions of these regressions to generate cohort-adjusted variables with the birth cohort 1945–1954 as reference group.

C.4 Unbiased wage profiles

We follow [Rupert and Zanella](#page-41-0) [\(2015\)](#page-41-0) and [Casanova](#page-37-0) [\(2013\)](#page-37-0) and estimate a selection model to remove biases in self reported wages. [Rupert and Zanella](#page-41-0) [\(2015\)](#page-41-0) use PSID and CPS data and then employ a Tobit 2-step procedure based on [Wooldridge](#page-42-0) [\(1995\)](#page-42-0) to estimate selection corrected wage profiles. They find that once wage profiles are bias corrected they tend to be very flat which contradicts the often used hump-shaped wage profiles. Similarly, [Casanova](#page-37-0) [\(2013\)](#page-37-0) uses HRS data and finds evidence of flat wage profiles but no selection bias.

In our selection model we include fourth order polynomials in age, a health status variable, whether someone lives with a partner, family size, schooling, gender, and an indicator for part-time work. We use indicator variables for whether an individual is older than 62 and a second indicator variable for whether an individual is older 65 in the selection equation as is customary in this literature. These two indicator variables are exclusion restrictions and not included in the outcome equation of the selection model. Figure [C.3](#page-113-0) shows the wage profiles for healthy and sick types and the three educational groups. We only use observations from individuals whose wage income exceeds 400 USD. ^{[47](#page-112-0)}

Figure C.2: Raw wages vs. unbiased and cohort adjusted wage profiles

Notes: Data source is MEPS 1996–2018, heads of HIEU, population weighted. We report raw hourly wages, cohort adjusted wages, and cohort adjust unbiased wages. Unbiased wages are based on a selection model. The latter is used as wage efficiency input. We use a dummy variable approach to estimate unbiased wages profiles for two health (healthy vs. sick) and two education (no college vs. college) types.

⁴⁷[Blundell, Reed and Stoker](#page-36-0) [\(2003\)](#page-36-0), [Arellano and Bonhomme](#page-35-0) [\(2017\)](#page-35-0), [Chiappori, Dias and Meghir](#page-37-1) [\(2018\)](#page-37-1), and more recently [De Nardi, Fella and Paz-Pardo](#page-37-2) [\(2024\)](#page-37-2) use selection type models with exclusion restrictions to estimate wages. Instruments that have been used in the literature in the participation equation include potential welfare income (when not working), home ownership status, college dummies, marital status, a decade of birth dummy, interactions of the latter two, dummies for the years that have passed since the birth of the first child, interactions of those with marital status, dummy for husband employment (when estimating the labor participation equation of of women), and dummy for the presence of grandparents in the household. Interestingly, [De Nardi, Fella and](#page-37-2) [Paz-Pardo](#page-37-2) [\(2024\)](#page-37-2) report fairly robust potential wage profiles across the different specifications.

Figure C.3: Selection bias adjusted wage profiles of heads of HIEUs

Notes: Data source is MEPS 1996–2018, heads of HIEU, population weighted. This is used as wage efficiency input by health and education type into the model.

Figure C.4: Cohort adjusted labor income profiles of heads of HIEUs

Notes: Data source is MEPS 1996–2018, heads of HIEU, population weighted. This is a calibration target.

C.5 Health care expenditure data

MEPS provides high quality health expenditure and health care utilization data. The MEPS Household Component (HC) collects data in each round on use and expenditures for office- and hospital-based care, home health care, dental services, vision aids, and prescribed medicines. In addition, the MEPS Medical Provider Component (MPC) is a follow-back survey that collects data from a sample of medical providers and pharmacies that were used by sample persons in a given year. Expenditure data collected in the MPC are generally regarded as more accurate than information collected in the HC and are used to improve the overall quality of MEPS expenditure data. Expenditures in MEPS refer to what is paid for health care services. Expenditures are defined as the sum of direct payments for care provided during the year, including out-of-pocket payments

and payments by private insurance, Medicaid, Medicare, and other sources. Payments for over-the-counter drugs are not included in MEPS and neither are payments for long-term care. Similarly payments not related to specific medical events, such as Medicaid Disproportionate Share and Medicare Direct Medical Education subsidies, are also not included. MEPS records actual payments made and not original charges which tend to be much higher. However, it has become customary to apply discounts. In addition charges associated with uncollected liabilities, bad debt and charitable care do not constitute actual health care expenses and are therefore not counted. We drop 443 observations (out of 239,170) with health expenditure larger than USD 100,000 so that our estimates are not driven by outliers.

Figure C.5: Average health spending by health state

Notes: Data source is MEPS 1996–2018, heads of HIEU, population weighted. Cohort adjusted average health spending by self-reported health state and age in 2009 USD.

Figure C.6: Conditional health status transition probabilities

Notes: Data source is MEPS 1996–2018, heads of HIEU, population weighted. The profiles are based on predictions of an ordered logit model with controls for cohort effects.

C.6 Private employer health insurance (ehi) status

MEPS asks detailed questions about the type and length of health insurance coverage. If health insurance is offered through the current main job (OFFER31X, OFFER42X, OFFER 53X) an individual can opt into buying employer sponsored (group) health insurance. The offer variable is automatically set to one (and skipped in the survey) if the individual reports having health insurance via their employer. We set the indicator variable GROUP-OFFER equal to one if the individual reports having received a health insurance offer from their employer in either one of the three interview rounds.

In addition, a second variable asks whether an individual has had public (PUBJAx–PUBDEx) or private health insurance (PRIJAx–PRIDEx) for each month. In addition, if it is private health insurance, the survey asks whether the insurance is from an employer or union (PEGJAx–PEGDEx). We define an individual as having employer provided group insurance (GHI) in a given year if she is covered for at least 8 months with

employer provided insurance, she is otherwise classified as having individual private health insurance (IHI).

We estimate an ordered logit model and use it to predict the GHI offer probability for each age-education group where we distinguish between individuals with less than high school, high school, or college level education. The predicted probabilities of receiving a GHI offer from an employer are shown in Figure [C.7.](#page-117-0)

Figure C.7: Conditional employer health insurance status transition probabilities

Notes: Data source is MEPS 1996–2018, heads of households, population weighted. Using spline interpolation to get annual frequencies.

C.7 Coinsurance rates

We define the coinsurance rate as the fraction of out-of-pocket health expenditures over total health expenditures. The coinsurance rates in our model therefore include copayments and other direct out-of-pocket payments. We use MEPS data from 1999–2000 and calculate the average coinsurance rate of heads of HIEU (population weighted) by age for all four insurance types represented in the model. Consequently we set the coinsurance rates for the different types of insurance plans to $\gamma^{\text{chi}} = 0.31$, $\gamma^{\text{maid}} = 0.11$, and $\gamma^{\text{mcare}} = 0.30$ respectively, as shown in Figure [C.8.](#page-118-0)

Figure C.8: Coinsurance rates

Notes: These are not calibration targets. Data sources: is MEPS 1996–2018, heads of HIEU, population weighted.

D Computational appendix

D.1 Solution algorithm

We solve the model on a grid over the state space $x = \left\{\vartheta, a_{j_i}, \varepsilon_j^{\text{incP}}, \varepsilon_j^h, \varepsilon_j^{\text{ehi}}\right\}$ and the choice space \mathscr{C}_j $\{(c_j, \alpha_j) \in R^{++} \times [0,1]\}\.$ The asset grid $a_j = [0, a_{max}]$. We choose the maximum asset value large enough so that in our simulation no household will hit this upper limit. We briefly restate the household problem here for clarity of exposition:

$$
V(x_j) = \max_{\{c_j, \alpha_j\}} \left\{ u(c_j) + \beta \mathbb{E}_{\epsilon_{j+1}^{\text{incP}}, \epsilon_{j+1}^h, \epsilon_{j+1}^{\text{chicP}}, \epsilon_j^h, \epsilon_j^{\text{chi}}} \left[\pi_j \left(\epsilon_j^h \right) V(x_{j+1}) + \left(1 - \pi_j \left(\epsilon_j^h \right) \right) b(a_{j+1}) \right] \right\}
$$

s.t.

$$
a_{j+1} = \tilde{R}_{j+1} \left(\overbrace{a_j + y_j \left(\vartheta, \epsilon_j^h, \epsilon_j^{\text{incP}} \right) + b_j^{\text{si}} - o_j(m) - 1_{\left[\epsilon_j^{\text{chi}} - 1 \right]} \text{prem}_j^{\text{chi}} - \text{tax}_j - (1 + \tau^c) c_j - 1_{\left[\alpha_j > 0 \right]} q} \right)
$$

$$
\tilde{R}_{j+1} = \left(\alpha_j \left(1 + \tilde{r}_{net,j+1}^s \right) + (1 - \alpha_j) \left(1 + \bar{r}_{net}^b \right) \right).
$$

While α_j , the share of risky stocks in the overall portfolio is naturally bounded by the interval [0,1], (as we do not allow borrowing in bonds to buy stocks) the search grid over consumption is assumed to be bounded by [*cmin*, cash-on-hand*max*]. The lower bound is chosen to be USD 2,000, scaled to model units. We scale the model to USD using model and data values of average earnings income of 40 year olds, which is the starting age in our model. The maximum possible cash-on-hand is then calculated using the expression from the household budget constraint and substituting *amax* for asset holdings, the maximum realization of highest earnings income of college graduates (the highest permanent income group) based off the shock realization of ε^h and $\varepsilon^{\text{incP}}$, and the lowest out-of-pocket payment shocks.

From the budget constraint we also see that tomorrow's combined assets a_{j+1} are a function of the future realization of the stock return shock ε_{j+1}^s that is embedded in the stock return expression $\tilde{r}_{net,j+1}^s$. This, in combination with nonlinear taxes and other targeted transfer programs, results in contingent future asset holdings a_{j+1} that depend on the realization of the future shock to stock returns. The household therefore has to form expectations about this future stock return realization. Also, the contingent combined assets a_{j+1} are off-grid values and need to be interpolated over the asset grid. The model is solved backwards by implementing nested search loops over grids of α_j and c_j .

 $\textbf{Interpolation issue.}$ When we interpolate over future total asset holding realizations $a_{j+1}\left(\pmb{\varepsilon}_{j+1}^{s}\right) \in\left[\underline{a}\left(\pmb{\varepsilon}_{j+1}^{s}\right),\bar{a}\left(\pmb{\varepsilon}_{j+1}^{s}\right)\right]$ where it should be noted that the value of future assets a_{j+1} (and therefore grid boundary points \hat{a} and \hat{a}) depends on the realization of the stock return shock ε_{j+1}^s . The values <u>a</u> and \bar{a} are two adjacent grid values on the asset grid. If $w\left(\varepsilon_{j+1}^s\right)$ is the associated interpolation weight we can write the expectation of the continuation value of the household problem as

$$
EV_{j+1}\left(\vartheta,a_{j+1},\epsilon_{j+1}^{\textrm{inP}},\epsilon_{j+1}^{h},\epsilon_{j+1}^{\textrm{inP}},\epsilon_{j+1}^{h}\right)=\\\int p\left(\epsilon_{j+1}^{\textrm{inP}}|\epsilon_{j}^{\textrm{inP}}\right)\int p\left(\epsilon_{j+1}^{h}|\epsilon_{j}^{h}\right)\int p\left(\epsilon_{j+1}^{\textrm{inP}}|\epsilon_{j}^{\textrm{inP}}\right)\int p\left(\epsilon_{j+1}^{\textrm{inP}}|\epsilon_{j}^{\textrm{inP}}\right)\left(\epsilon_{j+1}^{\textrm{inP}}|\epsilon_{j+1}^{\textrm{inP}}\right)\left(\epsilon_{j+1}^{\textrm{inP}},\epsilon_{j+1}^{\textrm{inP}},\epsilon_{j+1}^{h},\epsilon_{j+1}^{\textrm{inP}},\epsilon_{j+1}^{h}\right)\left(\epsilon_{j+1}^{\textrm{inP}}d\epsilon_{j+1}^{\textrm{inP}}d\epsilon_{j+1}^{\textrm{inP}}d\epsilon_{j+1}^{\textrm{inP}}d\epsilon_{j+1}^{\textrm{inP}}\right)\left(\epsilon_{j+1}^{\textrm{inP}}|\epsilon_{j+1}^{\textrm{inP}}\epsilon_{j+1}^{\textrm{inP}},\epsilon_{j+1}^{\textrm{inP}},\epsilon_{j+1}^{\textrm{inP}},\epsilon_{j+1}^{\textrm{inP}},\epsilon_{j+1}^{\textrm{inP}}\right)
$$

which can be rewritten as

$$
EV_{j+1}\left(\vartheta,a_{j+1},\varepsilon_{j+1}^{\text{ineP}},\varepsilon_{j+1}^{h},\varepsilon_{j+1}^{\text{hei}}\right)=\int p\left(\varepsilon_{j+1}^{\text{ineP}}|\varepsilon_{j}^{\text{ineP}}\right)\int p\left(\varepsilon_{j+1}^{\text{hei}}|\varepsilon_{j}^{\text{h}}\right)\int p\left(\varepsilon_{j+1}^{\text{ehi}}|\varepsilon_{j}^{\text{ehi}}\right)V_{j+1}\left(\vartheta,a_{\left(\varepsilon_{j+1}^{\text{sei}}\right),\varepsilon_{j+1}^{\text{ineP}},\varepsilon_{j+1}^{h},\varepsilon_{j+1}^{\text{ehi}}\right)d\varepsilon_{j+1}^{\text{ehi}}d\varepsilon_{j+1}^{\text{hei}}d\varepsilon_{j+1}^{\text{heiP}}\right)=\int p\left(\varepsilon_{j+1}^{\text{ineP}}|\varepsilon_{j}^{\text{ineP}}\right)\int p\left(\varepsilon_{j+1}^{\text{hei}}|\varepsilon_{j}^{\text{h}}\right)\int p\left(\varepsilon_{j+1}^{\text{hei}}|\varepsilon_{j}^{\text{h}}\right)V_{j+1}\left(\vartheta,a_{\left(\varepsilon_{j+1}^{\text{sei}}\right),\varepsilon_{j+1}^{\text{ineP}},\varepsilon_{j+1}^{\text{ehi}},\varepsilon_{j+1}^{\text{ehi}}\right)d\varepsilon_{j+1}^{\text{ehi}}d\varepsilon_{j+1}^{\text{heiP}}d\varepsilon_{j+1}^{\text{heiP}}+\left|\varepsilon_{j+1}^{\text{heiP}}\right|\int p\left(\varepsilon_{j+1}^{\text{heiP}}|\varepsilon_{j}^{\text{hei}}\right)\int p\left(\varepsilon_{j+1}^{\text{hei}}|\varepsilon_{j}^{\text{h}}\right)V_{j+1}\left(\vartheta,a_{\left(\varepsilon_{j+1}^{\text{sei}}\right),\varepsilon_{j+1}^{\text{ineP}},\varepsilon_{j+1}^{\text{hei}}\right)d\varepsilon_{j+1}^{\text{ehi}}d\varepsilon_{j+1}^{\text{heiP}}d\varepsilon_{j+1}^{\text{meP}}\right
$$

This allows us to pre-calculate the inner integrals

$$
\begin{split} &\text{EVopt}\Big(\vartheta, \underline{a}\left(\varepsilon_{j+1}^s\right), \varepsilon_{j+1}^{\text{incP}}, \varepsilon_{j+1}^h, \varepsilon_{j+1}^{\text{chi}}\Big)\coloneqq \int p\left(\varepsilon_{j+1}^{\text{incP}}\big|\varepsilon_j^{\text{incP}}\right) \int p\left(\varepsilon_{j+1}^h|\varepsilon_j^h\right) \int p\left(\varepsilon_{j+1}^{\text{chi}}\big|\varepsilon_j^{\text{ehi}}\right) V_{j+1}\left(\vartheta, \underline{a}\left(\varepsilon_{j+1}^s\right), \varepsilon_{j+1}^{\text{incP}}, \varepsilon_{j+1}^h, \varepsilon_{j+1}^{\text{chi}}\right) d\varepsilon_{j+1}^{\text{chi}} d\varepsilon_{j+1}^h d\vare
$$

outside the (c_j, α_j) search loops which speeds up the code by a factor of 3! Inside the search loops we can then calculate the expected value term as

$$
EV_{j+1}\left(\vartheta,a_{j+1},\varepsilon_{j+1}^{\text{incP}},\varepsilon_{j+1}^{h},\varepsilon_{j+1}^{\text{ehi}}\right)=\\\int p\left(\varepsilon_{j+1}^{s}\right)\left[\begin{array}{c}w\left(\varepsilon_{j+1}^{s}\right) \text{EVopt}\left(\vartheta,\underline{a}\left(\varepsilon_{j+1}^{s}\right),\varepsilon_{j+1}^{\text{incP}},\varepsilon_{j+1}^{h},\varepsilon_{j+1}^{\text{ehi}}\right)\\+\left(1-w\left(\varepsilon_{j+1}^{s}\right)\right) \text{EVopt}\left(\vartheta,\bar{a}\left(\varepsilon_{j+1}^{s}\right),\varepsilon_{j+1}^{\text{incP}},\varepsilon_{j+1}^{h},\varepsilon_{j+1}^{\text{ehi}}\right)\end{array}+\right]d\varepsilon_{j+1}^{s}
$$

D.2 Calculating net returns to portfolio investments

Net returns on bonds are

$$
\bar{r}_{net}^b = \frac{1 + \left[\left(1 + r^b\right)\left(1 + \pi\right) - 1\right]\left(1 - \tau^d\right)}{1 + \pi} - 1.
$$

We have realization of ε^s on a grid which gives us values for stock returns according to

$$
\tilde{r}^s = r^b + \mu^s + \varepsilon^s.
$$

In the model we assume that this random return comprises a constant nominal dividend yield *d* and a stochastic nominal capital gain \tilde{g} , deflated by the inflation rate π

$$
\tilde{r}^s = \frac{1+\tilde{g}+d}{1+\pi} - 1.
$$

We can solve this expression for \tilde{g} as

$$
1 + \tilde{r}^{s} = \frac{1 + \tilde{g} + d}{1 + \pi},
$$

\n
$$
\Rightarrow (1 + \tilde{r}^{s})(1 + \pi) = 1 + \tilde{g} + d
$$

\n
$$
\tilde{g} = (1 + \tilde{r}^{s})(1 + \pi) - (1 + d)
$$

Similar to [Gomes, Michaelides and Polkovnichenko](#page-39-0) [\(2009\)](#page-39-0) we impose that asset return taxes are paid on nominal returns at two different rates, τ_g is the capital gains tax and τ_d is the dividends tax. Assuming a constant rate of inflation π , the after-tax real return of the risky asset is:

$$
\widetilde{r}_{net}^{s} = \frac{1 + \widetilde{g}\left(1 - \tau^{g}\right) + d\left(1 - \tau^{d}\right)}{1 + \pi} - 1.
$$

And finally the after tax return of the portfolio is

$$
\tilde{R}_{j+1} = \left(\alpha_j \left(1 + \tilde{r}_{net,j+1}^s\right) + \left(1 - \alpha_j\right)\left(1 + \bar{r}_{net}^b\right)\right).
$$

E Model performance results

Figure E.1: Model performance: financial wealth by age group and health type

Notes: These are not calibration targets. Data is based on financial asset information of head of households in HRS 1992–2018 and s PSID 1984–2019. We use sample weights. Profiles are adjusted for time and cohort effects. HRS financial assets information includes assets in defined contribution pension plans such as 401Ks. HRS is not representative for ages 40–50.

Figure E.2: Model performance: labor income by education and health

Notes: Cohort adjusted labor income profiles by permanent income group and health state. These are not calibration targets. Data source is MEPS 1996-2018, heads of households, population weighted.

Figure E.3: Model performance: hours worked by education and health

Notes: Cohort adjusted work hours profiles by permanent income group and health state. These are not calibration targets. Data source is MEPS 1996–2018, heads of households, population weighted.

	PSID: Healthy					PSID: Sick					
	$0 - 20$	$20 - 40$	$40 - 60$	60-80	80-100		$0 - 20$	20-40	$40 - 60$	60-80	80-100
$0 - 20$	0.59	0.23	0.10	0.06	0.02	$0 - 20$	0.66	0.02	0.16	0.12	0.05
20-40	0.23	0.37	0.23	0.12	0.05	$20 - 40$	0.45	0.11	0.30	0.10	0.03
$40 - 60$	0.11	0.25	0.33	0.23	0.09	$40 - 60$	0.33	0.04	0.36	0.18	0.09
60-80	0.05	0.12	0.24	0.36	0.23	$60 - 80$	0.20	0.01	0.23	0.33	0.22
80-100	0.02	0.04	0.10	0.24	0.61	80-100	0.07	0.00	0.08	0.25	0.59
			HRS: Healthy				HRS: Sick				
	$0 - 20$	20-40	$40 - 60$	60-80	80-100		$0 - 20$	20-40	$40 - 60$	60-80	80-100
$0 - 20$	0.60	0.23	0.10	0.05	0.01	$0 - 20$	0.58	0.12	0.17	0.09	0.04
$20 - 40$	0.28	0.36	0.22	0.10	0.04	$20 - 40$	0.39	0.33	0.18	0.06	0.03
$40 - 60$	0.10	0.25	0.34	0.23	0.08	$40 - 60$	0.25	0.15	0.33	0.20	0.07
60-80	0.02	0.12	0.26	0.36	0.24	60-80	0.12	0.04	0.25	0.38	0.20
80-100	0.01	0.03	0.09	0.25	0.62	80-100	0.03	0.01	0.06	0.25	0.65
				Benchmark model: Healthy					Benchmark model: Sick		
	$0 - 20$	$20 - 40$	$40 - 60$	60-80	80-100		$0 - 20$	20-40	$40 - 60$	60-80	80-100
$0 - 20$	0.48	0.32	0.14	0.05	0.00	$0 - 20$	0.39	0.29	0.19	0.11	0.02
$20 - 40$	0.34	0.36	0.22	0.08	0.00	$20 - 40$	0.33	0.34	0.21	0.10	0.01
$40 - 60$	0.13	0.23	0.32	0.30	0.02	$40 - 60$	0.20	0.20	0.34	0.22	0.04
60-80	0.04	0.12	0.25	0.40	0.19	60-80	0.08	0.11	0.24	0.37	0.20
80-100	0.00	0.01	0.04	0.15	0.79	80-100	0.01	0.02	0.06	0.19	0.72
				One asset model: Healthy					One asset model: Sick		
	$0 - 20$	20-40	$40 - 60$	60-80	80-100		$0 - 20$	20-40	$40 - 60$	60-80	80-100
$0 - 20$	0.54	0.25	0.13	0.06	0.00	$0 - 20$	0.42	0.28	0.18	0.09	0.02
20-40	0.31	0.33	0.23	0.11	0.02	20-40	0.39	0.31	0.18	0.09	0.02
$40 - 60$	0.11	0.20	0.32	0.29	0.08	$40 - 60$	0.20	0.16	0.35	0.22	0.07
60-80	0.05	0.16	0.22	0.33	0.24	60-80	0.09	0.09	0.22	0.36	0.24

Table E.1: Wealth mobility transition matrix: data vs. model

Notes: The wealth mobility transition matrix calculates the fraction of individuals that transition from wealth quintile *x* in period *t* to wealth quintile *x* in period $t + 10$, (i.e., 10 years later) where *x* indicates the five wealth quintiles. The rows indicate period *t* and the columns indicate period $t + 10$.

	Shorrocks	Std Err		Shorrocks	Std Err	
PSID			HRS			
A11	0.679	0.011	A11	0.660	0.015	
Healthy	0.688	0.026	Healthy	0.680	0.026	
Sick	0.739	0.013	Sick	0.682	0.007	
Benchmark Model		Benchmark Model				
All	0.678	0.008	A11	0.678	0.010	
Healthy	0.662	0.012	Healthy	0.662	0.028	
Sick	0.709	0.015	Sick	0.709	0.006	
One Asset Model			One Asset Model			
All	0.669	0.035	A11	0.716	0.005	
Healthy	0.649	0.038	Healthy	0.702	0.012	
Sick	0.694	0.028	Sick	0.727	0.046	

Table E.2: Wealth mobility Shorrocks index: data vs. model

Notes: The wealth mobility index according to [Shorrocks](#page-42-1) [\(1978\)](#page-42-1) provides a measure for the off diagonal entries of the wealth transition matrix *M* from wealth quintile *k* in period *t* to wealth quintile *k* in period $t + 10$, where *k* indicates the five wealth quintiles. It is calculated as $1/(K-1) \times (K-\text{trace}(M))$ where $K=5$. With perfect immobility, the Shorrocks index is 0 and with perfect mobility it approximates 1 with small enough wealth quantile bins. Compare [Savegnago](#page-42-2) [\(2016\)](#page-42-2) for more details and code of a Stata implementation.

F Simulation results

F.1 Excellent health surprise for all periods

In this section we show the results of the counterfactual simulation where individuals are surprised with "excellent health" draws from age 40 until death. We report the lifecycle profiles of stock market participation, financial asset profiles, labor market effects as well as the effects on health insurance take up in Figures [F.1–](#page-125-0)[F.4.](#page-128-0)

Figure F.1: Experiment: Surprise good health shocks – Stock market activities *Notes:* Benchmark vs. experiment.

Figure F.2: Experiment: Surprise good health shocks – Asset profiles *Notes:* Benchmark vs. experiment.

Figure F.3: Experiment: Surprise good health shocks – Labor market comparison *Notes:* Benchmark vs. experiment.

Figure F.4: Experiment: Surprise good health shocks – Change of insurance by education *Notes:* Benchmark vs. experiment.

F.2 Medicare for all

In this section we show the results of the counterfactual simulation of a Medicare for all expansion. We report the lifecycle profiles of stock market participation, financial asset profiles, labor market effects as well as the effects on health insurance take up in Figures [F.5–](#page-129-0)[F.6.](#page-130-0)

Figure F.5: Experiment: Medicare for all – Stock market activities

Notes: Benchmark vs. experiment.

Figure F.6: Experiment: Medicare for all – Asset profiles

Notes: Benchmark vs. experiment.

Figure F.7: Experiment: Medicare for all – Labor market comparison *Notes:* Benchmark vs. experiment.

G Welfare calculation

We compare each individual in a specific regime with its hypothetical self under the benchmark parameterization. For each policy regime we calculate the percent change in annual consumption that makes the persons realized lifetime welfare under the new regime equal to her realized lifetime utility in the benchmark. Formally, the realized lifetime utility of an individual in the benchmark is

$$
V^B = \sum_{j=1}^J \beta^j \left(1_{\text{alive}_j} \times u\left(c_j^*, \ell_j^*\right) + 1_{\text{death}_j} \times u^{\text{beq}}\left(a_j^*\right) \right),
$$

where $\{c_j^*, e_j^*, a_j^*\}$ are optimal decisions, 1_{alive_j} is an indicator function equal to one if the person is alive and 1death*^j* is an indicator function equal to one if a person has died in period *j*. The realized welfare loss or gain, expressed as percent of realized lifetime consumption can then be written as

$$
\sum_{j=1}^{J} \beta^{j} \left(1_{\text{alive}_{j}} \times u \left(\left(1 - \phi \right) c_{j}^{**}, \ell_{j}^{**} \right) + 1_{\text{death}_{j}} \times u^{\text{beq}} \left(a_{j}^{**} \right) \right) = V^{B},
$$

where $\{c_j^{**}, c_j^{**}, a_j^{**}\}$ are optimal decisions in the new policy regime and ϕ is the compensating consumption needed to make the individual indifferent between the new regime outcome and the benchmark. Once we have established the compensating consumption for each individuals ϕ_i we can calculate the average across all *N* simulated individuals as $\bar{\phi} = \frac{1}{N} \sum_{i=1}^{N} \phi_i$. Similarly, we can calculate average compensating consumption conditional on individuals belonging to certain subgroups such as individuals with no high school degrees as

$$
\bar{\phi}\left(1_{\vartheta=1}\right)=\frac{1}{N_{noHS}}\sum_{i=1}^{N_{noHS}}\phi_i\left(1_{\vartheta=1}\right),\,
$$

where N_{noHS} would be the number of individuals (our of the *N* total) that "drew" a no-high-school permanent education state.

H The value of statistical life

The value of statistical life (VSL) represents the monetary value corresponding to the reduction in mortality risk that would prevent one statistical death. In order to calculate the VSL we follow a similar method in [Aldy and](#page-35-1) [Smyth](#page-35-1) [\(2014\)](#page-35-1). We consider at period (or age) *j* a small increase in the probability of survival to the next period, denoted $\Delta\pi_j\left(\varepsilon_j^h\right)$ which increases the probability of survival of this type of individual to $\pi_j\left(\varepsilon_j^h\right)+\Delta\pi_j\left(\varepsilon_j^h\right)$. We then solve the household problem with otherwise identical parameters again and store the resulting value function as $V^* (\vartheta, a_{j,}, \varepsilon_j^{\text{incP}}, \varepsilon_j^h, \varepsilon_j^{\text{ehi}})$. The change in mortality risk from period *j* to *j* + 1 is the only change in parameters and subsequently responsible for the change in the value function. In order to evaluate the value of the mortality risk reduction, we next search for the amount of additional wealth ∆*a^j* that we would have to give this individual in order to equalize their original value function at age *j* to the one with the reduced mortality risk at age *j*, or

$$
V\left(\vartheta,a_j+\Delta a_j,\varepsilon_j^{\text{incP}},\varepsilon_j^h,\varepsilon_j^{\text{ehi}}\right)=V^*\left(\vartheta,a_j,\varepsilon_j^{\text{incP}},\varepsilon_j^h,\varepsilon_j^{\text{ehi}}\right).
$$

The value of statistical life (VSL) of a particular agent type with state vector $(\vartheta, a_j, \varepsilon_j^{\text{incP}}, \varepsilon_j^h, \varepsilon_j^{\text{ehi}})$ can then be calculated as

$$
\text{VSL}_j\left(\vartheta,a_j,\boldsymbol{\varepsilon}_j^{\text{incP}},\boldsymbol{\varepsilon}_j^h,\boldsymbol{\varepsilon}_j^{\text{chi}}\right)=\frac{\Delta a_j}{\Delta \pi_j\left(\boldsymbol{\varepsilon}_j^h\right)}.
$$

Intuitively, the VSL is the marginal rate of substitution between wealth and survival probability.

The estimated values for VSL range between 1–16 million USD according to a survey by [Viscusi](#page-42-3) [\(1993\)](#page-42-3). We target a rather conservative value of 2.5 million USD for the working age population of 40–65 year olds which compares well with similar targets in the literature (e.g., [De Nardi, Pashchenko and Porapakkarm](#page-37-3) [\(2024\)](#page-37-3) target 2 million USD in their model that includes younger individuals who tend to have lower VSLs).

In Figure [H.1](#page-133-0) we report the VSL values over age average over the remaining state variables in the top panel. The VSL profiles show the typical hump shape that is reported in the literature. We next calculate the VSL profiles for individuals with good health, i.e., current health states of $\varepsilon_j^h \in \{1,2,3\}$ vs. bad health, i.e, current health states of $\varepsilon_j^h \in \{4, 5\}$ in panel B. There are significant gaps in the VSL between the sick and healthy over the life cycle, varying 0.6 and 0.8 million. For comparison, we also show the VSL values by permanent income status in the bottom panel C.

Figure H.1: Calibration target: Value of statistical life

Notes: We choose the constant in the utility function \bar{u} to match the peak value of statistical life (VSL) in panel A.