Stock Market Participation and Portfolio Shares Over the Life Cycle *

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Abstract:

We estimate the life-cycle profile of stock market participation and risky portfolio share. Our identification approach does not require any assumptions on time or cohort effects, thus avoiding the classical identification problem. We find that stock market participation is a hump-shaped function of age, while the conditional risky share is flat until mid-life and decreases afterwards. We investigate the economic mechanisms driving this behavior, and find empirical support for stock market participation costs, decreasing relative risk aversion, human capital as a close substitute for bonds, and background risks. We conclude with a structural life-cycle model that closely replicates these patterns.

JEL Classification: G5, G11, D14, D15.

Key Words: Life-cycle asset allocation, stock market participation, life-cycle models, human capital.

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1 Introduction

Do younger households invest in portfolios that are more or less risky than those held by older households, and what are the economic drivers of this behavior? The answers to these questions provide important insights into theories of life-cycle portfolio choice. A simple life-cycle portfolio choice model with borrowing constraints and undiversifiable income risk predicts that households should decrease their risky investments as they approach retirement (Cocco, Gomes, and Maenhout, 2005); this result underlies the popular target-date funds (TDFs) offered in most defined-contribution pension plans.[1] However, several extensions of this baseline model deliver a hump-shaped pattern, or even a risky share that increases with age (e.g., Cocco et al., 2005; Benzoni, Collin-Dufresne, and Goldstein, 2007; Campanale, Fugazza, and Gomes, 2015; Fagereng, Gottlieb, and Guiso, 2017; Bagliano, Fugazza, and Nicodano, 2017; or Catherine, 2019).[2]

Household-finance researchers have long tried to estimate the age profiles for stock market participation and the share of wealth invested in risky assets (e.g., Poterba and Samwick, 1997; Ameriks and Zeldes, 2004; Fagereng et al., 2017; Catherine, 2019; and Parker, Schoar, and Cole, 2021). The challenge to this apparently straightforward task is the classic problem of separately identifying age, time and cohort effects.[3] In this paper we consider a simple approach to this problem, taking first differences of the data. In first differences, cohort effects disappear, and we are left with age(-difference) and time(-difference) effects which we can estimate in a standard regression framework. This solution has only one drawback: we cannot recover the actual level of the conditional risky share or stock market participation at any age, and this is important in certain contexts. However, if we limit our attention to the question of how these elements change as a function of age, this approach provides a very simple solution to the identification problem.

[1] Choi and Robertson (2020) survey households directly and find that "years left until retirement" is the most cited explanation for the equity shares of stock market participants, reinforcing the importance of life-cycle considerations for household portfolio decisions.

[2] See Gomes (2020) for a detailed review of this literature.

[3] Since "current year" = "birth year" + "age", the three variables are perfectly collinear and we cannot identify them all simultaneously.

From a theoretical perspective, the average level of the risky share depends on a wide range of factors that are independent of the particular theory being considered; these factors include return expectations, risk aversion, IQ, education, financial literacy, and trust in the stock market.[4] However, the age profile is a more robust prediction of a given model and can, therefore, be used to distinguish between alternative theoretical frameworks. The levels are, to a large extent, determined by the particular model calibration, while the slope and the derivatives with respect to relevant economic variables are robust predictions of a particular theoretical channel. Therefore, our estimation in first differences is highly informative in respect of the economic mechanisms driving behaviors related to the risky share and stock market participation over the life cycle.

Furthermore, since household asset-allocation decisions are determined by several, often unobservable, characteristics, such as the previously mentioned risk aversion, IQ, financial sophistication, and return expectations; this poses a problem for empirical work. The inclusion of time fixed effects in the regressions allows researchers to capture any time variation in these variables that is common across households; however, it does not control for cross-sectional heterogeneity. In the absence of consistent measures for all variables, our estimation is more robust to this unobserved individual-level heterogeneity.[5,6]

We implement our approach by following individual portfolios over time, and therefore we thus use the Panel Study for Income Dynamics (PSID). We focus in our analysis on stock market participation and the conditional risky share, that is, the risky share held by stockholders. We find that stock market participation is a hump-shaped function of age, increasing early in life, flattening around mid-life, and, finally, decreasing as individuals approach retirement and again during retirement. For the conditional risky share, when

[4]For empirical evidence on the impact of these on asset allocation decisions, see, for example, Guiso, Haliassos, and Jappelli (2002), Calvet, Campbell, and Sodini (2007), Guiso, Sapienza, and Zingales (2008), Malmendier and Nagel (2011), Van Rooij, Lusardi, and Alessie (2011), Hurd, Van Rooij, and Winter (2011), Grinblatt, Keloharju, and Linnainmaa (2011), Dimmock, Kouwenberg, Mitchell, and Peijnenburg (2016), and Black, Devereux, Lundborg, and Majlesi (2018).

[5]For this purpose, an alternative would be to include individual fixed effects in our regression. Calvet and Sodini (2014) control for this heterogeneity by using a sample of matched twins.

[6]Unobserved heterogeneity that varies over time in different ways for different households is still not captured, but the same concern is present with the alternative estimation approaches.

considering total changes in the portfolio we identify an increasing profile before age 55 that flattens thereafter. However, when we consider active rebalancing decisions only, to control for the high levels of household portfolio inertia previously documented in the literature, we find that the share of wealth invested in stocks is actually constant with age until ages 55 to 60, and decreasing after that.[7]

We contrast our results with those obtained under the alternative identification assumptions of no cohort or time effects (as in Poterba and Samwick (1997) and Ameriks and Zeldes (2004)). Without cohort effects we would have estimated increasing profiles for both the stock market participation profile and the conditional risky share. If we had instead ruled out time effects, we would conclude that stock market participation is strongly decreasing with age, while the conditional risky share exhibits an inverse hump-shape. Contrasting these results with our own highlights the importance of controlling for both time and cohort effects when estimating life-cycle profiles.

In addition to estimating age profiles, we further investigate the economic mechanisms driving risk-taking behavior over the life cycle by studying the impact of wealth and human capital on these decisions. More precisely, we consider the direct effects of these variables on the risky share and stock market participation decision and the influence of these two elements on the investment age profile. The latter evidence is informative of how risk-taking behavior over the life cycle is shaped by the simultaneous evolution of these two particular variables as a function of age. The combined evidence allows us to disentangle the predictions implied by different asset-allocation models.

We find evidence of positive wealth effects for both outcome variables. In fact, we find that, the increase in stock market participation early in life is almost fully explained by the increase in household wealth during this period. These positive wealth effects for participation provide support for theories that emphasize the role of stock market participation costs in explaining why a large segment of households do not invest in equities (e.g., Vissing-Jørgensen, 2002; Haliassos and Michaelides, 2003; Gomes and Michaelides, 2005). The positive wealth

[7]For evidence on household portfolio inertia see the survey paper Gomes, Haliassos, and Ramadorai (2021)

effects in the conditional risky share evidence participant's decreasing relative risk aversion (e.g., Constantinides, 1990; Campbell and Cochrane, 1999).[8]

For modest changes in wealth the associated change in the conditional risky share is quite small, helping to explain why previous studies yield mixed results when estimating wealth effects in the demand for risky assets.[9] However, in both the cross-section and over the life cycle, we observe substantial changes in wealth that are then reflected in non-trivial implied differences in portfolio allocation. The evidence for a decreasing relative risk aversion explains the increasing risky share early in life. However, this pattern may also reflect high background risk, which leads young investors to hold more conservative portfolios, as shown by Viceira (2001) and Cocco et al. (2005).[10] Finally, a low equity allocation early in life is also consistent with models that include highly skewed returns (Fagereng et al., 2017) or transaction costs (Campanale et al., 2015).

The theoretical literature on portfolio choice identifies the ratio of the present value of future labor income to total wealth as an important determinant of optimal asset allocation (e.g., Heaton and Lucas, 1996; Viceira, 2001; and Cocco et al., 2005). In our paper we find that this ratio has a positive impact on both the risky share and stock market participation, consistent with models where labor income is a close substitute for bonds. Under these conditions the optimal equity allocation will decrease as agents approach retirement (see Viceira (2001) or Cocco et al. (2005)). This human capital channel, combined with decreasing relative risk aversion (DRRA) (and/or background risk) can explain the flat pattern of the risky share early in life; the two mechanisms offset each other. In principle, the results could be explained by increasing relative risk aversion and human capital being a close substitute for stocks. However, such a model would imply the opposite sign for the estimated coefficients

[8] Gomes and Michaelides (2003), Polkovnichenko (2007), Wachter and Yogo (2010), and Meeuwis (2020) estimate life-cycle models of portfolio choice with decreasing relative risk-aversion preferences.

[9] See, for example, Heaton and Lucas (1996), Campbell (2006), Brunnermeier and Nagel (2008), Wachter and Yogo (2010), Chiappori and Paiella (2011), Calvet and Sodini (2014), Bach, Calvet, and Sodini (2016), Fagereng, Guiso, Malacrino, and Pistaferri (2020), and Meeuwis (2020).

[10] Guiso, Jappelli, and Terlizzese (1996), Calvet and Sodini (2014), Bonaparte, Korniotis, and Kumar (2014), Knüpfer, Rantapuska, and Sarvimäki (2017), and Fagereng et al. (2020) provide direct evidence for the impact of income risk on household portfolio decisions. Relatedly, Cocco (2005), Yao and Zhang (2005), Chetty and Szeidl (2007), and Chetty, Sándor, and Szeidl (2017) document the importance of risks resulting from mortgage commitments.

of wealth and human capital. Our evidence is consistent with human capital being a close substitute for bonds. Nevertheless, it also indicates that this substitutability is weaker than that predicted by a model where income shocks are uncorrelated with stock returns. Our results thus provide support for a model with higher-order correlations as in Catherine (2019), or for a weak version of the channel proposed by Benzoni et al. (2007).

Consistent with previous literature (e.g., Brunnermeier and Nagel (2008) and Bonaparte et al. (2014)), we document significant stock market exit decisions, providing support for the role of per-period stock market participation costs (as in the work of Vissing-Jørgensen (2002) and Fagereng et al. (2017)). Finally, the late-in-life decreases in both the conditional risky share and stock market participation gives empirical support for models that include background risks during retirement (e.g., Hubbard, Skinner, and Zeldes, 1995; De Nardi, French, and Jones, 2010; Ameriks, Caplin, Laufer, and Van Nieuwerburgh, 2011; Yogo, 2016; or Koijen, Van Nieuwerburgh, and Yogo, 2016).[11]

Our paper is part of an extensive empirical literature that examines stock market participation and the asset allocation decisions of stockholders.[12] Among the studies already cited in this introduction, our work is, in particular, related to those attempting to estimate the life-cycle profiles of stock market participation and the conditional risky share, namely Poterba and Samwick (1997), Ameriks and Zeldes (2004), Fagereng et al. (2017), Catherine (2019), and Parker et al. (2021). These studies differ with respect to the data they use and their approaches to addressing the identification problem. Poterba and Samwick (1997) use data from the US Survey of Consumer Finances (SCF) and control for cohort effects. Ameriks and Zeldes (2004) report results with SCF data and retirement wealth data from TIAA-CREF. They consider the two special cases of excluding cohort or time effects. Fagereng et al. (2017) use Norwegian administrative data, and, by making assumptions about cohort and time effects, consider both simultaneously. In one specification, they capture cohort effects using individuals' lifetime-return experiences (based on the work of Malmendier and Nagel (2011)). In the other, they impose the Deaton and Paxson (1994)

[11] Guiso et al. (1996) empirically document the impact of health risks on household portfolio allocations.
[12] A detailed survey of this literature is available in Gomes (2020) and Gomes et al. (2021).

restriction that time effects sum to zero once the variables have been detrended. Catherine (2019) utilizes the SCF and the Deaton and Paxson (1994) methodology to capture time effects. Parker et al. (2021) use retirement wealth data only. As a result, they do not consider stock market participation and instead focus on the life-cycle patterns of contribution rates to retirement accounts. With regards to portfolio allocation, they find a hump-shaped association of allocation with age but also highlight the importance of institutional features, namely the default of TDFs, in determining the asset allocations in these accounts.

Unfortunately, there is no consensus among the previous papers. When using cohort dummies Ameriks and Zeldes (2004) document increasing stock market participation until retirement and flat thereafter, and the same result is obtained by Catherine (2019). However, when using time dummies Ameriks and Zeldes (2004) estimate a flat profile almost until retirement and decreasing thereafter. In contrast, Poterba and Samwick (1997) and Fagereng et al. (2017) estimate hump-shaped patterns, peaking around age 40 and age 60, respectively. Relative to these papers we use a different data set and time period and, crucially, a different identification approach. We thus avoid having to make assumptions about cohort or time effects (as in Fagereng et al. (2017) and Catherine (2019)), or having to ignore one or the other (as in Ameriks and Zeldes (2004) and Poterba and Samwick (1997)).

In the final section of the paper, we present a structural life-cycle model that closely replicates our main empirical findings. The features of this model are motivated by our earlier evidence, and therefore include stock market participation costs, preferences with decreasing relative risk aversion, and moderate correlation between labor income shocks and stock returns. In line with previous theoretical work on limited participation (e.g., Gomes and Michaelides, 2005), the heterogeneity of household preferences also plays an important role in the model, but we further highlight the role of heterogeneity in financial literacy.

The remainder of the paper is structured as follows. Section 2 describes our estimation approach, while Section 3 describes the data and presents some summary statistics. In Sections 4 and 5, we present results for the stock market participation decision and the conditional risky share, respectively. In Section 6, we present the life-cycle portfolio choice model, and Section 7 contains our concluding remarks.

2 Estimation Approach

We study both the stock market participation decision and the share of wealth invested in risky assets by stock market participants. Following the literature, we refer to the latter as the conditional risky share, that is, the risky share conditional on positive stock holdings. The discussion in this section focuses on the conditional risky share to avoid repetition.

2.1 Frictionless case

We first consider the outcome of a frictionless portfolio choice model, where investors can adjust their portfolios every period without cost.[13] The conditional risky share for individual i at time t (ω_{it}) is then represented in the following reduced form equation:

$$\omega_{it} = I(a_{it}) + I(t) + I(c_i) + \theta X_{it} + \Gamma F_i + \varepsilon_{it} \tag{1}$$

where the $I(a_{it})$, $I(t)$, and $I(c_i)$ are dummy variables for each age, time period and cohort, respectively. The variable F_i is a vector of time-invariant individual characteristics, while X_{it} is vector of time-varying characteristics that are not perfectly correlated across individuals.[14] Finally, ε_{it} is a (regression) residual.

Estimating equation (1) involves the classical problem of identification: it is impossible to separately identify age, time and cohort effects, since these three variables are perfectly collinear

$$t = c_i + a_{it} \tag{2}$$

Researchers have explored various methods for tackling this issue. These include imposing zero restrictions on either time or cohort effects (Poterba and Samwick (1997) and Ameriks and Zeldes (2004)), or modeling these as functions of other variables (Fagereng et al. (2017) and Catherine (2019)). In our paper, we take an alternative approach and estimate the

[13] Here we adopt a broad definition of frictions, including any constraints and/or biases that generate either partial or full inertia in portfolio adjustments.

[14] Time-varying characteristics that are perfectly correlated across individuals (e.g., stock market returns) are captured by the time dummies.

equation in first differences; that is, we replace equation (1) with

$$\Delta\omega_{it} = I(a_{it}) - I(a_{I,t-1}) + I(t) - I(t-1) + \theta\Delta X_{it} + u_{it} \tag{3}$$

where

$$u_{it} = \varepsilon_{it} - \varepsilon_{i,t-1} \tag{4}$$

Moving from equation (1) to equation (3) eliminates cohort effects ($I(c_i)$) and therefore resolves the identification problem. The drawback of this approach is that we cannot recover the actual conditional risk share at a given age; this is probably why the approach was not previously considered. However, if we want to estimate how the conditional risky share changes with the age and identify the economic channels that drive such behavior, this method provides a straightforward solution.

Another important advantage of our approach is that it is more robust to unobserved individual heterogeneity. Estimating equation (1) requires data for several individual characteristics that can be very hard to measure in a large cross-section of households, such as risk aversion, IQ, financial literacy, present value of labor income, and return expectations. In equation (3) the F_i terms drop out, thus eliminating (unobserved) characteristics that are constant over the sample.[15] Individual characteristics that are time-varying, and for which the time variation is driven by a common factor (e.g., realized returns that might drive changes in expected returns), are captured in the time fixed effects. This is the case for both equation (3) and equation (1). However, due to the identification problem, the latter equation is often estimated by restricting or completely ignoring the time fixed effects, in which case these characteristics are only imperfectly controlled for, if at all.

For the remainder of the paper we simplify the notation and re-write equation (3) as

$$\Delta\omega_{it} = \overline{I}(\Delta a_{it}) + \widetilde{I}(\Delta t) + \theta\Delta X_{it} + u_{it} \tag{5}$$

[15]This is likely to be the case, for example, with IQ, education, and individual preferences. These variables are expected to exhibit very limited (if any) variation from adulthood onward.

In this specification $\overline{I}(\Delta a_{it})$ refers to dummy variables that are equal to 1 when individual i is that specific age at time t. They are thus identical to the dummy variables in equation (1) but are differently interpreted, hence the new notation.[16] Estimating equation (5) still requires eliminating one of the age or time dummies, but this is simply a normalization of the data. Although the estimated coefficients will depend on which dummy we remove, the predicted average marginal effects are unaffected by this choice.[17]

Finally, in our empirical implementation, the vector ΔX_{it} includes changes in household wealth (different measures), changes in the present value of future labor income, and demographic variables.

2.2 Transaction costs and inertia

It is widely documented that a significant fraction of households rebalances their portfolios infrequently (see, for example, Choi, Laibson, Madrian, and Metrick (2002); Agnew, Balduzzi, and Sunden (2003); Ameriks and Zeldes (2004); Brunnermeier and Nagel (2008); Calvet, Campbell, and Sodini (2009); Bilias, Georgarakos, and Haliassos (2010); or Meeuwis (2020)).[18]

We address this concern by following the approach in Calvet et al. (2009). We first compute the active change in the risky share

$$\Delta\omega_{it}^{Active} = \omega_{it} - \omega_{it}^{P} \tag{6}$$

where ω_{it}^{P} is the passive risky share, that is, the risky share that would be obtained in the

[16] Alternatively, we could write out the regression as it is directly implied by equation (3), where these variables would actually take three values, -1, 0, or 1. Naturally, the estimated coefficients would be different, but the predicted average marginal effects are the same under both specifications.

[17] This is also the case if we use the previous approach, that is, estimating equation (1) without cohort or time effects. We would have to remove one of the remaining dummies, and the estimated coefficients would again depend on the choice made, but not the predicted marginal effects.

[18] For potential explanations of this behavior see, among others, Gabaix and Laibson (2001), Sims (2003), Alvarez, Guiso, and Lippi (2012), Abel, Eberly, and Panageas (2013), Campanale et al. (2015), or Pagel (2018).

absence of trading between $t-1$ and t,

$$\omega_{it}^{P} \equiv \frac{\omega_{i,t-1}R_t}{\omega_{i,t-1}R_t + (1-\omega_{i,t-1})R_t^f} \tag{7}$$

where R_t is the return on the risky assets, and R_t^f the return on the riskless asset(s). We then use the active change in the risky share ($\Delta\omega_{it}^{Active}$) as the right-hand-side variable in our regressions, thereby replacing equation (5) with

$$\Delta\omega_{it}^{Active} = \overline{I}(\Delta a_{it}) + \widetilde{I}(\Delta t) + \theta\Delta X_{it} + u_{it} \tag{8}$$

2.3 Human capital

An important variable to include in X_{it} is the ratio of the present value of future labor income (human capital) to current wealth (hereafter $PVYW$), as discussed, for example, in the theoretical works of Heaton and Lucas (1996), Viceira (2001), and Cocco et al. (2005).

2.3.1 Measuring changes in the ratio of human capital to financial wealth

The present value of future labor income for individual i at age a_0 is given by

$$PVY_{i,a_0} = E_{a_0} \sum_{a=a_0+1}^{A} \frac{p_{i,a}Y_{i,a}}{(R_i^Y)^{a-a_0}} \tag{9}$$

where A is an arbitrary maximum age, $p_{i,a}$ is the conditional survival probability from ages $a-1$ to a, $Y_{i,a}$ is income at age a, and R_i^Y is the discount rate for labor income.[19] From equation (9) the change in the ratio of the present value of future labor income to current

[19] More generally, the discount rate for labor income is also a function of age, so we would have

$$PVY_{i,a_0} = E_{a_0} \sum_{a=a_{0+1}}^{A} \frac{p_{i,a}Y_{i,a}}{\prod_{j=a_{0+1}}^{a} R_{i,j}^Y}$$

where $R_{i,j}^Y$ is the discount rate for labor income at age j.

wealth over a two-year period, is given by[20]

$$\Delta PVYW_{i,a_0} = E_{a_0} \sum_{a=a_0+1}^{A} \frac{p_{i,a} Y_{i,a}}{(R_i^Y)^{a-a_0} W_{i,a_0}} - E_{a_{0-2}} \sum_{a=a_0-1}^{A} \frac{p_{i,a} Y_{i,a}}{(R_i^Y)^{a-a_{0-2}} W_{i,a_{0-2}}} \tag{10}$$

$$= \left(E_{a_0} \sum_{a=a_0+1}^{A} \frac{p_{i,a} Y_{i,a}}{(R_i^Y)^{a-a_0} W_{i,a_0}} - E_{a_{0-2}} \sum_{a=a_0+1}^{A} \frac{p_{i,a} Y_{i,a}}{(R_i^Y)^{a-a_{0-2}} W_{a_{0-2}}} \right)$$
$$- E_{a_{0-2}} \left(\frac{p_{i,a_0} Y_{i,a_0}}{(R_i^Y)^2 W_{i,a_{0-2}}} + \frac{p_{i,a_{0-1}} Y_{i,a_{0-1}}}{R_i^Y W_{i,a_{0-2}}} \right) \tag{11}$$

These equations show that changes in $PVYW_{i,a_0}$ occur for four reasons: First, because of revisions in the expectation of income going forward: E_{a_0} replaces E_{a_0-2}. Second, because of changes in current wealth: W_{i,a_0} replaces $W_{i,a_{0-2}}$ in the denominator. Third, because the income from future years is now less discounted: the exponent on returns in the denominator changes from $a - (a_0 - 2)$ to $a - a_0$. These three effects are captured in the first term in parenthesis in equation (11). Finally, $PVYW_{i,a_0}$ also changes because some of the labor income that was included in the measure of human capital at age a_{0-2}, has been earned over the preceding two years. This is captured in the last term of equation (11).[21]

2.3.2 Empirical implementation

The two terms in equation (11) are not directly observable and must be replaced with empirical proxies. To construct these proxies, we must make certain assumptions, which are discussed in this section.

Assumption 1: discount rates and survival probabilities are non-stochastic.

Under Assumption 1, the change in the ratio of the present value of future labor income to financial wealth (equation (11)) becomes

$$\Delta PVYW_{i,a_0} = \sum_{a=a_0+1}^{A} \left(\frac{p_{i,a} E_{a_0} Y_{i,a}}{(R_i^Y)^{a-a_0} W_{i,a_0}} - \frac{p_{i,a} E_{a_0-2} Y_{i,a}}{(R_i^Y)^{a-(a_0-2)} W_{i,a_{0-2}}} \right)$$
$$- \left(\frac{p_{i,a_0} E_{a_{0-2}} Y_{i,a_0}}{(R_i^Y)^2 W_{i,a_{0-2}}} + \frac{p_{i,a_0-1} E_{a_{0-2}} Y_{i,a_{0-1}}}{R_i^Y W_{i,a_{0-2}}} \right) \tag{12}$$

[20] The frequency for our data is biannual, so we have to consider the change over a two-year period.
[21] The last two effects would be absent in an infinite-horizon setting but appear in a life-cycle model.

We define the two terms in equation (12) as

$$\xi^1_{i,a_0} \equiv \sum_{a=a_0+1}^{A} \frac{p_{i,a}}{(R^Y_i)^{a-a_0}} \left(\frac{E_{a_0} Y_{i,a}}{W_{i,a_0}} - \frac{E_{a_0-2} Y_{i,a}}{(R^Y_i)^2 W_{i,a_0-2}} \right) \tag{13}$$

$$\xi^2_{i,a_0} \equiv \frac{p_{i,a_0} E_{a_0-2} Y_{i,a_0}}{(R^Y_i)^2 W_{i,a_0-2}} + \frac{p_{i,a_0-1} E_{a_0-2} Y_{i,a_0-1}}{R^Y_i W_{i,a_0-2}} \tag{14}$$

We need to determine expectations of future labor income to compute these terms.[22]

Assumption 2: Log labor income is given by

$$y_{i,a} = \mu^y_a + v_{i,a} + \varepsilon^y_{i,a} \tag{15}$$

$$v_{i,a} = v_{i,a-1} + u^y_{i,a} \tag{16}$$

From Assumption 2 the expectation of future labor income is given by

$$E_{a_0}(Y_{i,a}) = E_{a_0}(\exp(\mu^y_a + v_{i,a} + \varepsilon^y_{i,a})) \tag{17}$$

$$= \exp Ln[E_{a_0}(\exp(\mu^y_a + v_{i,a} + \varepsilon^y_{i,a}))] \tag{18}$$

$$= \exp\left[E_{a_0}(\mu^y_a + v_{i,a} + \varepsilon^y_{i,a}) + \frac{1}{2}((a-a_0)\sigma^2_u + \sigma^2_\varepsilon)\right] \tag{19}$$

Since μ^y_a is a constant and

$$E_{a_0}(\varepsilon^y_{i,a}) = 0 \tag{20}$$

$$E_{a_0}(v_{i,a}) = v_{i,a_0} \tag{21}$$

we are left with

$$E_{a_0}(Y_{i,a}) = \exp(\mu^y_a)\exp(v_{i,a_0})\exp\left(\frac{1}{2}(a-a_0)\sigma^2_u + \sigma^2_\varepsilon\right) \tag{22}$$

Since we do not observe the permanent component of labor income ($v^i_{a_0}$) we first re-write

[22] Our approach is again beneficial here. First, we only need to identify revisions in expectations as opposed to actual expectations. Second, if survival probabilities and discount rates are (approximately) constant over one period, then their exact values become less important.

this expectation as

$$E_{a_0}(Y_{i,a}) = \exp(\mu_a^y)\frac{Y_{i,a_0}}{\exp(\mu_{a_0}^y)\exp(\varepsilon_{i,a_0}^y)}\exp\left(\frac{1}{2}((a-a_0)\sigma_u^2+\sigma_\varepsilon^2)\right) \tag{23}$$

and assume that the transitory shock equals its unconditional expectation ($\varepsilon_{i,a_0}^y = 0$)[23] hence,

$$E_{a_0}(Y_{i,a}) \simeq Y_{i,a_0}\frac{\exp(\mu_a^y)}{\exp(\mu_{a_0}^y)}\exp\left(\frac{1}{2}((a-a_0)\sigma_u^2+\sigma_\varepsilon^2)\right) \tag{24}$$

Discount rates for future labor are typically small values (see Cocco et al. (2005) or Lustig, Van Nieuwerburgh, and Verdelhan (2013)). We thus set R_a^Y equal to 1.02% in real terms, for all a. The survival probabilities are obtained from the National Center for Health Statistics with $A = 100$. Estimates for σ_ε^2, σ_u^2, and the deterministic income age profile (μ_a^y) are from Cocco et al. (2005). For each individual we use the values that match their education group.[24]

3 Data

Since taking first differences is at the core of our empirical approach, we use data from the PSID. The survey began in 1968, but wealth data were first collected in 1984 and repeated in five-year intervals (i.e., in 1989 and 1994). The PSID became a biannual survey in 1997, and the wealth module was included in each wave from 1999, so we take this as our starting date. The most recent available survey data are from the 2019 wave.

The timing of the data in the PSID is as follows. All personal characteristics and wealth data are reported on the date of interview and relate to the survey year. Income reported in the survey year relates to the previous tax year. Wealth and income data are collected at the household level. We assume the head of household or reference person is the family-unit's main decision maker, and therefore consider their age in our analysis.[25]

[23] We confirm the robustness of our results to this particular assumption in Appendix 3.

[24] As is common in the literature we decrease the estimates of the volatility of the transitory shocks, σ_ε^2, by 1/2 to adjust for potential measurement errors.

[25] Starting in 2017, the term "Reference Person" replaces "Head of Household".

3.1 Sample selection

We impose several requirements on the original data. First, as is common, we exclude the SEO subsample to ensure a representative sample. This leaves us with 64,933 observations from 11 survey waves.[26] Since our methodology relies on taking first differences of the data we drop "solo observations," that is, those that are not part of a series of at least two consecutive observations. We also exclude observations where the marital status of the reference person changes between t and t-1 and those pertaining to recently moved households. We do so to ensure that changes in assets are not due to the exclusion or addition of a family member. We impose a minimum level of liquid financial assets of $1,000; since the asset allocation decision is not particularly relevant for individuals with less.[27] Likewise, we impose a minimum level of $5,000 for family income and exclude families that own a farm or a business.

Finally, since our goal is to estimate age profiles, we require a minimum number of observations for each age. Table 1 reports the number of observations at each age after applying the filters just described.[28] For the regressions of stock market participation we exclude age changes of 19 to 21 and 20 to 22 since we have few observations for these. The risky share sample is also smaller since we have to condition on stock market participation. Therefore, we set the initial starting age for this analysis at 24.[29] In both cases, we consider a final age of 85 with the caveat that, at this point, the number of observations for the risky share is limited.

After applying these filters, we are left with 26,861 observations in our sample for the stock market participation regressions. For the risky share analysis, since we condition on stock market participants, and have a starting age of 24, the sample size is 5,094.[30]

[26] The 1999 to 2019 waves already exclude the Latino subsample.

[27] To calculate $\Delta PVYW$ we also impose a minimum level of total wealth of $1,000 in both the current and preceding wave; positive wealth levels are required for the variable construction.

[28] The interviews occurred at different times of the year but most were conducted between March and November. Hence, between two consecutive waves, the change in age of the individual could be 1, 2 or 3 years. Our empirical strategy assumes a uniform change in age for all agents, so we manually define auxiliary age as the age in 1999 plus the step to the next wave (that is if, in 1999, the person's age was 35, then in 2001 their age is recorded as 37, in 2003 as 39 and so on.)

[29] The first observation corresponds to the age change from 24 to 26 for the risky share and from 21 to 23 for stock market participation.

[30] In some of our empirical specifications we include changes in wealth and/or income as explanatory

3.2 Retirement wealth

The PSID does not include data on asset holdings in DC retirement accounts, such as 401(k) plans. Therefore, our analysis only considers non-retirement wealth.

We do not consider this to be a limitation with regard to stock market participation. Even if we did have information on stock holdings in DC accounts, we would prefer to exclude it. Access to 401k plans is mostly determined by institutional features, namely whether the employer offers such a plan, and job choice is naturally dictated by many factors other than the existence of a DC plan. It is likely that very few individuals have the option of choosing between jobs that are otherwise identical or similar, but one has a DB plan and the other a DC plan, particularly since similar jobs in similar industries tend to have the same pension plan structure (DB, DC or hybrid).[31]

For the risky share regressions, having access to retirement wealth data could be beneficial, but even here there are concerns. Portfolio allocations in 401(k) plans are influenced by institutional features such as the menu of available investment choices, and the predetermined default options. They are, therefore, less informative about the underlying economic mechanisms driving risk taking over the life cycle. Parker et al. (2021) show how the expansion of TDFs, and their increasing importance as default options in 401(k) plans in the US, has significantly affected the portfolio allocation of investors. Therefore, we would, in any event, choose to present results both with and without retirement wealth.[32]

3.3 Variable construction

The risk-free asset in our analysis (B) is the PSID cash category, which includes money in checking or savings accounts, money market funds, certificates of deposit, government bonds and treasury bills (excluding employer-based pensions or IRAs). Risky assets (S) include

variables. For these we must also impose the criterion that lagged wealth and lagged income are not missing, which eliminates a few additional observations.

[31] This concern does not apply directly to IRAs, but they represent a much smaller fraction of total retirement savings. Furthermore, individuals with a 401(k) have less need for an IRA, so selection concerns still apply.

[32] In addition, since in most countries DC plans with investment options are either non-existent or negligible, are results can be better extrapolated elsewhere if these are excluded.

shares of stock in publicly held corporations, stock mutual funds, or investment trusts (not including stocks in employer-based pensions or IRAs). We refer to the sum of these two as liquid financial assets (LFA). Stock market participation is defined as equal to 1 for an invidual if their S has a positive value and 0 otherwise.

We include four measures of wealth in our regressions: liquid financial assets (LFA), home equity (HE), and two measures of total wealth. The first measure of total wealth (TW) is the sum of liquid financial assets and home equity. For the second measure (NTW) we subtract uncollateralized debt. Home equity is computed as the difference between the home's value and mortgage debt. The value of the home is its present value, including the value of the lot if applicable, while mortgage debt is the total value currently owed on mortgages. Uncollaterized debt, used in our second measure of total wealth, is the sum of credit card, student , medical, legal, and family loan debt.

Total family income is the sum of taxable, transfer, and social security income of the head of household, their spouse or partner, and other family members. We also use the data on age, employment, marital status, and number of children in the household, and deflate all nominal variables to 2017 using the consumer CPI series from the St. Louis Federal Reserve. Log changes in financial assets, home equity and total wealth are direct computations from the original data. The ratio of the present value of future labor income (human capital) to current wealth ($\Delta PVYW_{i,a_0}$) is computed as outlined in Section 2.3, where current wealth is total wealth or financial wealth, depending on the empirical specification. Finally, we winsorize all explanatory variables in the various regressions at the 1st and 99th percentiles.

3.4 Summary statistics

Table 2 sets out initial summary statistics for our data. Panel (a) reports values for the sample used in the participation analysis (henceforth, the full sample). Panel (b) refers to the sample of stock market participants (henceforth, the participation sample), which is used in the conditional risky share regressions.[33] Note that all growth rates and changes are over a

[33]In the full sample, 28% of households are stock market participants, with an average (median) risky share of 65% (73%).

two-year period since that is the frequency of our data. We deflate income and wealth/asset data to 2017 dollars.

In the full sample, the average age is 49 years, while for the participation sample, the average age is higher at 54 years. The gender of the reference person in both samples is skewed male, and roughly 70% of the households in the sample are married couples. Of the full (participation) sample, 38% (31%) of households have children. Family income is lower in the full sample than the participation sample, both in mean ($101,557 versus $140,849) and median ($85,186 versus $113,927). Of the full sample, 77% own their home, while in the participation sample, the share of homeowners is 88%. The unconditional average value of home equity is also higher in the participation than the full sample ($122,835 versus $231,731). The levels of financial and total wealth are also higher in the participation sample.

In the full sample, the average 2-year growth of financial assets is 77%, but this reflects a very skewed distribution; the median is a more modest 23%, corresponding to about 10% per year. For the participation sample, these numbers are even smaller, 9% and 7%, for the mean and median, respectively.[34] For home equity, the distribution of growth rates is even more skewed, with a mean of 94% (39%) and a median of 11% (5%) over 2-years (in annual terms). The values are again smaller for the participation sample: 63% (27.7%) and 8% (3.9%) for the 2-year (annual) mean and median, respectively. Interestingly, the growth rate of total wealth is much less skewed than the rate for the other two measures of wealth, suggesting that, in a given year, most individuals either have a high (low) rate of financial-wealth growth or a high (low) rate of home-equity growth, but rarely both. The median growth rate of total wealth for the full (participation) sample is 16% (9%), corresponding to a rate of 7.7% (4.4%) per year.

Figure 1 plots wealth as a function of age, for the three wealth categories: financial wealth, home equity, and total wealth.[35] Panel (a) reports the mean and Panel (b) reports the median. All three measures of wealth increase with age until retirement. Home equity accumulation is more pronounced early in life, while financial assets increase more rapidly

[34] These correspond to 4.4% and 3.4% in annual terms.

[35] These are merely descriptive statistics, since we are not controlling for time and cohort effects.

from age 50 onwards, as households increase their retirement savings. After retirement, financial assets continue to increase, while home equity falls slightly.

Figure 2 plots the ratio of human capital to total wealth ($\Delta PVYW_{i,a_0}$) as a function of age, as well as its two components, ξ^1_{i,a_0} and ξ^2_{i,a_0}. Panel (a) reports means and Panel (b) reports medians. As previously discussed, the term ξ^1_{i,a_0} captures revisions in the expectation for the ratio going forward, and the lower discount rate applying to future income. This term is always negative; it is initially very large, reflecting the rapid increase in wealth at this stage of life, but then gradually converges to zero. The second term ξ^2_{i,a_0} captures the reduction in the ratio resulting from the two years of income that have been earned. Since both income and wealth are always positive this term is also positive by construction. Like the first term, this is also particular high early in life, when total wealth is relatively low. The difference between these two terms gives us $\Delta PVYW_{i,a_0}$.

4 Stock Market Participation

We first study the determinants of stock market participation and in the next section consider the portfolio allocation of stockholders. We define stock market participation as equal to 1 if the individual's risky financial assets have a positive value, and 0 otherwise. The variable change in participation can then take one of three values: 1 (stock market entry), 0 (no change from previous status), or -1 (stock market exit); we also study entry and exit decisions separately.

4.1 Descriptive statistics

We first present and discuss descriptive statistics that provide the background for our empirical analysis and motivate our approach.

4.1.1 Stock market participation over time

The average participation rate during the time of the 10 waves from 2001 to 2019 is around 28%. This is comparable to the value obtained in other sample periods and other datasets for direct participation.[36,37]

Figure 3 plots average stock market participation from our data and from the SCF. Average participation is higher in the SCF than the PSID, since the former over-samples wealthy individuals, but the same pattern is visible in both series. From 2001 onward the raw series has a clear downward trend. Direct stock market participation increased during the so-called "tech bubble" and then gradually returned to previous levels. The increasing pattern is visible when comparing the 1999 and 2001 values, and the subsequent decreasing trend is captured by the rest of the sample. These time effects are an example of the patterns for which we want to control when estimating age profiles.

4.1.2 Age profiles

Figure 4 plots average stock market participation over the life cycle based on simply averages across the full sample.[38] From this we conclude that stock market participation increases quite significantly with age, almost doubling over the life cycle, and that the relationship is very close to linear. Figure 5 depicts the same calculation for each separate PSID wave in our sample. We observe an overall increasing pattern for every cross-section. However, these are no longer simple linear fits, and in some cases the relationship is no longer monotonic.

The results in Figure 5 are based on cross-sectional data, so we are not concerned about time effects for each series; however, the conclusions can still be influenced by cohort effects. The data is not a representation of the same individuals over time. Rather, it captures individuals of the same age at a different time, depending on their cohort. Each individual

[36] When including wealth held in retirement accounts, such as IRAs or 401(k) plans, stock market participation in the US population is closer to 50%. However, the PSID does not include this data.

[37] See Mankiw and Zeldes (1991), Haliassos and Bertaut (1995), Guiso et al. (2002), Guiso et al. (2008), Christelis, Georgarakos, and Haliassos (2013), and Badarinza, Campbell, and Ramadorai (2016) for evidence on stock market participation rates across countries.

[38] We present the results in 5-year-age intervals to facilitate the visual interpretation, but all estimations in the paper consider each year of age as the unit of analysis; these are then aggregated to 5 years.

observation, therefore, reflects age, time, and cohort.

In Figure 6 we construct the life-cycle profile of stock market participation by first computing changes in participation at the individual level and then averaging these by age. By taking first differences, we eliminate the cohort effects, and by then taking averages across time, we average out the time effects. The life-cycle profile is obtained by computing the cumulative changes over age, thus making it comparable to the results reported in Figures 4 and 5.[39] Figure 6 reveals a hump-shaped pattern for stock market participation. The fraction of individuals investing in stocks increases early in life (until the early 40s), remains approximately constant at mid-life (until the late 50s), and eventually decreases, both as individuals approach retirement and during retirement itself.

Comparing the results in Figures 6 and 4 we see that the increasing profile early in life is very similar, but from that point on, the two diverge significantly. Previous results suggest that stock market participation continues to increase, and even slightly accelerate, with age after the early 40s. This is in sharp contrast with the evidence presented in Figure 6. The difference in results occurs because we are now conditioning on the change at the individual level and then taking averages, as opposed to first taking averages and then computing changes. Consider the age groups of those aged 61–65 and 66–70 in Figure 4. Their average participation rates are 30.91% and 33.67%, respectively, hence the increasing pattern. However, here we are not comparing the same individuals at different ages. When we focus on those in the 66–70 age bracket and consider their participation rate when they were in the 61–65 age bracket, that number is actually higher at 34.37%. This is what is depicted in Figure 6 and, therefore, an increasing pattern is observed.

The comparison between Figure 4 and Figure 6 illustrates the intuition underlying our identification approach and its importance. The distinction evident in the two figures will become even more important when studying the conditional risky share. Even if we had started with a balanced panel of households, the risky share sample would be unbalanced

[39] As before, we average these for 5-year intervals to facilitate graphical exposition. The only difference between the two figures is their scale since the line in 6 starts from zero. As previously discussed, taking first differences means we are only able to report how participation changes with age, rather than its absolute value at any given age.

due to the dynamics of stock market entry and exit. Therefore, comparing averages, across either time or ages, is not the same as computing differences at the individual level and then taking the average. In the next section, we consider a more formal regression analysis with additional explanatory variables, which will help us understand better the underlying economic mechanisms.

4.1.3 Stock market entry and exit

In our final set of descriptive statistics, we decompose the dynamics of stock market participation into separate entry and exit decisions. We consider two definitions of entry and exit shares. The first definition scales both by the total population in that age group:

$$Entry^1_{at} = \frac{\text{number of new stock market participants in agegroup } a \text{ at time } t}{\text{total population in age group } a \text{ at time } t-1} \tag{25}$$

$$Exit^1_{at} = \frac{\text{number of new stock market nonparticipants in age group } a \text{ at time } t}{\text{total population in age group } a \text{at time } t-1} \tag{26}$$

The advantage of this first definition is that they are directly comparable, since both shares are computed using the same denominator, and can be combined to compute the net change in stock market participation at each time. As an alternative, and following previous studies, we also compute relative entry and exit shares of nonparticipants and participants, respectively:[40]

$$Entry^2_{at} = \frac{\text{number of new stock market participants in age group } a \text{ at time } t}{\text{total stock market nonparticipants in age group } a \text{ at time } t-1} \tag{27}$$

$$Exit^2_{at} = \frac{\text{number of new stock market nonparticipants in age group } a \text{ at time } t}{\text{total stock market participants in age group } a \text{ at time } t} \tag{28}$$

Figure 7 plots entry and exit shares using the two alternative definitions. Panels (a) and (b) report results using the first classification (equations (25) and (26)), over time and as a function of age, respectively. Panel (c) considers the alternative definition (equations (27) and (28)). When expressed as a fraction of the total population (Panels (a) and (b)), entry and exit shares have similar values. Average entry and exit shares over the sample

[40] These are the measures reported in Brunnermeier and Nagel (2008) and Fagereng et al. (2017).

are almost identical, and equal to 8.4%. The former is roughly flat with age, while the exit share shows a slightly increasing pattern.

Turning to Panel (c), where exit and entry shares are computed relative to their corresponding initial populations (for participants and nonparticipants, respectively), we find that the exit rate is much higher than the entry rate. As a function of age, the exit share exhibits a pronounced decreasing pattern, while the entry share is slightly increasing.

4.2 Regression analysis

4.2.1 Specifications

We first estimate the age profile of stock market participation using the approach outlined in Section 2. More precisely, we consider equation (5), but with the left-hand-side variable being the change in stock market participation (ΔP_{it})

$$\Delta P_{it} = \overline{I}(\Delta a_{it}) + \widetilde{I}(\Delta t) + \theta \Delta X_{it} + u_{it} \tag{29}$$

The right-hand-side variables differ across specifications, as described below.[41]

In the first specification, the vector ΔX_{it} includes only the age dummies and two control variables (change in homeownership status and change in the number of children in the household). In the second specification we study wealth effects by including changes in total wealth, and in specifications three and four we examine the effect of changes in the ratio of human capital to total wealth.[42] Since changes in wealth can (partially) result from changes in stock participation status itself we address this potential endogeneity in Section 4.3; the results are qualitatively identical and quantitatively very similar to the ones presented here. The estimation results are shown in Table 3. We do not include the coefficients on the age dummies as the table would become too large. Instead we report the implied age profiles in

[41] Since participation is a binary variable, the left-hand-side variable can only take the values of 1, 0, or -1. In our main analysis we estimate equation (29) using a linear regression model. In Appendix 1 we report results obtained from estimating Probit models for entry and exit decisions separately.

[42] Here we consider the first definition of total wealth discussed in the Data section (TW) and report results with the alternative definition (NTW) in the Appendix; they are qualitatively identical and quantitatively very similar.

Figure 8. The standard errors in all regressions are cluster robust where each cluster is a household identifier.

4.2.2 The age profile of stock market participation

The first specification confirms the descriptive results presented in Figure 6 in a formal regression setting and controlling for time effects. As shown in Figure 8, participation is a hump-shaped function of age, increasing until the 40s, remaining flat during mid-life, and finally decreasing from age 55 onward, as individuals approach retirement and further still during retirement itself.

The increase in participation in the early stage of the life cycle is about 5 percentage points, which is economically significant when compared with the average participation rate in the sample of 28.44%. The decrease late in life is even larger: the participation rate for the mid-70s age group onward is lower than that of our starting age group (mid-20s). Our results are consistent with the findings of Poterba and Samwick (1997) and Fagereng et al. (2017) who also estimate a hump-shaped life-cycle profile for stock market participation. Catherine (2019) also documents n pattern of increasing participation early in life and constant thereafter. This is also the finding of Ameriks and Zeldes (2004) when using cohort dummies in their estimation. By contrast, when using time dummies, Ameriks and Zeldes (2004) estimate a decreasing profile late in life; this is consistent with our paper, but their results show flat participation at young ages.

The increasing pattern early in life indicates that the costs of stock market entry are likely important in explaining participation decisions. The exits late in life suggest that per-period costs are probably required to match the empirical evidence. The latter result is also consistent with models where background risks are particularly important late in life, for example, health shocks or medical expenditure risk, as in Hubbard et al. (1995), De Nardi et al. (2010), Ameriks et al. (2011), Yogo (2016), and Koijen et al. (2016). These risks decrease the optimal risky share, as shown empirically by Guiso et al. (1996), making it less likely that households would be willing to pay a per-period cost to remain as stockholders.

4.2.3 The role of wealth and human capital

Specifications 2, 3, and 4 reveal that (total) wealth is an important determinant of stock market participation. The coefficients on log changes in wealth are always positive and statistically significant, with p-values less than 0.000. The estimated coefficients in the more complete specifications (Specifications 3 and 4) imply that a 10% increase in total wealth over two years leads to an increase in the probability of stock market participation over the same period of 1.1 percentage points.[43] These effects are economically important when compared with an average participation rate of 28.44% in the sample.

The importance of these wealth effects is highlighted in Figure 8. The age pattern of stock market participation changes quite significantly from Specifications 1 to 2, where it becomes essentially flat over the life cycle. This indicates that, for example, conditional on having the same change in wealth, a 50-year old is just as likely to become a new stock market participant (or to exit the stock market) as a 30-year old. In other words, the increase in participation revealed in Specification 1 can be fully explained by the observed changes in wealth at this stage of life. These large wealth effects provide support for participation costs being a key determinant of stock market participation decisions, consistent with results in Vissing-Jørgensen (2002), Haliassos and Michaelides (2003), and Gomes and Michaelides (2005). Moreover, the hump-shaped pattern in Specification 1, and the documented large number of stock market exits, are consistent with per-period participation costs also playing an important role.[44]

In addition, when we later consider the risky share, we find evidence supporting decreasing relative risk aversion. This additional wealth channel can also contribute to the positive wealth effects in the participation decision if combined with other frictions, such as participation costs.

In Specification 3, we introduce a change in the ratio of human capital to total wealth

[43] The dependent variable can take the values of 1, 0, or -1, so that the coefficient captures the increase (decrease) in the probability of stock market entry (exit).

[44] Entry costs alone can generate stock market nonparticipation, but not stock market exit decisions. The importance of per period costs has been previously emphasized by Vissing-Jørgensen (2002) and Fagereng et al. (2017), for example.

($\Delta PVYW_{i,a_0}$) as an additional explanatory variable. The estimated coefficient is positive and highly statistically significant. Individuals who have experienced an increase in this ratio are more likely to become stock market participants.[45] This is consistent with life-cycle models with uninsurable labor income risk, where labor income is a close substitute for bonds. Since we are already controlling for changes in wealth, this ratio affects the participation decision indirectly through its impact on the optimal allocation to equity.[46] As individuals age, this ratio typically falls, and their optimal equity allocation therefore decreases. This reduces the incentive to participate in the stock market. In Specification 4 we decompose $\Delta PVYW_{i,a_0}$ in the two components, ξ^1_{i,a_0} and ξ^2_{i,a_0}. The coefficient on ξ^2_{i,a_0} is not statistically significant, but the coefficient on ξ^1_{i,a_0} is significant and positive; again, this is consistent with the notion that labor income is a closer substitute for bonds than for stocks.

The role of human capital is also evident in Figure 8 in comparing the age patterns resulting from Specification 3 with the other two.[47] Under Specification 3, we obtain a strongly decreasing age profile. This implies that conditional on the same changes in wealth and the ratio of human capital to total wealth, older individuals are less likely to participate in the stock market. This is consistent with a model including stock market entry costs since older individuals expect to have fewer years over which to amortize that cost. It is also consistent with a combination of per-period participation costs and increased background risks at retirement.

Comparing the age profile from Specification 1 with the other two, we conclude that the increase in participation early in life is largely explained by the increase in financial wealth over this period and, to a lesser extent, also by the reduction in the present value of human capital. The decrease in participation from age 60 onwards remains even after controlling

[45] Since this variable includes wealth in the denominator, and the wealth variable is highly significant by itself, a specification with changes in human capital only, and excluding the wealth variable, would be mis-specified.

[46] For this reason, we also postpone to the section on the conditional risky share, the discussion of the economic magnitude of the estimates.

[47] Specification 4 produces a very similar pattern, hence it is excluded from the figure to facilitate comparison.

for both changes in wealth and human capital (Specification 3), suggesting an increased role of background risks during retirement (as in the models of Hubbard et al., 1995; De Nardi et al., 2010; Ameriks et al., 2011; Yogo, 2016; and Koijen et al., 2016).

4.3 Robustness of wealth effects: non-linear effects, decomposing total wealth, and addressing endogeneity concerns

In Table 4, we estimate separate regressions for each wealth quartile to explore potential heterogeneity in the effects by wealth levels. We find that the coefficient on total wealth is highly statistically significant in all regressions. Interestingly, the point estimate increases quite noticeably across wealth quartiles, which again underscores the importance of participation costs. For a poor household, a 10% increase in wealth, for example, might not be sufficient to rise above the participation threshold. On the other hand, for a rich household, such an increase represents a much more significant change in the dollar value of their portfolio. Likewise, the coefficients on the human capital variable also increase with wealth, and in this case, the coefficient for the first quartile is not even significant. The interpretation is similar to that above: individuals with low wealth are sufficiently below the participation threshold, such that changes in the optimal portfolio are often insufficient to justify paying the fixed costs.

In Table 5, we consider financial assets instead of total wealth and also explore the role of home equity (Specification 6). Interestingly, when we decompose changes in total wealth into changes in financial assets and home equity, only the former is statistically significant. This is why we do not include the home equity variable in Specifications 7 and 8. Overall, the conclusions are similar to those in Specifications 2, 3, and 4. The coefficient on (difference in logs of) financial assets is highly significant (both economically and statistically). The point estimate is even slightly higher than the one previously obtained for (difference in logs of) total wealth, providing support for the importance of stock market participation costs. The coefficient on (difference in) the ratio of human capital variable to financial wealth is also statistically significant and positive, as in the previous results, consistent with human

capital being a close substitute for bonds.

One potential concern with the regressions above is that the changes in wealth might (partially) result from the change in participation status itself. We address this potential endogeneity in two ways. First, we implement an instrumental variables (IV) approach, where we use lagged changes in wealth as an instrument for current changes in wealth. Second, we first explicitly compute the change in wealth implied by the change in risky share:

$$\widetilde{\Delta W}_{it} = W_{it-1}\left(\omega_{it}R_t + (1-\omega_{it})\,R_t^f\right) - W_{it-1}\left(\omega_{it-1}R_t + (1-\omega_{it-1})\,R_t^f\right). \tag{30}$$

Here we make the conservative assumption that the change in portfolio took place right at the start of the period.[48] We then subtract the previous value ($\widetilde{\Delta W}_{it}$) from the total change in wealth to obtain the "active change in wealth":

$$\Delta W_{it}^{Active} = \Delta W_{it} - \widetilde{\Delta W}_{it}. \tag{31}$$

Finally, we substitute change in wealth (ΔW_{it}) with active change in wealth (ΔW_{it}^{Active}) in our regressions.

Both sets of results (for the IV and active-change-in-wealth approaches) are presented in Table 6, where we reestimate the regression specifications with total wealth (Specification 2 in Table 3), total wealth and human capital (Specification 3 in Table 3), and financial wealth and human capital (Specification 7 in Table 5). In all cases the conclusions are unchanged, and the estimated coefficients are very similar to those previously obtained.

4.4 Assessing the role of time and cohort effects

Our methodology allowed us to identify the life-cycle profile of stock market participation without having to make specific assumptions for time and cohort effects. In this section, we compare our results with those obtained under the two extreme identification assumptions,

[48] In the limit, if the portfolio allocation was instead fully implemented at the end of the period, the change in wealth could not have been affected and there would be no endogeneity issue.

setting either time effects or cohort effects equal to zero (as in Poterba and Samwick (1997) and Ameriks and Zeldes (2004)).

More precisely we estimate equation (1) for the participation decision,

$$P_{it} = I(a_{it}) + I(t) + I(c_i) + \theta X_{it} + \Gamma F_i + \varepsilon_{it} \tag{32}$$

with either $I(t) = 0$ for all t, or $I(c_i) = 0$ for all i. Under both assumptions the age effects are identifiable so we do not need to estimate the equation in first differences.

The age profiles of stock market participation implied by these two specifications are shown in Figure 9, which makes clear that the results are very different under the two identification schemes. The age pattern of participation shows a decrease after age 31 if we rule out time effects. By contrast, when we ignore cohort effects, it becomes strongly increasing. Both of these findings contrast with our baseline results (Figure 8), which exhibit a hump-shaped pattern, highlighting the importance of properly controlling for both cohort and time effects when estimating the age profile of stock market participation.

5 Conditional Risky Share

Having established the evolution of the participation decision over the life cycle, we now turn our attention to the portfolio decision of stock market participants. The object of interest is the conditional risky share, that is, the risky share conditional on stock market participation.

5.1 Descriptive statistics

Figure 10 plots the average cross-sectional conditional risky share across time (Panel (a)) and across age groups (Panel (b)). Time variation in the conditional risky share is fairly moderate and much smaller than previously reported for the participation rate (Figure 3). In Panel (b), we find that, in the absence of any controls, the conditional risky share is a positive function of age until retirement and essentially flat thereafter. The increasing pattern before retirement is economically substantial, with a rise of 20 percentage points in

the average allocation to risky assets over this period. However, as previously discussed, the data in Figure 10 combines age, time and cohort effects.

Repeating the same approach as for participation, we isolate age effects by taking the first differences of the conditional risky share for each individual at each date and then averaging across all observations of the same age. The result, reported in Figure 11, reveals an increasing profile until around age 55 and flat thereafter. As in Figure 10, we observe an increasing pattern early in life, but here it peaks before retirement. Furthermore, the magnitude of this increase is about one-third smaller in Figure 11: 13 percentage points versus 20 in the previous estimations.

5.2 Estimation results

We now consider a formal regression framework by estimating equation (5) for the conditional risky share. With regards to the explanatory variables included in the vector ΔX_{it} we consider the same specifications as for the decision to participate. Therefore, the first regression includes the age dummies and two controls, change in homeownership status, and change in the number of children. In the second regression, we add log changes in total wealth, and in the third and fourth, we include the human capital variables.[49] The estimated coefficients are reported in Table 7 and Figure 12 depicts the corresponding age effects. As we did for stock market participation, we consider specifications with financial wealth instead of total wealth, and those results are presented in Table 8.

Finally, as discussed in Section 2.2, a significant fraction of households only rebalance their portfolios infrequently. Therefore, we repeat our estimations following the approach in Calvet, Campbell, and Sodini (2009); that is, we consider active rebalancing decisions only. More precisely, we replace changes in the risky share with active changes in the risky share, computed from equations (6) and (7). In our implementation of these equations the return on risky asset (R_t) is the value-weighted return on equities from CRSP, while the return on the riskless asset (R_f) is the real return on the 90-Day T-Bill. These results are reported in

[49] In Section 5.3, we address potential endogeneity concerns with the wealth variables, using the same approach as for the participation regressions. As before, the conclusions remain unchanged.

Tables 9 and 10, and in Figure 13.

5.2.1 Age profiles

Figure 12 plots the age profile of the conditional risky share implied by the two specifications for the left-hand-side variable, namely total changes and active changes. When considering total changes, we obtain an initially increasing and then flat profile. However, when we focus on active changes, the conditional risky share is constant until ages 55 to 60 and then decreases as agents approach retirement and during the retirement period. The difference in results indicates that the increase in the conditional risky share early in life is the result of portfolio inertia combined with a positive realized risk premium. Household portfolios shift toward equities not because of active-rebalancing decisions but simply because the value of their stock holdings is increasing faster than the value of their bond holdings.[50]

The evidence for a flat or even increasing risky share early in life is consistent with models with DRRA (as in Gomes and Michaelides (2003); Polkovnichenko (2007); and Wachter and Yogo (2010)), background risks, and where labor income is a close substitute for bonds. Background risks and DRRA generate the flat or increasing pattern early in life. This pattern can also arise in the presence of liquidity demands (as in Campanale et al. (2015)) and/or a high level of skewness in risky asset returns (as in Fagereng et al. (2017)). Finally, the substitutability of human capital and bonds delivers the decreasing profile as individuals approach retirement and during retirement. The presence of DRRA preferences explains why the reduction in the risky share late in life is much weaker than predicted by models with constant relative risk aversion.

The previous evidence could also be consistent with labor income being a close substitute for stocks and increasing relative aversion to risk. The former would deliver the flat or increasing profile for young individuals, and the latter would be the dominating effect late in life. However, as discussed below, regression Specifications 2 through 8 help us disentangle these different economic mechanisms by including the wealth and human capital variables.

[50] It is, of course, theoretically possible that households do not rebalance their portfolios to offset this effect because it matches their optimal age profile.

The estimated coefficients on these variables are consistent with decreasing relative risk aversion and human capital being a close substitute for bonds, and this was already the case in the stock market participation regressions.

Models with CRRA preferences and labor income uncorrelated with stock returns imply a pronounced decreasing risky share with age. As discussed above, references with DRRA and/or background risks can deliver the flat or increasing pattern early in life. However, the mild decrease in the risky share late in life suggests that the substitutability between labor income and bonds, although positive, is not as strong as predicted by the model where labor income shocks are completely uncorrelated with stock returns. In principle, this could be evidence for strong DRRA, but our regressions indicate that this channel is fairly moderate. Therefore, our combined results suggest that there is some limited correlation between labor income and stock returns.[51] This limited correlation could arise from the cointegration channel proposed by Benzoni et al. (2007) but is weaker than under their calibration, such that human capital is still a closer substitute for bonds than for stocks. Alternatively, it could result from the higher-order correlations identified in Catherine (2019).

Our results are closest to those obtained by Ameriks and Zeldes (2004) when considering time effects. They find a slightly decreasing risky share late in life and a flat profile before that. For the pre-retirement period Catherine (2019) estimates a slightly increasing conditional risky share until retirement, while Ameriks and Zeldes (2004) estimate a strong increasing pattern when controlling for cohort effects. Neither of these estimations delivers a decreasing risky share late in life, and the results for earlier ages are also at odds with our evidence, particularly when considering active rebalancing decisions. Finally, Fagereng et al. (2017) estimate that the conditional risky asset share is a decreasing function of age.[52]

[51] Consistent with this, as we discuss next, the coefficient on human capital is not significant in some regression specifications.

[52] Poterba and Samwick (1997) do not estimate a conditional risky share but, they obtain very similar hump-shaped age profiles for stock market participation and the unconditional risky share. These results suggest that the conditional risky share is approximately constant with age.

5.2.2 The role of wealth

The estimated coefficients of log changes in wealth are almost identical in the regressions for total changes in risky share and only active changes, respectively as reported in Tables 7, 8, 9, and 10. Therefore, to avoid repetition in our discussion, we refer to the active share results only. The coefficients on log differences in total wealth (Specifications 2 to 4) and log differences in financial assets (Specifications 5 to 8) are highly significant and, their coefficients are also very similar across the different regressions. Qualitatively these results are essentially identical to those obtained for the stock market participation regressions, providing additional supporting evidence for a decreasing relative risk aversion: wealthier investors hold riskier portfolios. The economic magnitude of the wealth effects is modest. For example, the estimated coefficient of 0.0711 in Specification 2 of Table 9, implies that a 10% growth in total wealth leads to an increase in the conditional risky share of 0.711 percentage points. However, when we compare the age profile from Specification 1 with that from Specification 2 (in Figure 13), we find more significant differences.[53] This apparent contrast can be understood from the substantial cross-sectional differences in the growth rate of wealth. As shown in Table 2 Panel (b), the 25th and 75th percentiles of the total-wealth growth rate are −18% and 41%, respectively. In other words, although moderate changes in wealth have a small impact on the risky share, in the data, we observe several very large fluctuations in wealth and significant portfolio reallocations as a result. This contrast might help explain why previous studies yield conflicting results when testing for wealth effects in portfolio demand.[54] These effects will be hard to detect when considering modest changes in wealth.

Finally, and as we found in the participation decision regression, the coefficient on log changes in home equity is not statistically significant (Specification 6 in Table 8), and the point estimate is also very small.

[53] As before, we omit Specifications 4 to 8 in Figure 13 to facilitate the visual comparison.

[54] Heaton and Lucas (2000), Campbell (2006), Wachter and Yogo (2010), Calvet and Sodini (2014), Bach et al. (2016), Meeuwis (2020), and Fagereng et al. (2020) find evidence for increasing risky shares as a function of wealth, although the estimated effects are relatively small in several cases. By contrast, the estimates in Brunnermeier and Nagel (2008) and Chiappori and Paiella (2011) suggest that the wealth effects on the risky share of households' portfolios are not statistically significant.

5.2.3 The role of human capital

The coefficient on changes in the ratio of human capital to total wealth in Specification 3 is positive, consistent with models where labor income is a close substitute for bonds.[55] When decomposing this variable into its two components, ξ^1_{i,a_0} and ξ^2_{i,a_0}, we find that only the estimated coefficient on the first term is statistically significant, just as in the stock market participation regressions.

The point estimate for the PVYW coefficient in Specification 3 in Table 9 implies that a one standard deviation increase in the ratio leads to a 1.58 percentage point in the risky share. This significant but moderate role of human capital is also evident in Figure 13 in the comparison of results from Specifications 2 and 3. This suggests, as previously noted, that although human capital is a closer substitute for bonds than stocks, this substitutability is not as high as in a model where labor income and stock returns are assumed to be uncorrelated. Along these lines, the estimate for the PVYW variables in Specification 7 in Table 10, although also positive, is not statistically significant.

5.3 Non-linear wealth effects and endogeneity concerns

If households have a strong demand for liquidity, for example, due to transaction costs or precautionary saving, this could generate the observed positive correlation between wealth and conditional risky share; these precautionary savings and liquid wealth are likely primarily invested in safe assets. For less wealthy households, those savings represent a higher fraction of their total wealth and the impact on their optimal risky share would be larger. Consequently, as households become wealthier (poorer), we would observe an increase (decrease) in their conditional risky share.

We explore this possibility and more generally analyze whether our earlier results change with changes in wealth by estimating Specifications 2 and 3 by total wealth quartiles. The regression results are reported in Table 11. Interestingly, the wealth coefficient is similar across specifications, consistent with the DRRA interpretation. In fact, the wealth coefficient

[55] As before, the conclusions are identical for total changes in risky share or active changes only, and therefore we only discuss the results for the second case.

is only significantly different for the first wealth quartile, but it is actually much smaller than for the other quartiles; this is exactly the opposite of what the liquidity and precautionary savings channels imply. One possible explanation for this is that most households that have a higher demand for bonds due to their high demand for liquidity or precautionary savings are not even stock market participants. Given their low demand for stocks, they do not have an incentive to pay the participation costs and, therefore, they are not present in these regressions.

Finally, we address potential endogeneity in the wealth measures by implementing the two approaches we used for the participation regressions (described in Section 4.3). More precisely, we estimate IV regressions using the lagged change in wealth as an instrument, and we replace change in wealth with active change wealth (equations (30), and (31)). The results are reported in Table 12 and our conclusions remain the same; the estimated coefficients are very close to those previously obtained (in Tables 9 and 10).

5.4 Assessing the role of time and cohort effects

Repeating our exercise for stock market participation, we now compare the results for the conditional risky share with those obtained under the identification assumptions of either time or cohort effects being set to zero. More precisely, we estimate regression (1) with either $I(t) = 0$ for all t, or $I(c_i) = 0$ for all i.

The age profiles of the conditional risky share implied by these two specifications are shown in Figure 14. The results are significantly different under the two identification schemes, as was the case for the stock market participation regressions. When controlling for cohort effects only, we conclude that the conditional risky share is an inverse hump-shaped function of age. However, if we only include time effects, we estimate an increasing profile. Both results are qualitatively very different from our baseline (Specification 1 in Figure 13), again re-emphasizing the importance of an estimation approach that controls for time, cohort, and age simultaneously.

6 Life-Cycle Model

In this section, we present a relatively simple life-cycle model that captures most of the important economic mechanisms identified in our empirical analysis. There are certainly additional features that we could have included or that could have replaced some of those selected while delivering similar results. We discuss these options in presenting the model setup. However, the objective here is to consider a framework with a minimum set of features that can closely replicate our empirical findings while preserving the essential economic channels. Complicating the model along some dimensions could potentially bring its results closer to our empirical estimates, and we will discuss these later. Finally, we abstract from multiple sources of risk that are particularly relevant late in life, such as longevity (e.g., Horneff, Maurer, Mitchell, and Stamos (2009); Cocco and Gomes (2012); and Yogo (2016)), medical-expenditure (e.g., De Nardi et al. (2010) and Ameriks et al. (2011)), and health (e.g., Yogo (2016)) risks.[56] For this reason, we focus on the asset allocation and stock market participation decisions before retirement.[57].

6.1 Model set-up

6.1.1 Labor income process and retirement income

Households have a stochastic finite horizon divided into two periods: working life and retirement. Before retirement, they earn labor income subject to undiversifiable shocks, and after retirement, they receive a fixed pension. The estimated age profile for the risky share suggests that background risks are likely relevant early in life.[58] Therefore, the labor income process before retirement extends the standard permanent and transitory combination by considering a separate unemployment state.[59] Specifically, households suffer an unemploy-

[56] Having a realistic representation of these risks is challenging given that we consider a utility function with an exogenous subsistence level, as described below.

[57] In addition, it is fairly straightforward to change the age-slope of the risky share during retirement by simply varying the strength of the bequest motive (see Gomes (2020)).

[58] A similar result could be obtained by replacing this additional background risk with negative-return skewness, as in Fagereng et al. (2017).

[59] For an alternative formulation to capture time-varying downside risk see Catherine (2019) and Shen (2019), which considered the income process estimated by Guvenen, Ozkan, and Song (2014).

ment spell with probability π^u, in which case they receive a replacement income (Y^u), while with probability $1 - \pi^u$ their labor income is given by

$$\begin{aligned} Ln(Y_t) &= f(t, \theta) + p_t + u_t && (33) \\ p_t &= p_{t-1} + z_t, \ z_t \sim N(0, \sigma_z^2) && (34) \\ & \quad u_t \sim N(0, \sigma_u^2) && (35) \end{aligned}$$

where $f(t, \theta)$ is a deterministic function of age and other household characteristics (θ), here education. For convenience, we refer to the current level of permanent income as

$$Y_t^P = \exp(p_t) \exp(f(t, \theta)) \tag{36}$$

Income in a year with a period of unemployment is specified as a deterministic function of the current level of permanent income

$$Y^u = \lambda^u Y_t^P \tag{37}$$

Households retire at age K, and retirement income is a deterministic function of permanent income in the last year of working life:

$$Y_t = \lambda^R Y_K^P, \ t > K \tag{38}$$

where λ^R is the retirement income replacement ratio.

6.1.2 Preferences

Households have Epstein–Zin utility functions (Epstein and Zin, 1989) defined over the consumption of a single non-durable good (C_t) but with a consumption floor ($\overline{C}_t$):[60]

$$V_t = \{(1-\beta)(C_t - \overline{C}_t)^{1-1/\psi} + \beta E_t \tag{39}$$

where ψ is the elasticity of intertemporal substitution, β is the subjective discount factor, and π_t^s is the conditional survival probability from age t to age $t+1$.[61] The parameter γ determines atemporal risk aversion and would be equal to the coefficient of relative risk aversion if we had $\overline{C}_t = 0$.

The consumption floor ($\overline{C}_t$) generates decreasing relative risk aversion in the model, consistent with our empirical evidence.[62] In line with the habit-formation interpretation, we scale the consumption floor by the permanent level of income:

$$\overline{C}_t = \overline{C} Y_t^P \tag{40}$$

This formulation guarantees that $\overline{C}_t$ increases with age, as consumption also rises.

6.1.3 Financial assets, participation costs and budget constraint

Households can invest in a riskless one-period bond and an aggregate stock market index. The return on the riskless bond (R_f) is constant, while the return on the stock market follows a normal distribution and is potentially correlated with the labor income shocks (as noted in the section addressing calibration). Investing in the stock market requires the payment of a first-time entry cost (F^0) and a per-period cost (F^1). As is standard in the literature

[60] Since our focus is on the pre-retirement period and to simplify the model and reduce the number of free parameters we do not consider a bequest motive.

[61] The conditional survival probability is equal to zero at a pre-determined maximum age, which we calibrate to 100.

[62] In the models of Gomes and Michaelides (2003) and Polkovnichenko (2007) decreasing relative risk aversion arises from habit-formation preferences. Wachter and Yogo (2010) find a decreasing relative risk aversion from non-homothetic preferences over multiple goods, a basic good, and a luxury good. The consumption floor can also represent consumption commitments, as in the work of Chetty and Szeidl (2007).

(e.g., Gomes and Michaelides (2005)), these costs are expressed as a fraction of permanent income. This is done for tractability and because they partially capture an opportunity cost of time.

Letting W_t and α_t denote wealth and the risky share at time t, respectively, the household's budget constraint is

$$W_{t+1} = (\alpha_t R_{t+1} + (1 - \alpha_t) R_f)(W_t - C_t - F^0 Y_t^P I^{firstentry} - F^1 Y_t^P I^{\alpha>0}) + Y_{t+1} \tag{41}$$

where $I^{firstentry}$ is a dummy variable that is equal to 1 if the household is participating in the stock market for the first time and $I^{\alpha>0}$ is a dummy variable that is equal to 1 if the household has positive stock holdings in the current year.

6.1.4 Household heterogeneity

Following Gomes and Michaelides (2005), we consider two groups of households with heterogeneous savings motives. This is important for matching limited participation with moderate participation costs. One group of households has a low discount factor and high retirement income replacement ratio, and as such, they will have limited wealth accumulation over the life cycle. Where there are stock market participation costs, most of these households will have no incentive to become stockholders. By contrast, the households in the other group have a high discount factor and a low retirement income replacement ratio, and consequently, most will be regular stock market participants.[63]

In addition, we consider heterogeneity in financial literacy building on the work of Lusardi and Mitchell (2011) and Lusardi and Mitchell (2014). Some households have high financial literacy, and therefore their stock market participation costs are very low, while for others, those costs are more substantial. This heterogeneity will be important for matching our empirical evidence on stock market participation.

[63] We could consider many forms of heterogeneity in preferences and income profiles. We present a simple two point-distribution that captures high and low savers, but several other combinations could deliver the same result.

6.2 Empirical counterparts to the model predictions

Our previous estimates are based on PSID data, which does not include retirement wealth. Therefore, we now address how we adjust our empirical results to make them more directly comparable with the predictions of the model. Crucially, as shown below, the different adjustments that we consider imply very small changes to our previous results.

First, we consider our estimates of the cumulative changes in stock market participation. Here we use SCF data to scale our empirical estimates. More precisely, we first use the SCF to compute the ratio of total to direct stock market participation (i.e., excluding retirement accounts) and obtain the value of 1.45. The series "Empirical 1" in Figure 15 is then calculated by applying this factor uniformly to our previous estimates.

One potential concern with the previous adjustment is that it assumes that participation in DC accounts follows the same pattern as direct stock market participation, which is unlikely. For example, we expect a much slower decreasing pattern in participation in DC accounts late in life. Therefore, we consider a second adjustment where we assume that only direct stock market participation decreases late in life and adjust the scaling factor for the previous ages accordingly. The corresponding profile is the series "Empirical 2" in Figure 15; the two life-cycle profiles are actually very similar.

Next, we consider the cumulative changes in the risky share. In our first scenario, we make the conservative assumption that the behavior of the risky share with age is identical in both the tax-deferred retirement accounts (TDAs), which we do not observe and the liquid taxable accounts (TAs) that are included in our data. Under this assumption, no adjustment is required. Therefore, the series "Empirical 1" in Figure 16 is identical to the one reported before.

In our second scenario, we consider that in the later years of our sample, a significant fraction of retirement wealth is invested in TDFs, which have a strong age profile for their risky share. Therefore, denoting the fraction of wealth in tax-deferred accounts invested in

TDFs by θ, the adjusted risky portfolio share becomes:

$$\alpha^{adjusted} = \frac{\alpha^{TA}W^{TA} + \alpha^{TA}W^{TDA}(1-\theta) + \alpha^{TDF}W^{TDA}\theta}{W^{TA} + W^{TDA}} \tag{42}$$

where W^{TA} and W^{TDA} are, respectively, total wealth in taxable and tax-deferred accounts, and α^{TDF} is the risky share in the TDF.

To implement this adjustment, we use data from the SCF to compute the ratio of W^{TDA} to W^{TA} at each age and obtain the fraction of TDA wealth invested in TDFs (θ) from the Vanguard surveys, "How America Saves" (Vanguard, 2009, 2020), and the portfolio allocation of the TDF (α^{TDF}) from Vanguard's website. The implied cumulative change in the risky share is the series "Empirical 2" in Figure 16 below.

6.3 Calibration

6.3.1 Income process and preferences

As is standard in the literature, we set the starting age to 20, the retirement age to 65, and the maximum age to 100. The deterministic income profile and the retirement income replacement ratio are taken from Cocco et al. (2005). For the variances of the income shocks, we consider the values in Brown, Fang, and Gomes (2015) for their more recent sample period ($1991 - 2011$) since it matches that in our empirical analysis.[64]

The probability of unemployment (π^u) represents the probability of suffering a period of unemployment during the year. Therefore, the corresponding income includes both unemployment subsidies received during the unemployment period and labor income earned during the rest of the year. Estimates for these values are taken from Brown et al. (2015), giving us $\pi^u = 0.14$ and $\lambda^u = 0.7$.

As previously noted, we have two equal-sized groups of households with different discount factors and retirement income replacement ratios. The more patient households have $\beta = 0.99$ and $\lambda^R = 0.68$, while the others have $\beta = 0.9$, and $\lambda^R = 0.9$. For both groups, we set

[64] Their estimate for the standard deviation of transitory income shocks is 28.1%. We consider 20% to account for potential measurement errors.

the parameter γ equal to 6 and the EIS (ψ) equal to 0.5. The retirement income replacement ratios reflect the range reported in Cocco et al. (2005) and the preference parameters are standard and in line with those estimated in Calvet, Campbell, Gomes, and Sodini (2019).[65]

We set the consumption floor parameter ($\overline{C}$) to 0.5, corresponding to 50% of the current permanent labor income. This delivers only a moderate increase in risk aversion relative to the power utility case and a moderate and decreasing relative risk aversion, consistent with our empirical estimates. All households receive an initial wealth endowment equal to 50% of their income at age 20.

6.3.2 Returns and correlation with income

We set the real riskless rate to 1.5% and the equity premium to 4%. The correlations between stock market returns and permanent and transitory labor income shocks are set to 0.15. Empirical estimates of these correlations are essentially equal to zero (see Campbell, Cocco, Gomes, and Maenhout (2001) and Davis and Willen (2014)). These values are meant to capture, in a reduced form, the higher-order correlations estimated in Catherine (2019) and the low-frequency correlations suggested by Benzoni et al. (2007). Nevertheless, the values that we consider are not very high because our empirical results indicate that human capital is a closer substitute for bonds than for stocks.

6.3.3 Participation costs and financial literacy

We consider heterogeneity in financial literacy, captured by heterogeneity in stock market participation costs. We have three groups of households with different levels of financial literacy. The more financially educated group represents 40% of the population, while the other groups account for 30% each. For simplicity, we assume that financial literacy is uncorrelated with preferences; that is, the two sources of ex-ante household heterogeneity are independent.

For the group of households with high financial literacy, we set $F^0 = F^1 = 0$, for

[65] The low discount rate for the second group can also be interpreted as a reduced form for hyperbolic discounting (see Laibson, 1997).

simplicity. The second group has lower financial literacy and faces an entry cost (F^0) of 3% of annual income and a per-period cost (F^1) of 0.5%. Finally, the third group faces very high participation costs: $F^0 = 25\%$ and $F^1 = 2.5\%$. These very high values should be interpreted as a reduced form for other concerns that leave individuals extremely unwilling to invest in stocks.[66] We could exclude this group from our model and still match overall participation rates, as in Gomes and Michaelides (2005), for example. However, under such a formulation, it would be hard to prevent most households from temporarily becoming stockholders around retirement when even those with a low discount factor accumulate significant savings. This particular implication would be inconsistent with our empirical estimates (see Figure 8). Modeling some of those other features (e.g., low trust in the stock market, pessimistic beliefs, or first-order risk aversion) directly would do away with the need to include this group with very high costs of participation.

6.4 Results

6.4.1 Baseline model

We first solve and simulate the model for the different household groups. We then compute the model-implied counterparts to our empirical life-cycle profiles for the risky share and stock market participation and compare the two (model-implied and data-determined) in Figures 15 and 16, respectively. In addition to our baseline results (model version: "Baseline"), we also plot results for a case without ex-ante household heterogeneity (model version: "NH"), and for a case where we also set the consumption floor to zero (model version: "NH_$\overline{C}$0").[67]

Figure 15 shows that the baseline model (series "Baseline") is a good match to the life-cycle pattern of stock market participation. In the model, stock market entry takes place

[66] For example, a lack of trust in financial markets (Guiso et al., 2008), pessimism about expected returns, or preferences with first-order risk aversion (see, for example, Chapman and Polkovnichenko (2009); Campanale (2011); Peijnenburg (2018); or Pagel (2018)).

[67] In the two cases without ex-ante heterogeneity we set the common discount factor to 0.96, the common retirement income replacement ratio to 0.8 and the unique level of financial literacy to that of the "medium group" ($F^0 = 3\%$ and $F^1 = 0.5\%$). The results are not sensitive to modest deviations around these values.

slightly earlier than in the data, and there is an additional increase just before retirement when household wealth accumulation is at its maximum; for all other ages, the fit is very good. By comparison, the model with no ex-ante heterogeneity (series "NH") fails quite dramatically. Unless we include a group of households with a low savings motive, eventually all households will decide to participate in the stock market, as shown by Gomes and Michaelides (2005).[68] Extremely high participation is also seen when, in addition to excluding ex-ante heterogeneity, we remove the consumption floor (series "NH_$\overline{C}$0"); now all households optimally become stockholders from a very young age. Therefore, by age 23, the participation rate is already almost 100%, and there is no further cumulative increase evident in Figure 15.

In Figure 16 we plot the cumulative change in the risky share. The baseline model (series "Baseline") delivers a moderate decreasing pattern over the life cycle, in contrast to the steep decreasing profiles of the standard model without heterogeneity and with constant relative risk aversion (series "NH_$\overline{C}$0"). The cumulative decrease in the risky share over the working life is very similar in the baseline model and the data, particularly if we consider the series "Empirical 2." In the former, however, the reduction in the equity share takes place slightly earlier than in the data. The inclusion of a decreasing relative risk aversion plays an important role in bringing the theoretical predictions close to the data. Without the consumption floor, the optimal risky share decreases quite significantly with age (series "NH_$\overline{C}$0"). By contrast, if we keep the consumption floor and remove ex-ante heterogeneity instead, the results are very similar (series "NH" and series "Baseline"). Although this last set of results (series "NH") matches the cumulative change in risky share slightly better, it fails quite dramatically for the stock market participation decision, as previously shown in Figure 15.

[68] This is the case unless we assume very high costs of participation. In this version, without ex-ante heterogeneity, every household faces the same (moderate) costs $F^0 = 3\%$ and $F^1 = 0.5\%$.

6.4.2 Additional comparative statistics

To further understand the role of the model's various features, we consider two additional restricted versions: no ex-ante heterogeneity in financial literacy (model version: "NHFL") and no ex-ante heterogeneity in preferences and the retirement income replacement ratio (model version: "NHPR"). In addition, we report results with a higher correlation between stock returns and income shocks, namely a 0.2 correlation with both transitory and permanent income innovations (model version: "HighCorr"). The results are shown in Figures 17 and 18 for cumulative changes in stock market participation and cumulative changes in the risky share, respectively.

Similar to the results obtained when excluding all ex-ante heterogeneity (series "NH"), the results for homogeneous financial literacy or homogeneous savings motives (preferences and retirement income replacement ratio) both generate very high stock market participation (Figure 17). Furthermore, compared with the baseline model, the implied change in the risky share (Figure 18) is either an even steeper function of age (model version: "NPHR") or essentially the same ("model version: "NHFL"). Increasing the correlation between stock returns and labor income shocks improves the fit of the model with regard to the cumulative changes in the risky share since labor income becomes a weaker substitute for bonds. However, as shown in Figure 17, since the optimal risky share of young households is now lower, they are also less likely to pay the participation costs and become stockholders. Therefore, under this level of correlation, stock market participation increases gradually with age, in contrast to our empirical results.

7 Conclusion

We estimate the life-cycle profiles of stock market participation and the conditional risky share. We find that the former is a hump-shaped function of age, while the conditional risky share is flat early on and decreases late in life. We address the classical problem of separately identifying time, age, and cohort effects by running the estimations in first differences. Although we cannot recover the levels of the risky share and stock market participation at each age, we can identify the age profiles without making assumptions in respect of time or cohort effects. While the levels of are likely influenced by several (potentially unobserved) individual characteristics, the age profiles are more direct implications of the various theories.

By estimating these profiles and showing how they are related to changes in wealth and human capital, we can understand which life-cycle models are consistent with our findings. In particular, we find empirical support for stock market participation costs, background risks, decreasing relative risk aversion, and human capital that has some correlation with stock returns but remains a closer substitute for bonds than for stocks. We confirm these implications in a structural life-cycle model of portfolio choice.

Crucially, we also show that our empirical results are qualitatively different from those obtained if we impose the common exclusion restrictions concerning time and cohort effects. For both stock market participation and the conditional risky share, results without time effects or without cohort effects give rise to very different age profiles, and neither of these possibilities replicates our baseline results.

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Table 1: Number of observations in the sample

Table 1 reports the number of observations at each age in the PSID data after applying our sample restrictions. Columns 1 to 4 show the number of observations for changes in participation for each age interval starting with the 19 to 21 age group and ending with the 88 to 90 age group for the full sample. Columns 5 to 8 show the number of observations for changes in the risky share for the sample of stock market participants, which additionally conditions on stock market participation in both current and previous waves.

All				Stock market participants			
ΔAge	N	ΔAge	N	ΔAge	N	ΔAge	N
19-21	42	54-56	519	19-21	2	54-56	117
20-22	88	55-57	496	20-22	6	55-57	112
21-23	115	56-58	525	21-23	4	56-58	114
22-24	233	57-59	490	22-24	22	57-59	110
23-25	322	58-60	480	23-25	21	58-60	100
24-26	420	59-61	454	**24-26**	53	59-61	88
25-27	496	60-62	460	25-27	54	60-62	87
26-28	528	61-63	413	26-28	76	61-63	98
27-29	586	62-64	424	27-29	68	62-64	102
28-30	577	63-65	397	28-30	77	63-65	94
29-31	606	64-66	376	29-31	75	64-66	90
30-32	601	65-67	344	30-32	84	65-67	92
31-33	632	66-68	346	31-33	92	66-68	86
32-34	612	67-69	328	32-34	101	67-69	83
33-35	619	68-70	308	33-35	94	68-70	81
34-36	612	69-71	281	34-36	91	69-71	78
35-37	609	70-72	276	35-37	89	70-72	76
36-38	577	71-73	270	36-38	96	71-73	73
37-39	570	72-74	224	37-39	86	72-74	68
38-40	563	73-75	242	38-40	98	73-75	69
39-41	566	74-76	228	39-41	90	74-76	63
40-42	569	75-77	216	40-42	91	75-77	61
41-43	550	76-78	194	41-43	90	76-78	56
42-44	530	77-79	225	42-44	89	77-79	62
43-45	532	78-80	177	43-45	87	78-80	62
44-46	551	79-81	185	44-46	92	79-81	52
45-47	547	80-82	156	45-47	94	80-82	57
46-48	525	81-83	174	46-48	110	81-83	51
47-49	553	82-84	136	47-49	102	82-84	44
48-50	519	83-85	143	48-50	105	83-85	41
49-51	526	84-86	103	49-51	106	84-86	36
50-52	548	85-87	116	50-52	116	85-87	23
51-53	521	86-88	80	51-53	97	86-88	26
52-54	542	87-89	89	52-54	116	87-89	16
53-55	517	88-90	64	53-55	108	88-90	14
Total			27443	Total			5264

Table 2: Summary statistics

Table 2 reports summary statistics for the variables in our sample. Panel (a) reports values for the sample used in the participation analysis, while the values in Panel (b) refer to the sample of stock market participants, which is used in the conditional risky share regressions. Row 2 in Panels (a) and (b) describes the samples' age structure. Rows 3 to 7 summarize other individual characteristics. Row 8 summarizes household income. Rows 9, 10, and 11 (LFA, HE and TW, respectively), provide descriptive statistics for wealth variables in the corresponding samples. Row 12 (partic and ω) in Panels (a) and (b) summarizes participation and risky share, respectively. For both panels, Rows 13 (ΔlogLFA), 14 (ΔlogHE), and 15 (ΔlogTW) show growth rates for wealth variables in the corresponding samples. Rows 16 (ΔPVYW), 17 (ξ^1), and 18 (ξ^2) summarize changes in the ratio of human capital to financial wealth explained in Section 2.3. All growth rates and changes are over a two-year period since that is the frequency of our data. Income and wealth/asset data are deflated to 2017 dollars

Stats	N	Mean	SD	p25	p50	p75	Max
age	26861	49.42	15.7	36	48	61	85
male	26861	0.82	0.39	1	1	1	1
married	26861	0.67	0.47	0	1	1	1
has kids	26861	0.38	0.49	0	0	1	1
# of kids	26861	0.71	1.07	0	0	1	9
home owner	26861	0.77	0.42	1	1	1	1
income	26861	101557.3	70962.8	52343.8	85186.8	129887.6	408856.0
LFA	26861	84174.8	212592.2	4136.5	12547.1	54650.1	1418440.0
HE	26861	122835.2	168312.2	0	67114.1	169385.2	934903.0
TW	26861	209675.1	332561.8	22233.7	95139.6	245714.3	2073684.0
partic	26861	0.28	0.45	0	0	1	1
ΔlogLFA	26860	0.77	2.43	-0.43	0.23	1.16	9.93
ΔlogHE	19606	0.94	2.87	-0.09	0.11	0.49	12.00
ΔlogTW	26078	0.49	1.72	-0.19	0.16	0.67	8.93
ΔPVYW	24188	-24.28	193.73	-12.89	-1.06	2.17	717.76
ξ^1	24188	-16.28	183.81	-9.22	-0.23	3.47	736.11
ξ^2	24188	7.89	16.98	0.66	1.79	5.64	102.77

(a) Full sample

Stats	N	Mean	SD	p25	p50	p75	Max
age	5094	54.02	15.7	41	54	66	85
male	5094	0.85	0.36	1	1	1	1
married	5094	0.73	0.44	0	1	1	1
has kids	5094	0.31	0.46	0	0	1	1
# of kids	5094	0.55	0.94	0	0	1	6
home owner	5094	0.88	0.32	1	1	1	1
income	5094	140849.9	111551.4	68337.1	113927.7	175334.5	697494.3
LFA	5094	314323.6	538573.9	38857.1	119197.0	331428.6	3401662.0
HE	5094	231731.9	261916.4	60942	160065.4	305010.9	1464714.0
TW	5094	550553.3	713769.0	140000.0	320000.0	651965.5	4446743.0
risky share	5094	0.65	0.30	0	0.73	0.92	1
ΔlogLFA	5094	0.09	0.99	-0.40	0.07	0.55	3.27
ΔlogHE	4366	0.62	2.37	-0.07	0.08	0.35	12.20
ΔlogTW	5041	0.13	0.67	-0.18	0.09	0.41	2.42
ΔPVYW	5027	-8.34	48.52	-4.18	-0.47	0.75	143.68
ξ^1	5027	-6.13	44.79	-2.73	-0.06	1.32	147.41
ξ^2	5027	2.13	4.28	0.30	0.76	1.94	30.05

(b) Stock market participants

Table 3: Regression results for changes in participation (with total wealth)

Table 3 reports results of OLS regressions of changes in participation on wealth, human capital variables, and controls. Specification 1 in Column 2 includes only two control variables, change in homeownership status and change in the number of children in the household. Column 3 reports results for Specification 2, which includes changes in total wealth. Columns 4 and 5 show Specifications 3 and 4 with indicators for the ratio of the present value of human capital to total wealth. All specifications include changes in age (starting with the 21-to-23 age change and ending with the 83-to-85 age change), and year dummies. The wealth-variable coefficients are the 2-year growth rates.

	(1)	(2)	(3)	(4)
owner	0.00948	-0.0118	-0.0164*	-0.0178*
	(1.11)	(-1.36)	(-1.68)	(-1.82)
kids	-0.00875	-0.0113	-0.0108	-0.0108
	(-1.29)	(-1.63)	(-1.46)	(-1.46)
ΔlogTW		0.0310***	0.110***	0.111***
		(20.49)	(22.89)	(22.92)
ΔPVYW			0.000174***	
			(9.08)	
ξ^1				0.000192***
				(8.97)
ξ^2				0.000141
				(1.14)
N	26861	26078	24188	24188
adj. R^2	0.002	0.018	0.044	0.044
F	1.801	7.491	9.635	9.592

cluster-robust t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4: Regression results for changes in participation (by total wealth quartiles)

Table 4 reports results of OLS regressions of changes in participation on different wealth, human capital variables, and controls. Columns 2 to 5 report results for quartile regressions for Specification 2 (with total wealth). Columns 6 to 9 show estimation results for quartile regressions in Specification 3 (with total wealth and the ratio of the present value of human capital to total wealth). All specifications include change in homeownership status and change in the number of children in the household as controls. Regression equations also include changes in age (starting with the 21-to-23 age change and ending with the 83-to-85 age change), and year dummies. The wealth-variables coefficients are the 2-year growth rates.

	(2)				(3)			
	q1	q2	q3	q4	q1	q2	q3	q4
owner	-0.00374	-0.0464***	-0.119***	-0.145***	0.0164	-0.0413**	-0.0794**	-0.0935**
	(-0.30)	(-2.60)	(-3.91)	(-3.82)	(1.12)	(-2.05)	(-2.42)	(-2.50)
kids	-0.00210	-0.0131	-0.0290*	0.00704	0.00407	-0.0120	-0.0273*	0.0118
	(-0.21)	(-1.02)	(-1.90)	(0.35)	(0.33)	(-0.92)	(-1.79)	(0.59)
ΔlogTW	0.0121***	0.0402***	0.0802***	0.152***	0.0487***	0.0925***	0.153***	0.234***
	(9.68)	(10.11)	(11.53)	(13.60)	(7.21)	(10.50)	(13.83)	(19.42)
ΔPVYW					-0.0000112	0.000169***	0.000541***	0.00104***
					(-0.55)	(3.39)	(6.37)	(4.55)
N	6104	6590	6680	6704	4526	6374	6610	6678
adj. R^2	0.014	0.024	0.030	0.072	0.037	0.033	0.043	0.098
F	2.284	2.653	3.255	4.076	2.284	2.939	4.079	7.118

cluster (id) robust t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5: Regression results for changes in participation (with liquid financial assets)

Table 5 reports results of OLS regressions of changes in participation on liquid financial assets, human capital variables, and controls. Column 2 reports results for Specification 5, which includes changes in liquid financial assets. Specification 6 in Column 3 includes liquid financial assets and home equity. Columns 4 and 5 show Specifications 7 and 8 with liquid financial assets and indicators for the ratio of the present value of human capital to liquid financial assets. All specifications include changes in homeownership status, the number of children in the household, and age (starting with the 21-to-23 age change and ending with the 83-to-85 age change), and year dummies. The wealth-variable coefficients are the 2-year growth rates.

	(5)	(6)	(7)	(8)
owner	0.00569	0.0186	0.0166*	0.0164*
	(0.69)	(0.63)	(1.76)	(1.74)
kids	-0.0155**	-0.0164**	-0.00592	-0.00634
	(-2.34)	(-1.98)	(-0.79)	(-0.84)
ΔlogLFA	0.0415***	0.0526***	0.152***	0.152***
	(32.04)	(28.66)	(39.74)	(39.74)
ΔlogHE		-0.00223		
		(-0.83)		
ΔPVYW			0.000101***	
			(9.63)	
ξ^1				0.000107***
				(9.54)
ξ^2				0.00000227
				(0.04)
N	26860	19606	22687	22687
adj. R^2	0.062	0.079	0.164	0.164
F	16.09	13.31	28.23	27.88

cluster-robust t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6: Regression results for changes in participation: endogeneity controls

Table 6 addresses the potential wealth-effect endogeneity concern. Columns 2 to 4 report results of IV regressions of changes in participation on changes in wealth instrumented by lagged changes in wealth. Columns 5 to 8 show results of OLS regressions of changes in participation on active changes in wealth. As before, Specification 2 includes total wealth, Specification 3 includes total wealth and human capital, and Specification 7 includes financial wealth and human capital. All specifications include changes in homeownership status, the number of children in the household, and age (starting with the 21-to-23 age change and ending with the 83-to-85 age change), and year dummies. The wealth-variable coefficients are the 2-year growth rates.

	IV			Active Change in Wealth		
	(2)	(3)	(7)	(2)	(3)	(7)
owner	-0.0100	-0.0211*	0.0133	-0.0319***	-0.0240**	0.0160*
	(-0.89)	(-1.75)	(1.16)	(-3.43)	(-2.43)	(1.69)
kids	-0.00972	-0.00947	-0.00569	-0.00951	-0.00984	-0.00611
	(-1.19)	(-1.10)	(-0.68)	(-1.29)	(-1.27)	(-0.81)
ΔlogTW	0.0225***	0.153***				
	(5.36)	(4.88)				
ΔlogLFA			0.159***			
			(9.33)			
ΔlogTW^A				0.0690***	0.101***	
				(22.07)	(20.51)	
ΔlogLFA^A						0.147***
						(37.96)
ΔPVYW		0.000323***	0.000131***		0.000135***	0.0000873***
		(3.30)	(3.35)		(7.04)	(8.32)
N	21119	19832	18808	24479	23327	22687

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7: Regression results for changes in risky share (with total wealth)

Table 7 reports results of OLS regressions of changes in the conditional risky share on total wealth, human capital variables, and controls. Sample comprises only stock market participants in current and previous waves. Specification 1 in Column 2 includes only two control variables, change in homeownership status and change in the number of children in the household. Column 3 reports results for Specification 2, which includes changes in total wealth. Columns 4 and 5 show Specifications 3 and 4 with indicators for the ratio of the present value of human capital to total wealth. All specifications include changes in age (starting with the 24-to-26 age change and ending with the 83-to-85 age change) and year dummies. The wealth-variable coefficients are the 2-year growth rates.

	(1)	(2)	(3)	(4)
owner	0.0102	-0.000626	0.00829	0.00721
	(0.55)	(-0.03)	(0.44)	(0.38)
kids	0.0109	0.0114	0.00985	0.00989
	(0.83)	(0.89)	(0.77)	(0.77)
ΔlogTW		0.0720***	0.0896***	0.0898***
		(8.34)	(8.92)	(8.89)
ΔPVYW			0.000337***	
			(2.87)	
ξ^1				0.000389**
				(2.49)
ξ^2				0.000435
				(0.31)
N	5094	5041	5027	5027
adj. R^2	0.007	0.033	0.039	0.039
F	1.452	2.645	2.928	2.883

cluster-robust t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 8: Regression results for changes in risky share (with liquid financial assets)

Table 8 reports results of OLS regressions of changes in the conditional risky share on liquid financial assets, human capital variables, and controls. Sample comprises only stock market participants in current and previous waves. Column 2 reports results for Specification 5, which includes changes in liquid financial assets. Specification 6 in Column 3 includes liquid financial assets and home equity. Columns 4 and 5 show Specifications 7 and 8 with liquid financial assets and indicators for the ratio of the present value of human capital to liquid financial assets. All specifications include changes in homeownership status, the number of children in the household, and age (starting with the 24-to-26 age change and ending with the 83-to-85 age change), and year dummies. The wealth-variable coefficients are the 2-year growth rates.

	(5)	(6)	(7)	(8)
owner	0.0253	0.0268	0.0719***	0.0727***
	(1.39)	(0.39)	(2.95)	(2.99)
kids	0.0103	0.0115	0.0128	0.0128
	(0.82)	(0.85)	(0.95)	(0.95)
ΔlogLFA	0.0663***	0.0735***	0.0819***	0.0820***
	(10.40)	(10.44)	(11.07)	(11.08)
ΔlogHE		0.00369		
		(0.62)		
ΔPVYW			0.000113	
			(1.55)	
ξ^1				0.0000916
				(1.19)
ξ^2				-0.000524
				(-1.05)
N	5094	4366	4356	4356
adj. R^2	0.058	0.070	0.075	0.075
F	3.257	3.330	3.616	3.620

cluster-robust t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 9: Regression results for active change in risky share (with total wealth)

Table 9 reports results of OLS regressions of active changes in the conditional risky share on total wealth, human capital variables, and controls. Sample comprises only stock market participants in current and previous waves. Active changes in the risky share are computed from equations (6) and (7) with the value-weighted return on equities from CRSP and the return on the riskless asset (Rf) being the real return on the 90-Day T-Bill. Specification 1 in Column 2 includes only two control variables, change in homeownership status and change in the number of children in the household. Column 3 reports results for Specification 2, which includes changes in total wealth. Columns 4 and 5 show Specifications 3 and 4 with indicators for the ratio of the present value of human capital to total wealth. All specifications include changes in age (starting with the 24-to-26 age change and ending with the 83-to-85 age change), and year dummies. The wealth-variable coefficients are the 2-year growth rates.

	(1)	(2)	(3)	(4)
owner	0.00939	-0.00177	0.00705	0.00617
	(0.51)	(-0.09)	(0.37)	(0.32)
kids	0.00961	0.0102	0.00864	0.00868
	(0.74)	(0.79)	(0.68)	(0.68)
ΔlogTW		0.0711***	0.0889***	0.0891***
		(8.23)	(8.87)	(8.84)
ΔPVYW			0.000343***	
			(2.89)	
ξ^1				0.000384**
				(2.45)
ξ^2				0.000273
				(0.20)
N	5094	5041	5027	5027
adj. R^2	0.002	0.029	0.034	0.034
F	1.328	2.391	2.653	2.622

cluster-robust t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 10: Regression results for active change in risky share (with liquid financial assets)

Table 10 reports results of OLS regressions of active changes in the conditional risky share on total wealth, human capital variables, and controls. Sample comprises stock market participants in current and previous waves. Active changes in the risky share are computed from equations (6) and (7) with value-weighted return on equities from CRSP, and the return on the riskless asset (Rf) being the real return on the 90-Day T-Bill. Column 2 reports results for Specification 5, which includes changes in liquid financial assets. Specification 6 in Column 3 includes liquid financial assets and home equity. Columns 4 and 5 show Specifications 7 and 8 with liquid financial assets and indicators for the ratio of the present value of human capital to liquid financial assets. All specifications include changes in homeownership status, the number of children in the household, and age (starting with the 24-to-26 age change and ending with the 83-to-85 age change), and year dummies. The wealth-variable coefficients are the 2-year growth rates.

	(5)	(6)	(7)	(8)
owner	0.0242	0.0263	0.0717***	0.0725***
	(1.34)	(0.37)	(2.94)	(2.98)
kids	0.00908	0.00999	0.0111	0.0112
	(0.72)	(0.74)	(0.83)	(0.83)
ΔlogLFA	0.0652***	0.0726***	0.0809***	0.0810***
	(10.28)	(10.39)	(11.04)	(11.05)
ΔlogHE		0.00375		
		(0.62)		
ΔPVYW			0.000112	
			(1.54)	
ξ^1				0.0000890
				(1.16)
ξ^2				-0.000563
				(-1.12)
N	5094	4366	4356	4356
adj. R^2	0.052	0.063	0.068	0.068
F	3.079	3.163	3.406	3.397

cluster-robust t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 11: Regression results for active change in risky share (by total wealth quartiles)

Table 11 reports results of OLS regressions of active change in the conditional risky share on total wealth, human capital variables, and controls. Sample comprises only stock market participants in current and previous waves. Active changes in the risky share are computed from equations (6) and (7) with the value-weighted return on equities from CRSP, and the return on the riskless asset (Rf) being the real return on the 90-Day T-Bill. Columns 2 to 5 report results for quartile regressions for Specification 2 (with total wealth). Columns 6 to 9 show estimation results for quartile regressions in Specification 3 (with total wealth and the ratio of the present value of human capital to total wealth). All specifications include changes in homeownership status and the number of children in the household as controls. Regression equations also include changes in age (starting with the 24-to-26 age change and ending with the 83-to-85 age change), and year dummies. The wealth-variable coefficients are the 2-year growth rates.

	(2)				(3)			
	q1	q2	q3	q4	q1	q2	q3	q4
owner	0.00263	-0.0126	-0.0218	0.000282	0.00507	-0.00840	-0.0199	-0.000894
	(0.09)	(-0.35)	(-0.45)	(0.01)	(0.18)	(-0.23)	(-0.41)	(-0.02)
kids	-0.00380	0.0117	0.0232	0.00452	-0.00627	0.0110	0.0235	0.00526
	(-0.15)	(0.48)	(0.82)	(0.16)	(-0.26)	(0.45)	(0.83)	(0.19)
ΔlogTW	0.0123	0.111***	0.0978***	0.118***	0.0212	0.119***	0.100***	0.118***
	(1.16)	(8.16)	(6.43)	(9.07)	(1.43)	(7.08)	(6.00)	(8.32)
ΔPVYW					-0.0000268	0.000301	0.000201	-0.000385
					(-0.19)	(0.81)	(0.33)	(-0.41)
N	1222	1274	1272	1273	1210	1273	1272	1272
adj. R^2	0.025	0.068	0.044	0.077	0.025	0.068	0.044	0.077
F	1.427	2.287	1.818	2.566	1.429	2.263	1.794	2.549

cluster-robust t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

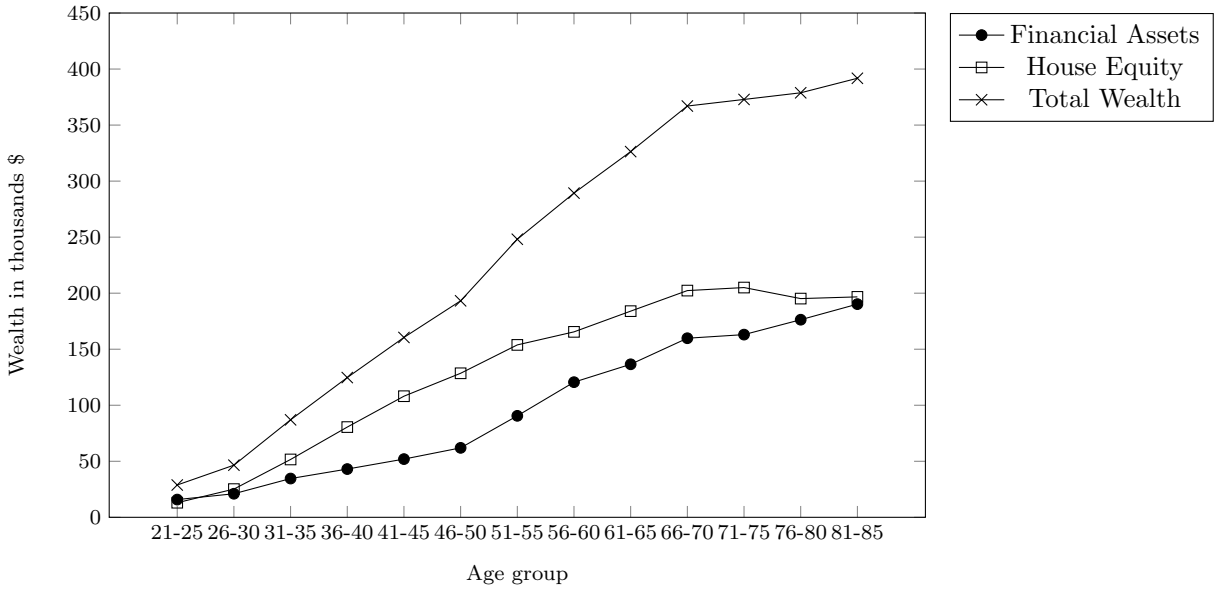
Table 12: Regression results for active change in risky share: endogeneity controls

Table 12 addresses the potential wealth-effect endogeneity concern. Columns 2 to 4 report results of IV regressions of active changes in risky share on change in wealth instrumented by the lagged change in wealth. Columns 5 to 8 show results of OLS regressions of active change in risky share on active change in wealth. As before, Specification 2 includes total wealth, Specification 3 includes total wealth and human capital, and Specification 7 includes financial wealth and human capital. All specifications include changes in homeownership status, the number of children in the household, and age (starting with the 24-to-26 age change and ending with the 83-to-85 age change), and year dummies. The wealth-variable coefficients are the 2-year growth rates.

	IV			Active Change in Wealth		
	(2)	(3)	(7)	(2)	(3)	(7)
owner	-0.00215	0.00567	0.0204	-0.000716	0.00601	0.0294
	(-0.11)	(0.28)	(1.03)	(-0.04)	(0.32)	(1.64)
kids	0.00153	0.000109	0.00148	0.0101	0.00865	0.00827
	(0.11)	(0.01)	(0.11)	(0.78)	(0.67)	(0.66)
ΔlogTW	0.0565**	0.0700**				
	(2.43)	(2.35)				
ΔlogLFA			0.0627***			
			(2.87)			
ΔlogTW^A				0.0600***	0.0741***	
				(7.00)	(7.46)	
ΔlogLFA^A						0.0715***
						(10.45)
ΔPVYW		0.000279	0.0000721		0.000244**	0.0000899
		(1.13)	(0.60)		(2.06)	(1.47)
N	4127	4118	4180	5041	5027	5069

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

(a) Mean



(b) Median

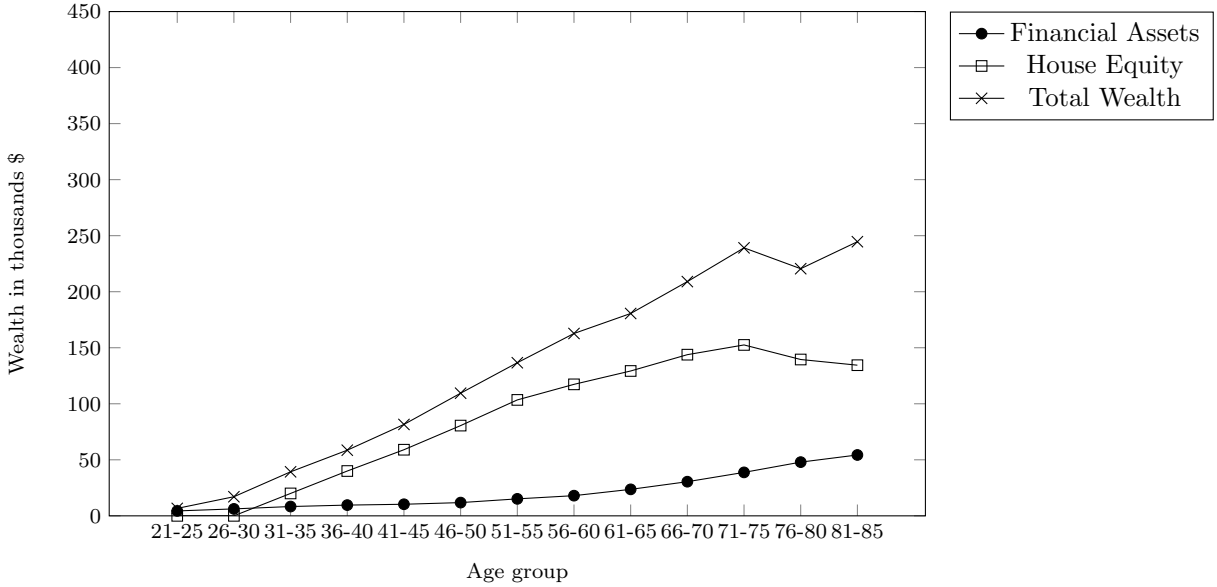


Figure 1: Wealth as a function of age

Figure 1 shows mean and median wealth as a function of age, for three wealth categories: total wealth, financial assets and home equity, as defined in Section 3.2. The data is taken from the PSID and corresponds to our baseline sample, which is obtained after applying the filters described in Section 3.1.

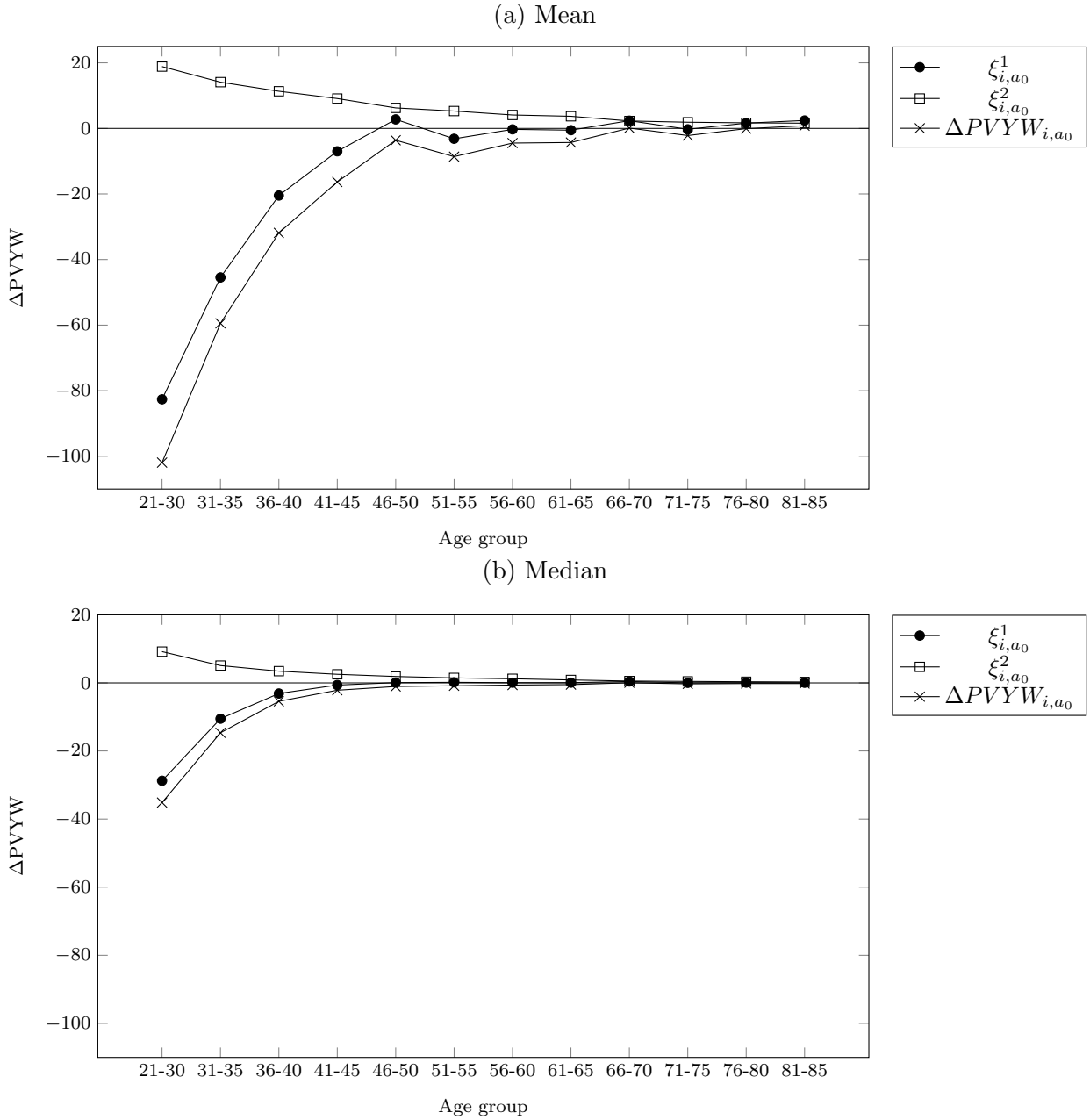


Figure 2: Summary of change in present value of income over wealth over age

Figure 2 shows mean and median values for changes in the ratio of human capital to total wealth ($\Delta PVYW_{i,a_0}$) as a function of age, as well as to its two components, ξ^1_{i,a_0} and ξ^2_{i,a_0}. Details on the calculation of these variables appear in Section 2.3.2. The data is taken from the PSID and corresponds to our baseline sample, which is obtained after applying the filters described in Section 3.1.

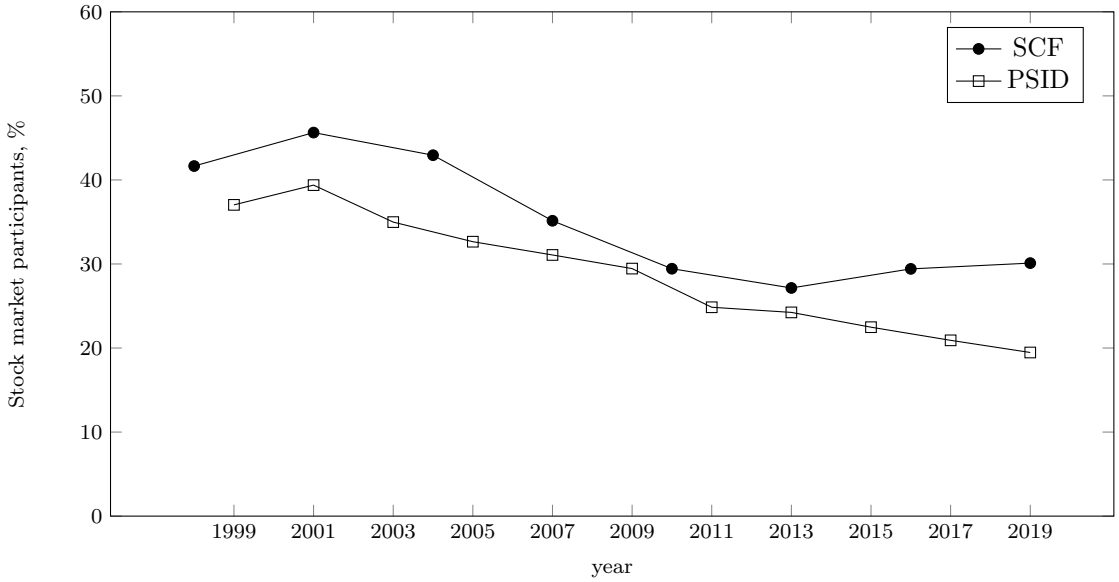


Figure 3: Average stock market participation, PSID sample and the full SCF

Figure 3 shows the average stock market participation from the filtered PSID data and the SCF. Stock market participation is equal to 1 if the value of an individual's risky financial assets is positive and 0 otherwise. For a clean comparison, we exclude wealth in retirement accounts when considering the SCF data.

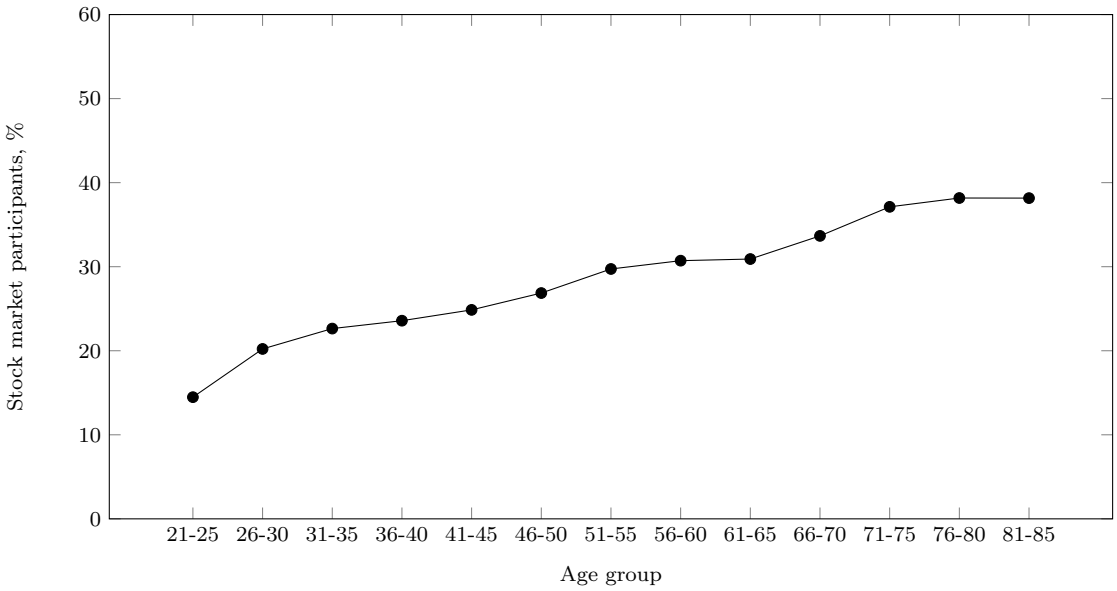


Figure 4: Average stock market participation over the life-cycle

Figure 4 shows the average stock market participation in our filtered PSID sample by age cohort. Stock market participation is equal to 1 if the value of an individual's risky financial assets is positive and 0 otherwise. Risky financial assets are shares of stock in publicly held corporations, stock mutual funds, or investment trusts (not including stocks in employer-based pensions or IRAs).

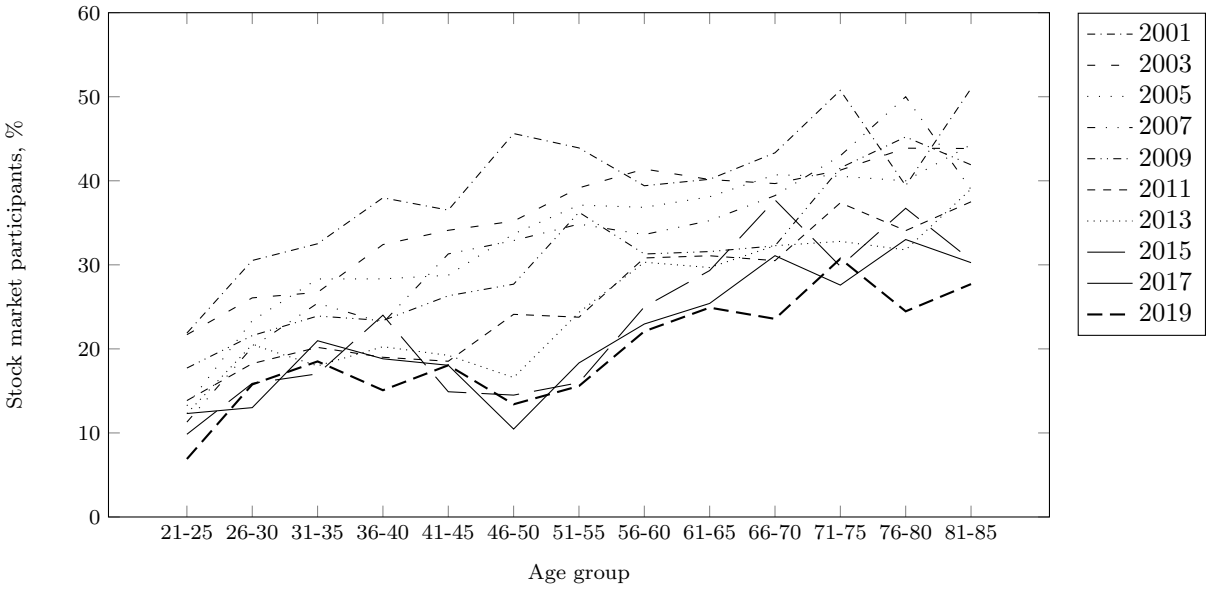


Figure 5: Average stock market participation over the life cycle (by PSID wave)

Figure 5 shows average stock market participation in the filtered PSID sample by age cohort in each separate wave of the data. Stock market participation is equal to 1 if the value of an individual's risky financial assets is positive and 0 otherwise. Risky financial assets are shares of stock in publicly held corporations, stock mutual funds, or investment trusts (not including stocks in employer-based pensions or IRAs).

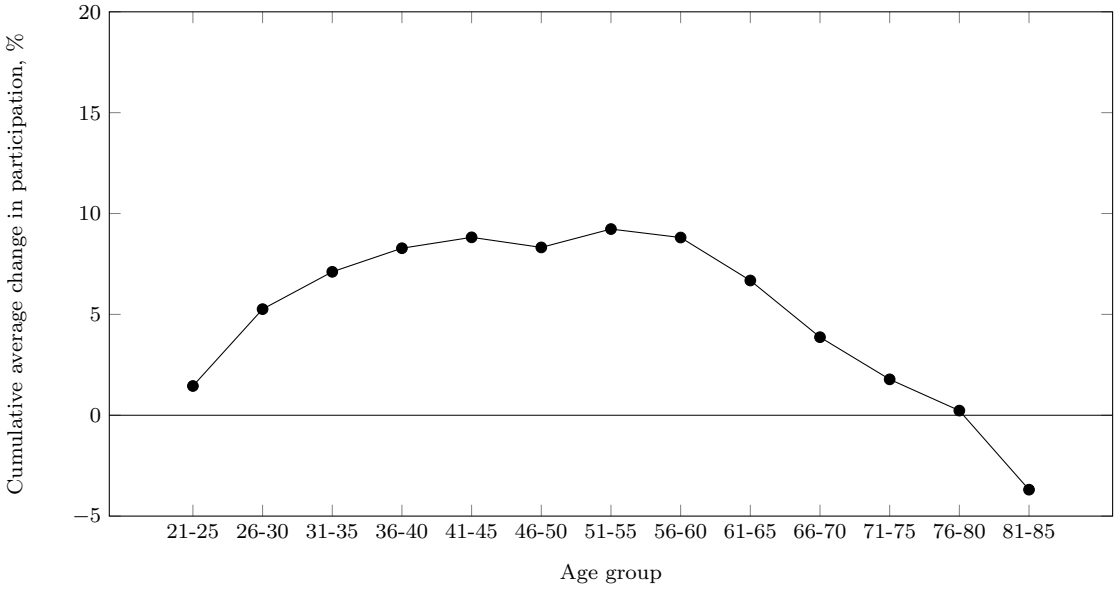
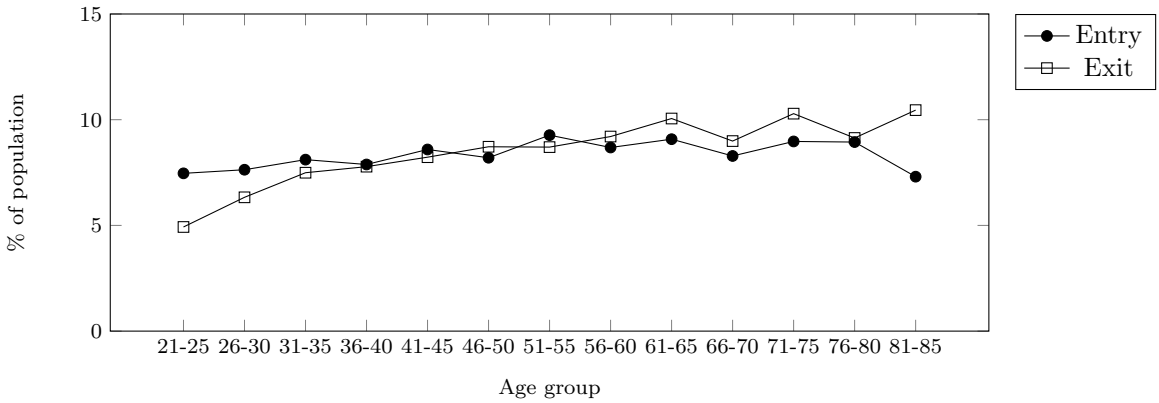


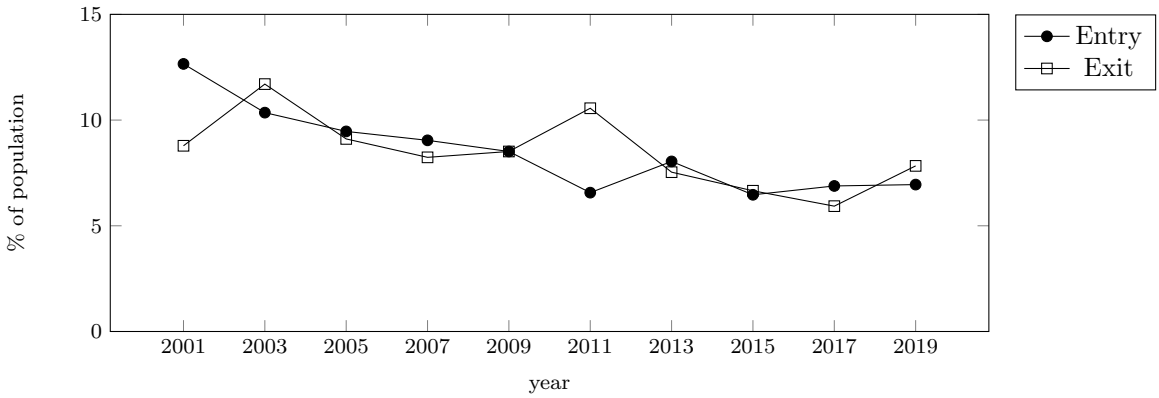
Figure 6: Cumulative average change in participation over the life cycle

Figure 6 shows the life-cycle profile of stock market participation calculated by first computing changes in participation at the individual level, and then averaging these by age. The life-cycle profile is generated by computing the cumulative changes over age.

(a) Entry and exit as share of total age population



(b) Entry and exit as share of total wave population



(c) Entry and exit as share of nonparticipants and participants

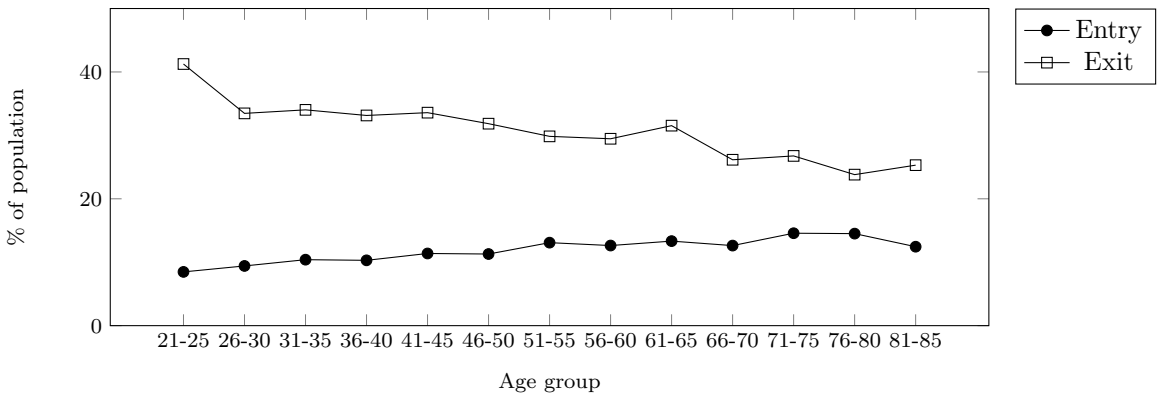


Figure 7: Entry and exit shares

Figure 7 shows stock market entry and exit shares in the filtered PSID sample. In Panel (a) entry and exit rates are scaled by the total population in each age group. Panel (b) shows entry and exit rates scaled by the total population in each wave. Panel (c) plots entry and exits relative to the fraction of nonparticipants and participants, respectively.

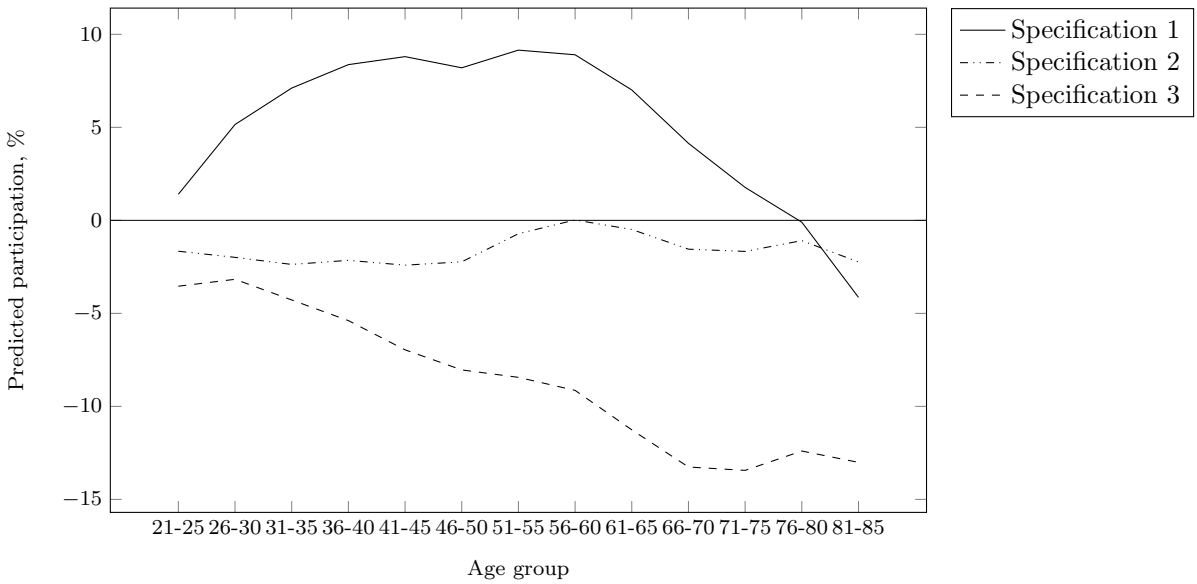


Figure 8: Predicted cumulative change in participation

Figure 8 shows the predicted cumulative change in stock market participation from OLS regressions of changes in participation on age and time dummies, wealth, human capital variables, and controls. For the estimation we considered our filtered PSID sample. Specification 1 includes only two control variables, change in homeownership status and change in the number of children in the household. Specification 2 also includes changes in total wealth and Specification 3 includes changes in the ratio of the present value of human capital to total wealth. Results are presented in 5-year age intervals to facilitate visual interpretation, but the model solution considers each age as the unit of analysis.

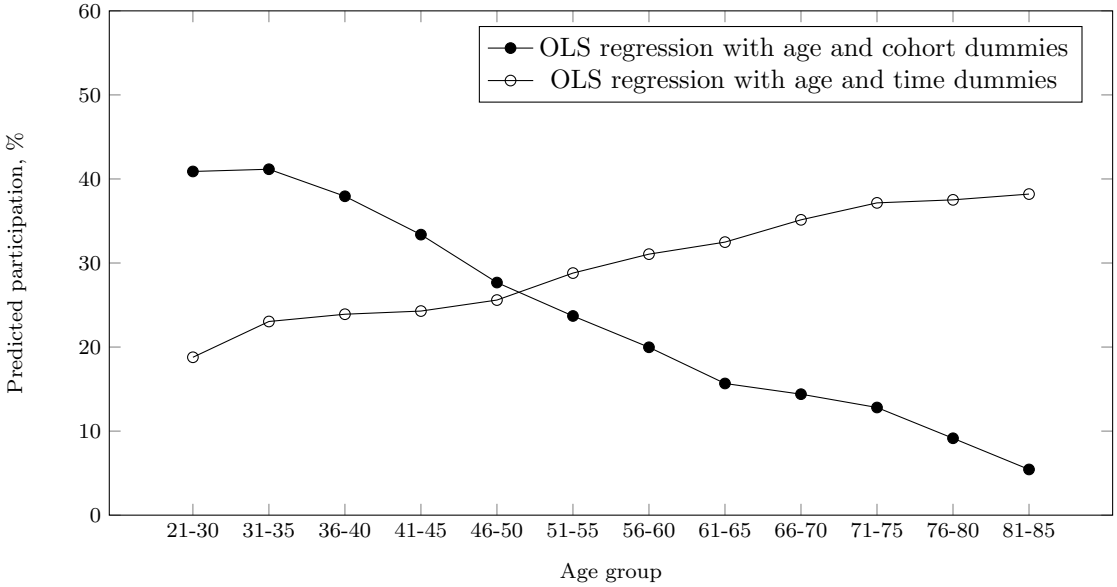


Figure 9: Time and cohort effects for predicted participation over age

Figure 9 shows predicted values for the cumulative change in participation implied by OLS regressions of changes in participation, considering either age and cohort dummies only or age and time dummies only. For the estimations, we use our filtered PSID sample, and predictions are made for the full filtered sample using actual observed values.

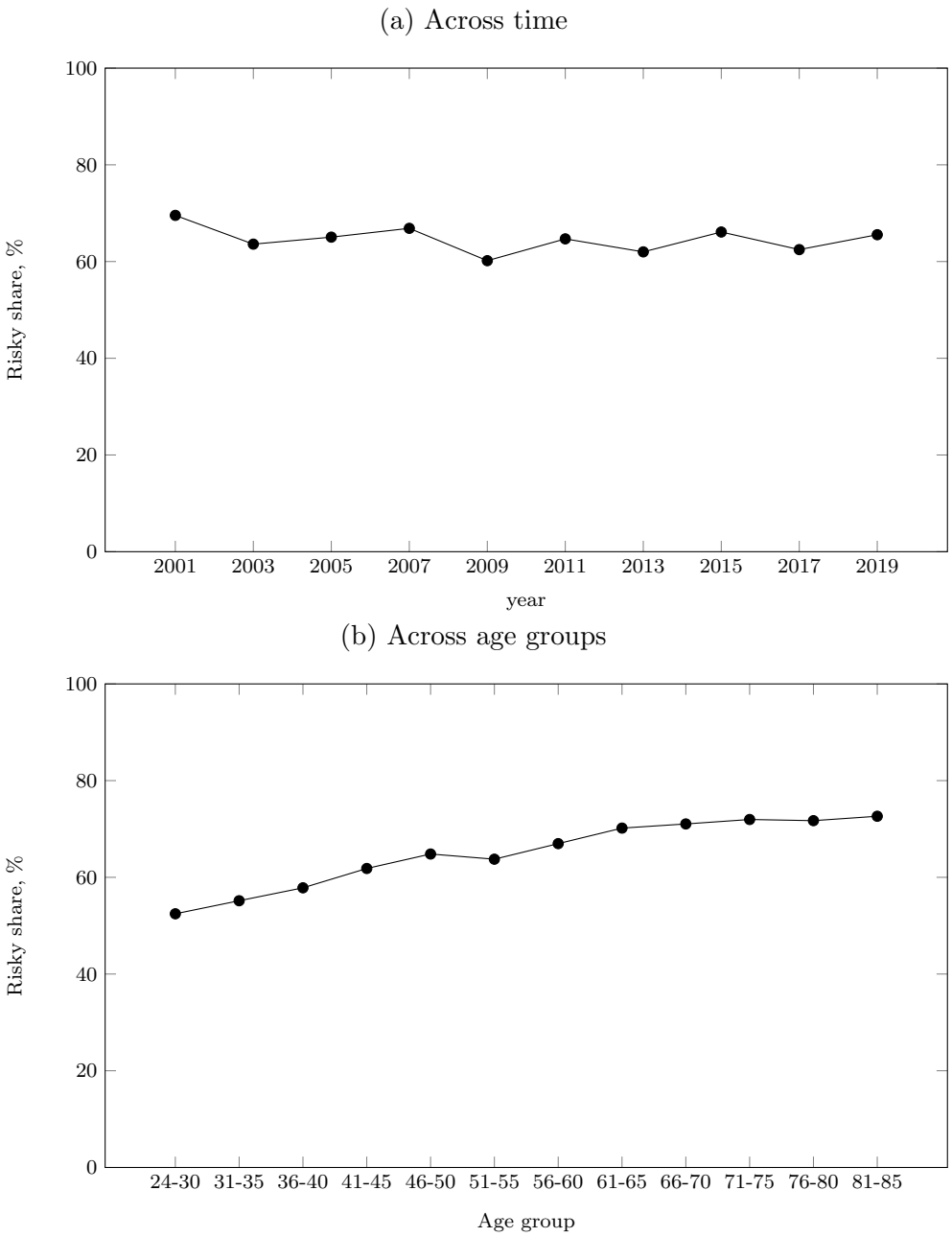


Figure 10: Average cross-sectional conditional risky share

Figure 10 shows the time and age profiles of the conditional risky share in our filtered PSID sample. The conditional risky share is the share of risky assets (shares of stock in publicly held corporations, stock mutual funds, or investment trusts excluding IRAs) in liquid financial assets of stock market participants.

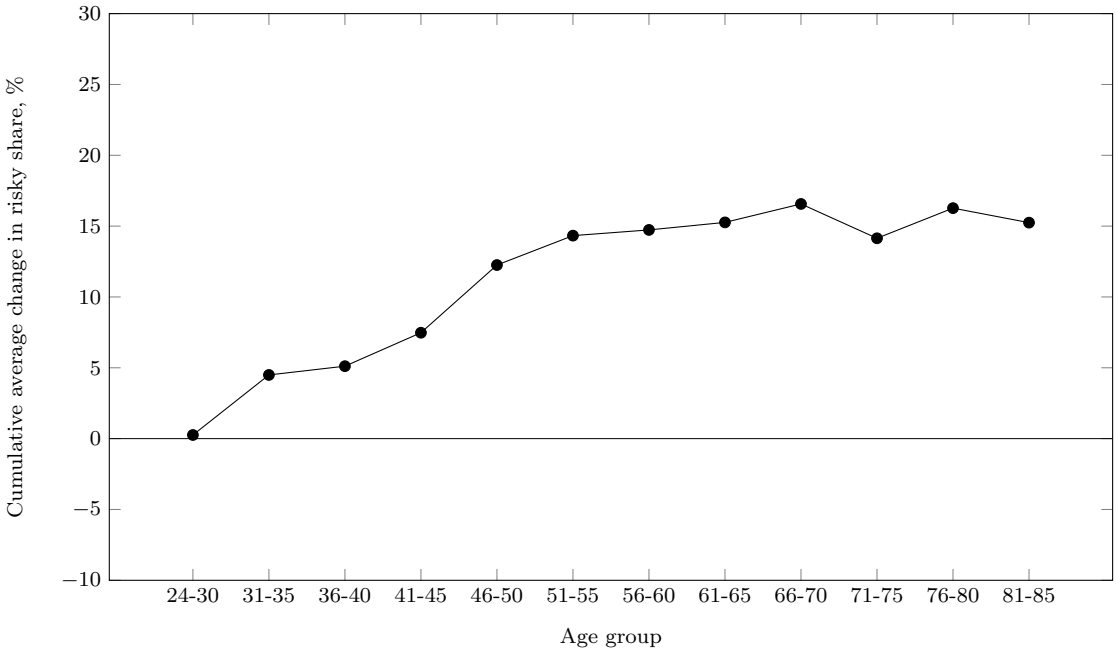


Figure 11: Cumulative average change in risky share over the life cycle

Figure 11 shows the life-cycle profile of the conditional risky share based on changes in the risky share at the individual level and then averaging these by age. The life-cycle profile is generated by computing the cumulative changes over age. Results are obtained from our filtered PSID sample.

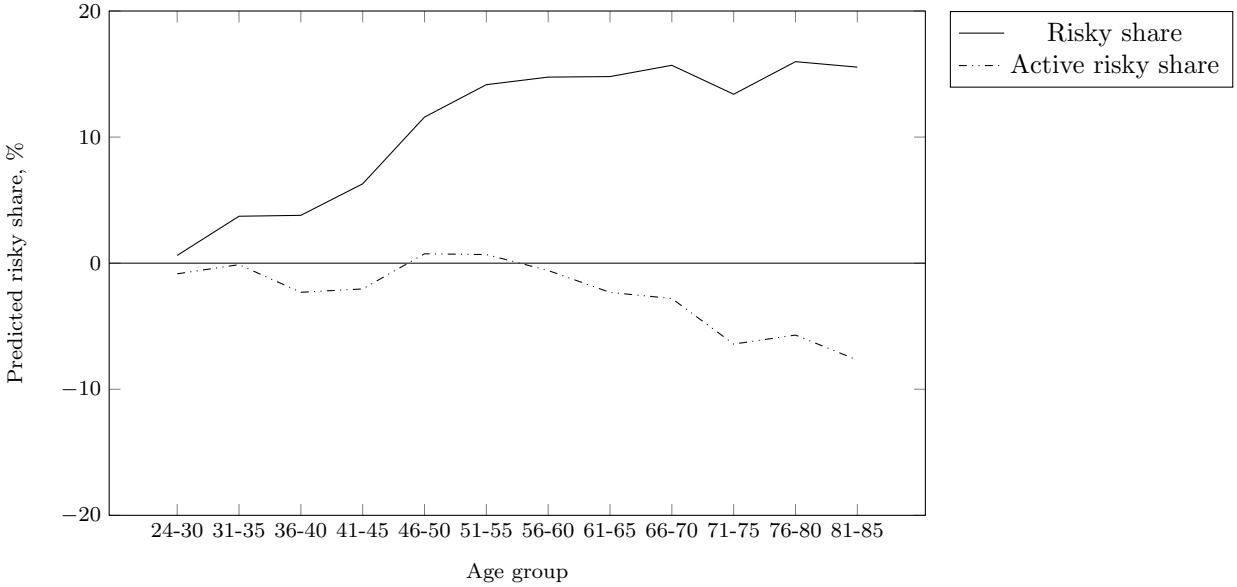


Figure 12: Predicted cumulative change in risky share

Figure 12 shows the predicted cumulative change in the risky share from OLS regressions of risky share on age and time dummies, change in homeownership status, and change in the number of children in the household, using our filtered PSID sample. This corresponds to Specification 1 in our regression tables. The figure includes results for both change in risky share, and active change in risky share (based on the value-weighted return on equities from CRSP to compute passive changes). Results are presented in 5-year age intervals to facilitate visual interpretation, but the model solution considers each age as the unit of analysis.

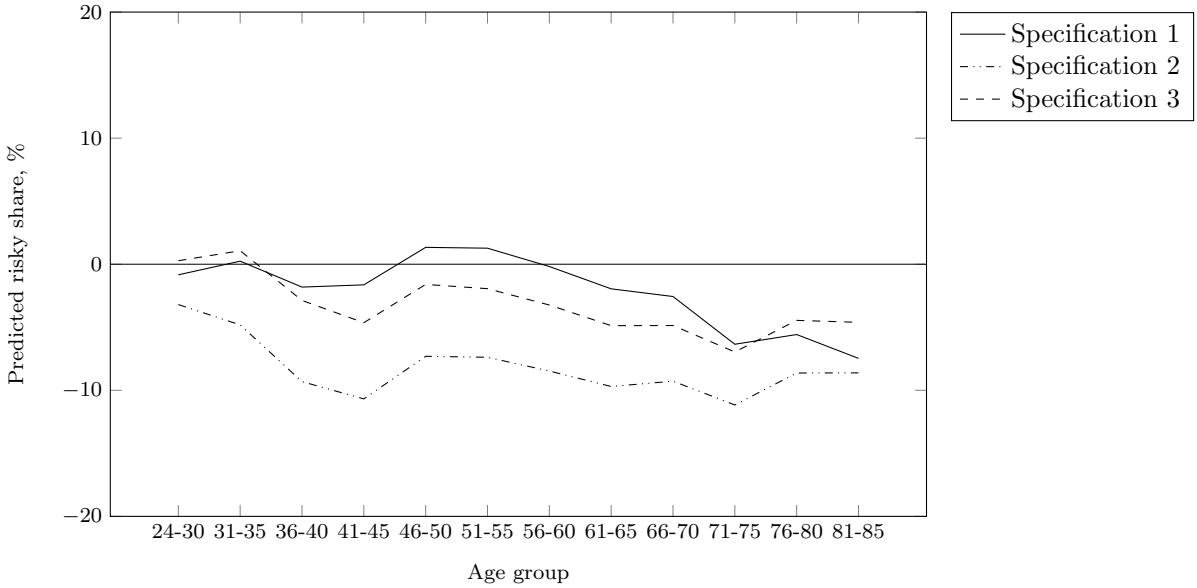


Figure 13: Predicted cumulative active change in risky share

Figure 13 shows the predicted cumulative active change in risky share from OLS regressions of active risky share on age and time dummies, wealth and human capital variables, and other controls, using our filtered PSID sample. We use the value-weighted return on equities from CRSP, which includes dividends, to calculate the active risky share. Specification 1 includes only two control variables, change in homeownership status and change in the number of children in the household. Specification 2 also includes changes in total wealth. Specification 3 also includes changes in the ratio of the present value of human capital to total wealth. Results are presented in 5-year age intervals to facilitate visual interpretation, but the model solution considers each age as the unit of analysis.

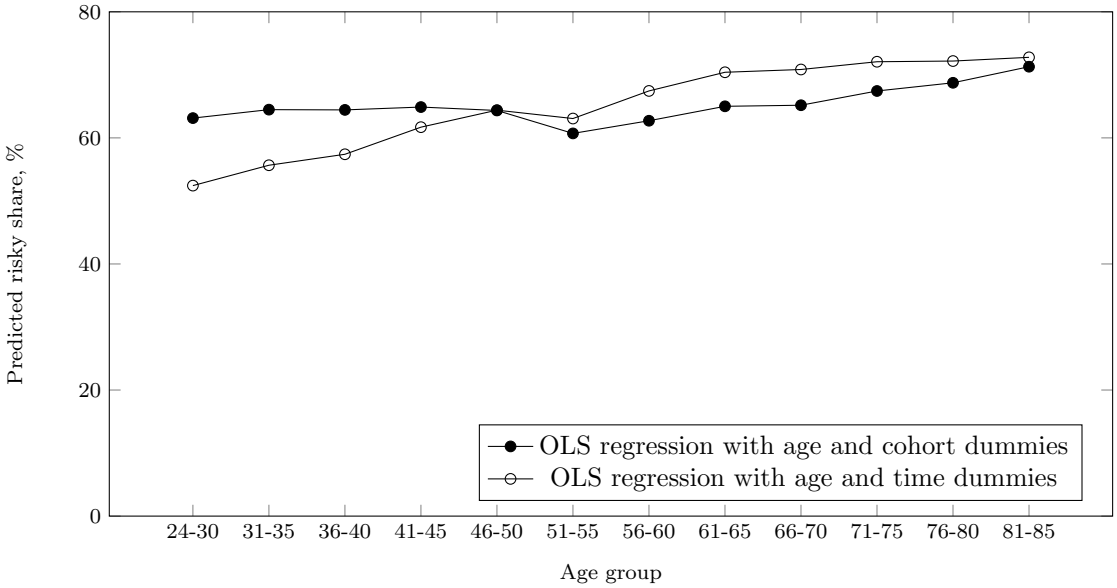


Figure 14: Time and cohort effects in predicted conditional risky share over age

Figure 14 shows the predicted values for the conditional risky share from OLS regressions of risky share on either age and cohort dummies or age and time dummies, using our filtered PSID sample. Predictions are made for the full filtered sample using actual observed values.

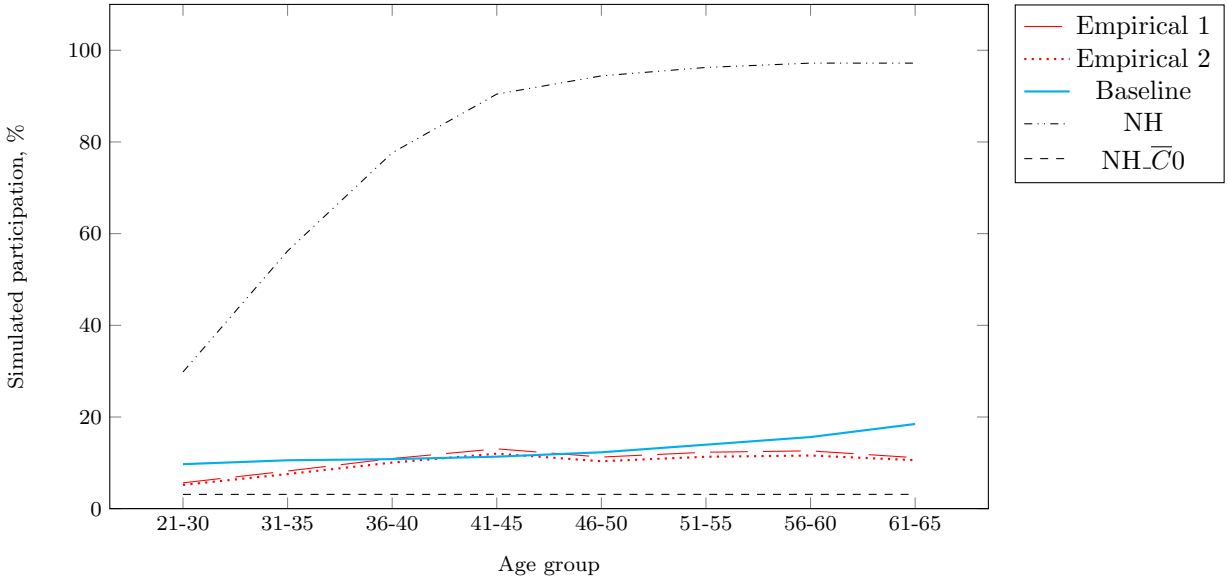


Figure 15: Cumulative change in participation

Figure 15 shows the cumulative change in participation from data and life-cycle model simulations. The values from the data correspond to our baseline estimation of predictive cumulative changes, adjusted to reflect participation through DC accounts using SCF data. The series "Empirical 1" assumes that participation in DC accounts follows the same life-cycle pattern as direct participation, while the series "Empirical 2" assumes that participation in DC accounts does not fall with age late in life. We plot results for three different versions of the life-cycle model: our baseline specification (model version:"Baseline"), without ex-ante household heterogeneity (model version: "NH"), and without ex-ante heterogeneity or consumption (model version: "NH_$\overline{C}$0").

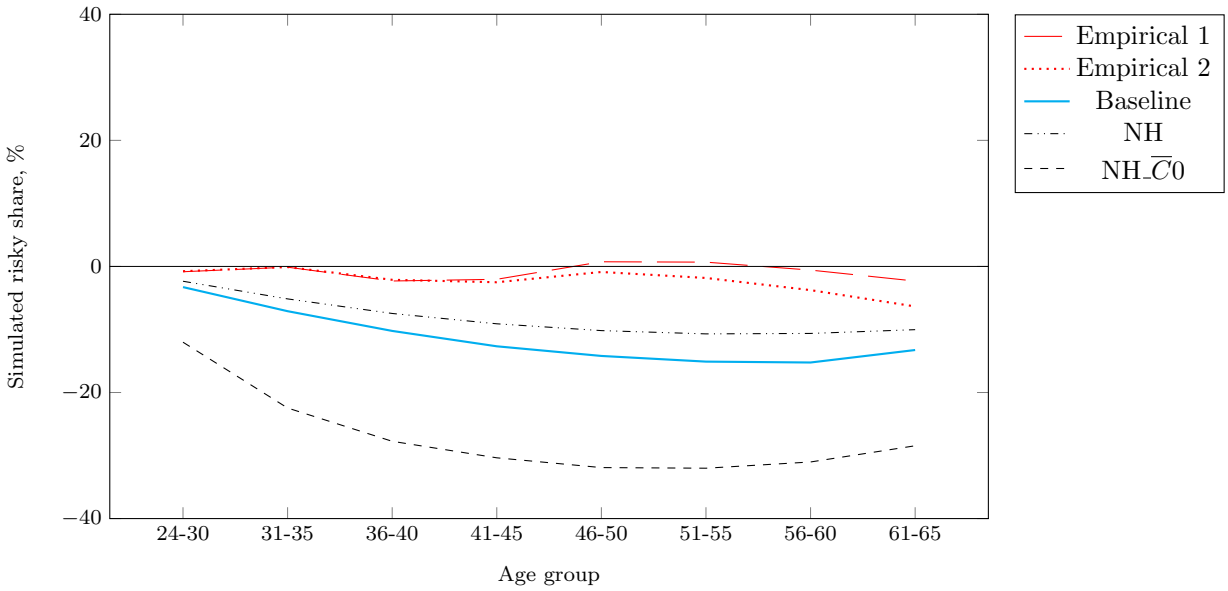


Figure 16: Cumulative change in risky share

Figure 16 shows the cumulative change in risky share from data and life-cycle model simulations. The series "Empirical 1" corresponds to our baseline estimation of predictive cumulative changes in the risky share. The series "Empirical 2" adjusts for the fact that a significant fraction of retirement wealth is being invested in Target-Date Funds (TDFs), which have a strong age profile for their risky share. We plot results for three different versions of the life-cycle model: our baseline specification (model version:"Baseline"), without ex-ante household heterogeneity (model version: "NH"), and without ex-ante heterogeneity or consumption (model version: "NH_$\overline{C}$0").

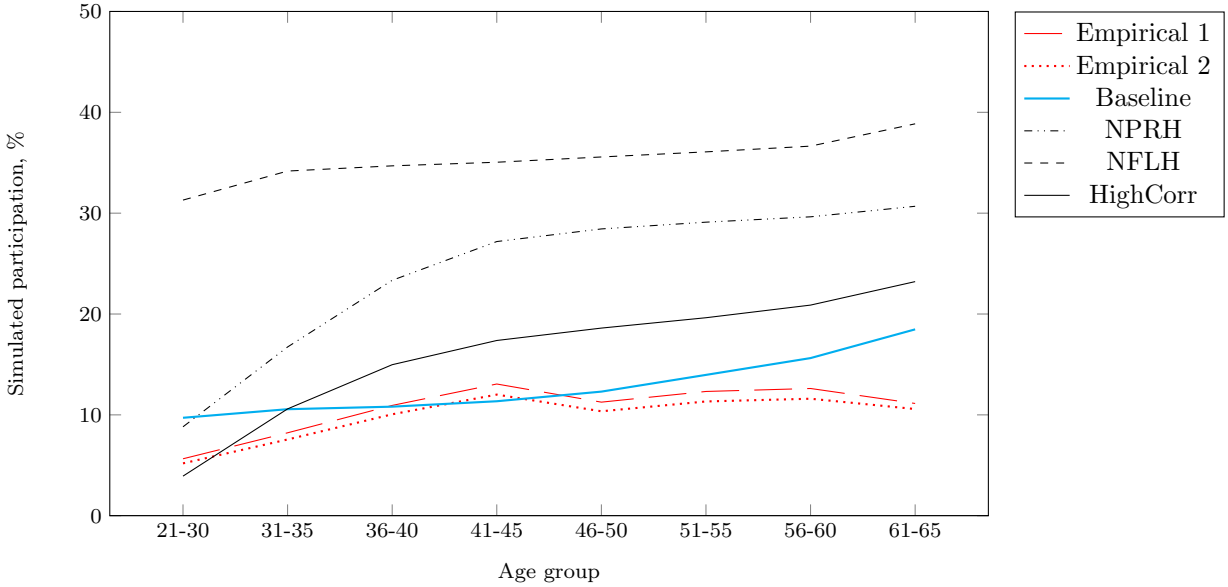


Figure 17: Cumulative change in participation

Figure 17 shows the cumulative change in participation from data and life-cycle model simulations. The values from the data correspond to our baseline estimation of predictive cumulative changes, adjusted to reflect participation through DC accounts using SCF data. The series "Empirical 1" assumes that participation in DC accounts follows the same life-cycle pattern as direct participation. The series "Empirical 2" assumes that participation in DC accounts does not fall with age late in life. We plot results for four different versions of the life-cycle model: our baseline specification (model version:"Baseline"), no ex-ante heterogeneity in financial literacy (model version:"NHFL"), no ex-ante heterogeneity in preferences and retirement income replacement ratio (model version: "NHPR"), and with a high-value correlation between stock returns and income shocks, namely a 0.2 correlation with both transitory and permanent income innovations (model version: "HighCorr").

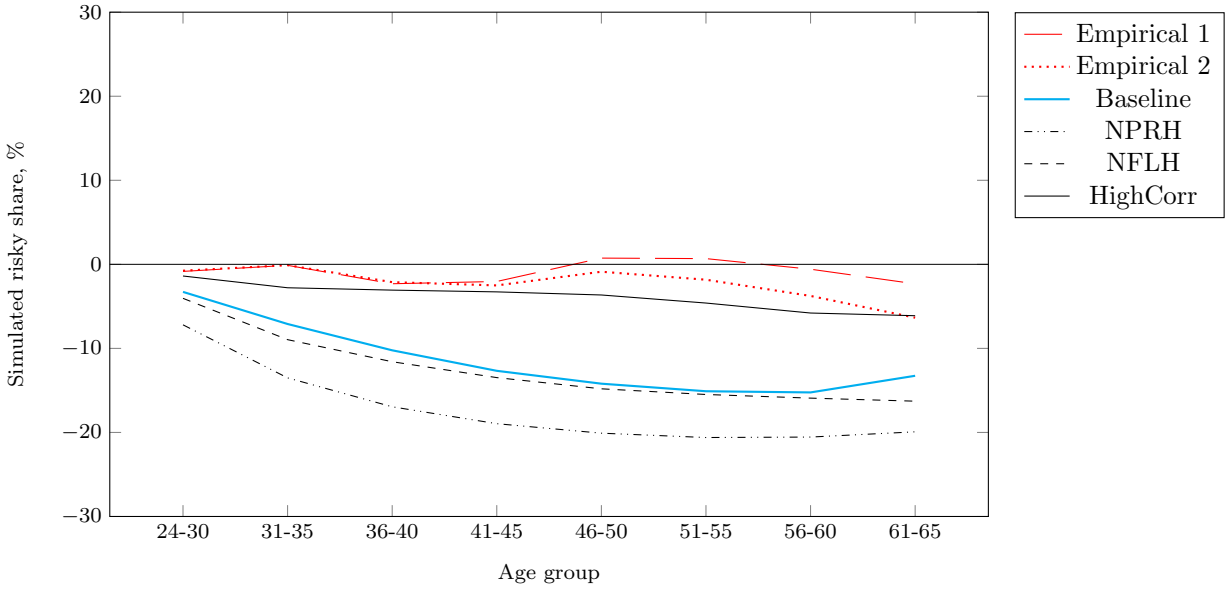


Figure 18: Cumulative change in risky share

Figure 18 shows the cumulative change in the risky share from data and life-cycle model simulations. The series "Empirical 1" corresponds to our baseline estimation of predictive cumulative changes in the risky share. The series "Empirical 2" adjusts for the fact that a significant fraction of retirement wealth is invested in Target-Date Funds (TDFs), which have a strong age profile for their risky share. We plot results for our baseline (model version:"Baseline"), no ex-ante heterogeneity in financial literacy (model version:"NHFL"), no ex-ante heterogeneity in preferences and retirement income replacement ratio (model version: "NHPR"), and with a high-value correlation between stock returns and income shocks, namely a 0.2 correlation with both transitory and permanent income innovations (model version: "HighCorr"). Results are presented in 5-year age intervals to facilitate visual interpretation, but the model solution considers each age as the unit of analysis.

Appendix 1: Probit Regressions for Stock Market Entry and Exit Decisions

Stock market participation is a binary variable, so its first difference can take one of three values (-1, 0 or 1). In our main analysis, we estimated linear regressions to facilitate the interpretation of the coefficients, and in line with our identification strategy for the age effects. In Appendix 1 we re-examine our conclusions regarding the impact of the wealth and human capital variables using Probit models.

Tables A1 and A2 report results for entry decisions while Tables A3 and A4 present results for exit decisions. Here we consider the more standard classification of entry and exit shares, given by equations (27) and (28), below we report results for the alternative definitions.

The conclusions are very similar to those previously obtained. Consistent with models of participation costs and the results in Brunnermeier and Nagel (2008), changes in wealth, and in particular changes in financial wealth, are positively (negatively) associated with stock market entry (exit). Changes in the ratio of human capital to total wealth are also positively (negatively) associated with stock market entry (exit), consistent with models where labor income is a close substitute for the riskless asset.

In Tables A5, A6,A7, A8 we report the results from regressions of stock market entry and exit using alternative definitions (25) and (26), where entry and exit rates are computed as a share of the total population. We consider the same eight regression specifications as the estimations reported above. The results for the two sets of regressions are qualitatively identical, and quantitatively very similar. Higher financial or total wealth predicts higher (lower) rates of stock market entry (exit). Likewise, an increase in the ratio of human capital to total wealth also predicts higher rates of stock market entry, and lower rates of stock market exit.

Table A1: Regression results for entries (with total wealth)

Table A1 reports results of probit regressions of stock market entries (as a share of total stock market nonparticipants in the previous wave) on wealth, human capital variables, and controls. The numbers reflect marginal effects on the probability of entry, evaluated at the sample means of the explanatory variables. Specification 1 in Column 2 includes only two control variables, change in homeownership status and change in the number of children in the household. Column 3 reports results for Specification 2, which includes changes in total wealth. Columns 4 and 5 show Specifications 3 and 4 with indicators for the ratio of the present value of human capital to total wealth. All specifications include changes in age (starting with the 21-to-23 age change and ending with the 83-to-85 age change), and year dummies. The wealth-variable coefficients are the 2-year growth rates.

	(1)	(2)	(3)	(4)
owner	-0.00231	-0.00902	-0.0326***	-0.0192*
	(-0.29)	(-1.08)	(-3.04)	(-1.80)
kids	-0.0111*	-0.0123*	-0.0124*	-0.0121*
	(-1.72)	(-1.86)	(-1.76)	(-1.75)
ΔlogTW		0.00672***	0.0672***	0.0653***
		(6.54)	(19.09)	(18.46)
ΔPVYW			0.000127***	
			(7.86)	
ξ^1				-0.0000437
				(-1.58)
ξ^2				-0.00284***
				(-9.99)
N	19461	18777	16892	16892
pseudo R^2	0.022	0.024	0.059	0.073
chi2	282.6	317.1	639.9	649.5

cluster (id) robust t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A2: Regression results for entries (with liquid financial assets)

Table A2 reports results of probit regressions of stock market entries (as a share of total stock market nonparticipants in the previous wave) on liquid financial assets, human capital variables, and controls. The numbers reflect the marginal effects on the probability of entry, evaluated at the sample means of the explanatory variables. Column 2 reports results for Specification 5, which includes changes in liquid financial assets. Specification 6 in Column 3 includes liquid financial assets and home equity. Columns 4 and 5 show Specifications 7 and 8 with liquid financial assets and indicators for the ratio of the present value of human capital to liquid financial assets. All specifications include changes in homeownership status, the number of children in the household, and age (starting with the 21-to-23 age change and ending with the 83-to-85 age change), and year dummies. The wealth-variable coefficients are the 2-year growth rates.

	(5)	(6)	(7)	(8)
owner	-0.00402	-0.0504**	-0.00279	-0.00129
	(-0.50)	(-2.10)	(-0.31)	(-0.16)
kids	-0.0129**	-0.0180**	-0.00256	0.00579
	(-2.01)	(-2.19)	(-0.37)	(0.90)
ΔlogLFA	0.0107***	0.0150***	0.0856***	0.0731***
	(14.92)	(15.10)	(31.03)	(24.81)
ΔlogHE		0.00219		
		(1.01)		
ΔPVYW			0.0000758***	
			(10.12)	
ξ^1				-0.0000709***
				(-4.80)
ξ^2				-0.00203***
				(-16.98)
N	19460	13375	15364	15364
pseudo R^2	0.034	0.041	0.154	0.192
chi2	494.1	446.3	1243.0	1384.5

cluster-robust t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A3: Regression results for exits (with total wealth)

Table A3 reports results of probit regressions of stock market exits (as a share of total stock market participants in the previous wave) on wealth, human capital variables, and controls. The numbers reflect the marginal effects on the probability of entry, evaluated at the sample means of the explanatory variables. Specification 1 in Column 2 includes only two control variables, change in homeownership status and change in the number of children in the household. Column 3 reports results for Specification 2, which includes changes in total wealth. Columns 4 and 5 show Specifications 3 and 4 with indicators for the ratio of the present value of human capital to total wealth. All specifications include changes in age (starting with the 21-to-23 age change and ending with the 83-to-85 age change), and year dummies. The wealth-variable coefficients are the 2-year growth rates.

	(1)	(2)	(3)	(4)
owner	0.0298	0.0449*	0.0400	0.0240
	(1.30)	(1.83)	(1.59)	(0.95)
kids	0.0298*	0.0333*	0.0315*	0.0322*
	(1.79)	(1.93)	(1.83)	(1.87)
ΔlogTW		-0.116***	-0.153***	-0.155***
		(-11.62)	(-16.48)	(-16.65)
ΔPVYW			-0.000241***	
			(-3.85)	
ξ^1				-0.0000218
				(-0.32)
ξ^2				0.00768***
				(7.19)
N	7400	7301	7248	7248
pseudo R^2	0.019	0.054	0.063	0.072
chi2	166.2	289.9	435.8	484.8

cluster (id) robust t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A4: Regression results for exits (with liquid financial assets)

Table A4 reports results of probit regressions of stock market exits (as a share of total stock market participants in the previous wave) on liquid financial assets, human capital variables, and controls. The numbers reflect the marginal effects on the probability of entry, evaluated at the sample means of the explanatory variables. Column 2 reports results for Specification 5, which includes changes in liquid financial assets. Specification 6 in Column 3 includes liquid financial assets and home equity. Columns 4 and 5 show Specifications 7 and 8 with liquid financial assets and indicators for the ratio of the present value of human capital to liquid financial assets. All specifications include changes in homeownership status, the number of children in the household, and age (starting with the 21-to-23 age change and ending with the 83-to-85 age change), and year dummies. The wealth-variables coefficients are the 2-year growth rates.

	(5)	(6)	(7)	(8)
owner	-0.0100	-0.174**	-0.00367	-0.00971
	(-0.41)	(-2.35)	(-0.15)	(-0.39)
kids	0.0253	0.0169	0.0245	0.0198
	(1.46)	(0.92)	(1.41)	(1.12)
ΔlogLFA	-0.163***	-0.173***	-0.163***	-0.169***
	(-29.20)	(-28.67)	(-24.53)	(-25.71)
ΔlogHE		0.0103		
		(1.61)		
ΔPVYW			0.0000425	
			(1.09)	
ξ^1				0.000242***
				(5.71)
ξ^2				0.00838***
				(11.10)
N	7400	6231	7279	7279
pseudo R^2	0.167	0.186	0.172	0.217
chi2	919.0	884.9	969.3	1133.1

cluster-robust t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A5: Regression results for entries (as share of all, with total wealth)

Table A5 reports results of probit regressions of stock market entries (as share of all) on wealth, human capital variables, and controls. The numbers reflect marginal effects on the probability of entry, evaluated at the sample means of the explanatory variables. Specification 1 in Column 2 includes only two control variables, change in homeownership status and change in the number of children in the household. Column 3 reports results for Specification 2, which includes changes in total wealth. Columns 4 and 5 show Specifications 3 and 4 with indicators for the ratio of the present value of human capital to total wealth. All specifications include changes in age (starting with the 21-to-23 age change and ending with the 83-to-85 age change), and year dummies. The wealth-variable coefficients are the 2-year growth rates.

	(1)	(2)	(3)	(4)
owner	0.00374	-0.00442	-0.0220***	-0.0169**
	(0.62)	(-0.71)	(-2.87)	(-2.21)
kids	-0.00590	-0.00687	-0.00587	-0.00563
	(-1.23)	(-1.40)	(-1.18)	(-1.14)
ΔlogTW		0.00972***	0.0528***	0.0524***
		(12.00)	(20.89)	(20.60)
ΔPVYW			0.0000860***	
			(6.89)	
ξ^1				0.00000560
				(0.29)
ξ^2				-0.00138***
				(-7.51)
N	26861	26078	24134	24134
pseudo R^2	0.011	0.018	0.053	0.058
chi2	174.2	315.5	639.2	633.4

cluster (id) robust t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A6: Regression results for entries (as share of all, with financial wealth)

Table A6 reports results of probit regressions of stock market entries (as share of all) on wealth, human capital variables, and controls. The numbers reflect marginal effects on the probability of entry, evaluated at the sample means of the explanatory variables. Column 2 reports results for Specification 5, which includes changes in financial wealth. Specification 6 in Column 3 includes financial wealth and home equity. Columns 4 and 5 show Specifications 7 and 8 with financial wealth and indicators for the ratio of the present value of human capital to total wealth. All specifications include changes in homeownership status, number of children in the household, and age (starting with the 21-to-23 age change and ending with the 83-to-85 age change), and year dummies. The wealth-variable coefficients are the 2-year growth rates.

	(5)	(6)	(7)	(8)
owner	0.00152	-0.0283	0.00401	0.00513
	(0.26)	(-1.61)	(0.70)	(0.92)
kids	-0.00797*	-0.0103*	-0.000523	0.00196
	(-1.70)	(-1.81)	(-0.12)	(0.46)
ΔlogLFA	0.0130***	0.0166***	0.0557***	0.0525***
	(23.01)	(22.15)	(34.86)	(31.22)
ΔlogHE		0.00145		
		(0.92)		
ΔPVYW			0.0000334***	
			(6.41)	
ξ^1				-0.0000208**
				(-2.31)
ξ^2				-0.000743***
				(-10.68)
N	26860	19606	22637	22637
pseudo R^2	0.041	0.052	0.150	0.160
chi2	761.0	700.2	1351.7	1405.9

cluster-robust t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A7: Regression results for exits (as share of all, with total wealth)

Table A7 reports results of probit regressions of stock market exits (as a share of all) on wealth, human capital variables, and controls. The numbers reflect marginal effects on the probability of entry, evaluated at the sample means of the explanatory variables. Specification 1 in Column 2 includes only two control variables, change in homeownership status and change in the number of children in the household. Column 3 reports results for Specification 2, which includes changes in total wealth. Columns 4 and 5 show Specifications 3 and 4 with indicators for the ratio of the present value of human capital to total wealth. All specifications include changes in age (starting with the 21-to-23 age change and ending with the 83-to-85 age change), and year dummies. The wealth-variable coefficients are the 2-year growth rates.

	(1)	(2)	(3)	(4)
owner	-0.00524	-0.00304	-0.00623	-0.000297
	(-0.83)	(-0.47)	(-0.82)	(-0.04)
kids	0.00317	0.00445	0.00502	0.00488
	(0.67)	(1.03)	(1.00)	(1.00)
ΔlogTW		-0.0361***	-0.0505***	-0.0508***
		(-20.60)	(-18.82)	(-18.58)
ΔPVYW			-0.0000630***	
			(-5.61)	
ξ^1				-0.000140***
				(-7.53)
ξ^2				-0.00188***
				(-8.74)
N	26861	26078	24188	24188
pseudo R^2	0.014	0.058	0.048	0.057
chi2	233.7	505.6	574.5	608.7

cluster-robust t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A8: Regression results for exits (as share of all, with financial wealth)

Table A8 reports results of probit regressions of stock market exits (as share of total stock market participants in previous wave) on wealth, human capital variables, and controls. The numbers reflect marginal effects on the probability of entry, evaluated at the sample means of the explanatory variables. Column 2 reports results for Specification 5, which includes changes in financial wealth. Specification 6 in Column 3 includes financial wealth and home equity. Columns 4 and 5 show Specifications 7 and 8 with financial wealth and indicators for the ratio of the present value of human capital to total wealth. All specifications include changes in homeownership status, the number of children in the household, and age (starting with the 21-to-23 age change and ending with the 83 to 85 age change), and year dummies. The wealth-variable coefficients are the 2-year growth rates.

	(5)	(6)	(7)	(8)
owner	-0.00671*	-0.0420***	-0.00988	-0.00916
	(-1.80)	(-3.48)	(-1.52)	(-1.46)
kids	0.00246	0.00143	0.00449	0.00699
	(0.91)	(0.40)	(0.97)	(1.54)
ΔlogLFA	-0.0345***	-0.0428***	-0.0649***	-0.0593***
	(-43.47)	(-41.14)	(-35.30)	(-29.10)
ΔlogHE		0.00227**		
		(2.20)		
ΔPVYW			-0.0000379***	
			(-6.40)	
ξ^1				-0.0000583***
				(-7.66)
ξ^2				-0.000942***
				(-10.21)
N	26860	19606	22687	22687
pseudo R^2	0.180	0.188	0.153	0.165
chi2	1426.0	1298.0	1334.2	1362.4

cluster-robust t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Appendix 2: Regression Results with Alternative Total Wealth Definition

In Appendix 2 we report the results from re-estimating our regressions for changes in participation, stock market entry, stock market exit and change in risky share with our second definition of total wealth (NTW), in which we also consider uncollateralized debt. The results are shown in Tables A9, A10, A11, and A12, respectively, for the four endogenous variables. To facilitate the comparison, each table considers the same set of specifications as the corresponding table in the main paper.

The results are qualitatively identical, and very similar quantitatively, to those obtained using the alternative definition of total wealth. Higher total net wealth predicts an increase in stock market participation, higher stock market entry and lower stock market exit, and an increase in the conditional risky share. Likewise positive changes in the present value of future labor income to total net wealth also predict an increase in stock market participation, higher stock market entry and lower stock market exit, and an increase in the conditional risky share.

Table A9: Regression results for changes in participation

Table A9 reports results of OLS regressions of changes in participation on wealth, human capital variables, and controls. Compared to Table 3, Total Wealth in this setting also takes non-mortgage debt into account. Specification 1 in Column 2 includes only two control variables, change in homeownership status and change in the number of children in the household. Column 3 reports results for Specification 2, which includes changes in total wealth. Columns 4 and 5 show Specifications 3 and 4 with indicators for the ratio of the present value of human capital to total wealth. All specifications include changes in age (starting with the 21-to-23 age change and ending with the 83 to 85 age change), and year dummies. The wealth-variable coefficients are the 2-year growth rates. Since total wealth does not enter Specification 1, the result in the corresponding column is identical to the one previously reported.

	(1)	(2)	(3)	(4)
owner	0.00948	-0.0163	0.00365	0.00267
	(1.11)	(-1.43)	(0.29)	(0.21)
kids	-0.00875	-0.00932	-0.00912	-0.00906
	(-1.29)	(-1.14)	(-1.07)	(-1.06)
ΔlogTW		0.0400***	0.131***	0.131***
		(17.78)	(22.14)	(22.14)
ΔPVYW			0.000429***	
			(12.10)	
ξ^1				0.000451***
				(10.83)
ξ^2				-0.000208
				(-0.83)
N	26861	21081	20177	20177
adj. R^2	0.002	0.021	0.050	0.050
F	1.801	6.150	8.811	8.717

cluster-robust t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A10: Regression results for entries

Table A10 reports results of probit regressions of stock market entries (as the share of total stock market nonparticipants in the previous wave) on wealth, human capital variables, and controls. Compared to Table A1, Total Wealth in this setting also takes non-mortgage debt into account. The numbers reflect marginal effects on the probability of entry, evaluated at the sample means of the explanatory variables. Specification 1 in Column 2 includes only two control variables, change in homeownership status and change in the number of children in the household. Column 3 reports results for Specification 2, which includes changes in total wealth. Columns 4 and 5 show Specifications 3 and 4 with indicators for the ratio of the present value of human capital to total wealth. All specifications include changes in age (starting with the 21-to-23 age change and ending with the 83 to 85 age change), and year dummies. The wealth-variable coefficients are the 2-year growth rates. Since total wealth does not enter Specification 1, the result in the corresponding column is identical to the one previously reported.

	(1)	(2)	(3)	(4)
owner	-0.00231	-0.0116	-0.00974	0.00539
	(-0.29)	(-1.00)	(-0.70)	(0.38)
kids	-0.0111*	-0.0143*	-0.0139*	-0.0149*
	(-1.72)	(-1.75)	(-1.65)	(-1.81)
ΔlogTW		0.0116***	0.0827***	0.0808***
		(8.18)	(18.27)	(17.38)
ΔPVYW			0.000311***	
			(9.47)	
ξ^1				0.00000168
				(0.03)
ξ^2				-0.00453***
				(-7.99)
N	19461	14328	13449	13449
pseudo R^2	0.022	0.025	0.062	0.074
chi2	282.6	283.3	542.2	529.9

cluster (id) robust t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A11: Regression results for exits

Table A11 reports results of probit regressions of stock market exits (as share of total stock market participants in previous wave) on wealth, human capital variables, and controls. Compared to Table A3, Total Wealth in this setting also takes non-mortgage debt into account. The numbers reflect marginal effects, the effect on the probability of entry evaluated at the sample means of the explanatory variables. The numbers reflect marginal effects on the probability of exit, evaluated at the sample means of the explanatory variables. Specification 1 in Column 2 includes only two control variables, change in homeownership status and change in the number of children in the household. Column 3 reports results for Specification 2 which includes changes in total wealth. Columns 4 and 5 show Specifications 3 and 4 with indicators for the ratio of the present value of human capital to total wealth. All specifications include changes in age (starting with the 21-to-23 age change and ending with the 83 to 85 age change), and year dummies. The wealth-variable coefficients are the 2-year growth rates. Since total wealth does not enter Specification 1, the result in the corresponding column is identical to the one previously reported.

	(1)	(2)	(3)	(4)
owner	0.0298	0.0343	0.0208	-0.00184
	(1.30)	(1.21)	(0.71)	(-0.06)
kids	0.0298*	0.0231	0.0270	0.0274
	(1.79)	(1.28)	(1.49)	(1.51)
ΔlogTW		-0.110***	-0.159***	-0.156***
		(-11.69)	(-16.18)	(-16.02)
ΔPVYW			-0.000580***	
			(-6.82)	
ξ^1				-0.0000976
				(-0.92)
ξ^2				0.00938***
				(7.12)
N	7400	6753	6705	6705
pseudo R^2	0.019	0.053	0.064	0.071
chi2	166.2	281.8	393.1	440.2

cluster-robust t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A12: Regression results for changes in risky share

Table A12 reports results of OLS regressions of changes in conditional risky share on wealth, human capital variables, and controls. Compared to Table 7, Total Wealth in this setting also takes non-mortgage debt into account. Sample comprises only stock market participants in current and previous waves. Specification 1 in Column 2 includes only two control variables, change in homeownership status and change in the number of children in the household. Column 3 reports results for Specification 2, which includes changes in total wealth. Columns 4 and 5 show Specifications 3 and 4 with indicators for the ratio of the present value of human capital to total wealth. All specifications include changes in age (starting with the 24-to-26 age change and ending with the 83 to 85 age change), and year dummies. The wealth-variable coefficients are the 2-year growth rates. Since total wealth does not enter Specification 1, the result in the corresponding column is identical to the one previously reported.

	(1)	(2)	(3)	(4)
owner	0.0102	-0.00653	0.00581	0.00291
	(0.55)	(-0.31)	(0.27)	(0.14)
kids	0.0109	0.00737	0.00901	0.00852
	(0.83)	(0.54)	(0.66)	(0.62)
ΔlogTW		0.0687***	0.0900***	0.0906***
		(8.46)	(8.69)	(8.68)
ΔPVYW			0.000528***	
			(3.70)	
ξ^1				0.000691***
				(3.51)
ξ^2				0.00196
				(1.06)
N	5094	4756	4740	4740
adj. R^2	0.007	0.035	0.040	0.040
F	1.452	2.641	2.758	2.724

cluster-robust t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Appendix 3: Robustness to the Calculation of the Present-Value of Human Capital

Since we don't observe the separate realizations of permanent and transitory income shocks for each individual, in the calculation of the present-value of future labor income (Equation (11)), we assumed that the current realization of the transitory shock equals its expected mean (zero). Since this is only about the one-year realization of the transitory income shock, this particular assumption is unlikely to impact the results significantly. In this Appendix we confirm this by excluding observations for which the realization of the transitory shock is likely to have been more significantly different from the mean. More precisely we exclude all observations for which the growth rate of income was either one standard deviation higher or lower than its unconditional mean.[69]

The results for stock market participation are reported in Table A13 while the results for the active risky share are presented in Table A14. In both cases we obtain the same conclusions as before. The coefficients on the wealth variables (except for home equity) are all positive and highly statistically significant, confirming the evidence in favor of stock market participation costs and DRRA. Likewise, the coefficient on human capital is also positive and highly statistically significant, confirming that human capital is a closer substitute for bonds than for stocks.

[69]Results where we exclude realizations for which the growth rate of income was either two standard deviations higher or lower than the unconditional mean are available upon request. They are naturally more conservative, and therefore also consistent with our baseline estimates.

Table A13: Regression results for changes in stock market participation

Table A13 reports results of OLS regressions of changes in participation on wealth, human capital variables, and controls. Compared to Tables 3 and 5, the data for the analysis includes only individuals with growth of family income falling within one standard deviation window. Specification 1 in Column 2 has only two control variables, change in homeownership status and change in the number of children in the household. Specification 2 in Column 3 additionally includes change in total wealth. Column 4 show Specification 3 with total wealth and indicator for the ratio of the present value of human capital to total wealth. The last three columns show Specifications 5 to 7 which have change in liquid financial assets, change in home equity and change in present value of income over liquid financial wealth. All specifications include changes in age (starting with the 21-to-23 age change and ending with the 83 to 85 age change), and year dummies. The wealth-variable coefficients are the 2-year growth rates.

	(1)	(2)	(3)	(5)	(6)	(7)
owner	0.00714	-0.0142	-0.0162	0.00298	-0.00672	0.0188*
	(0.81)	(-1.56)	(-1.59)	(0.34)	(-0.22)	(1.90)
kids	-0.00702	-0.00863	-0.0101	-0.0125*	-0.0166*	-0.00361
	(-0.96)	(-1.16)	(-1.28)	(-1.74)	(-1.90)	(-0.46)
ΔlogTW		0.0329***	0.113***			
		(18.82)	(21.18)			
ΔlogLFA				0.0441***	0.0552***	0.157***
				(30.35)	(27.54)	(38.12)
ΔlogHE					-0.000169	
					(-0.06)	
ΔPVYW			0.000193***			0.000116***
			(9.26)			(10.33)
N	23845	23128	21731	23844	17863	20418
adj. R^2	0.002	0.017	0.043	0.065	0.081	0.167
F	1.460	6.210	8.252	14.23	12.01	26.17

cluster-robust t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A14: Regression results for changes in risky share

Table A14 reports results of OLS regressions of active change in risky share on wealth, human capital variables, and controls. Compared to Tables 9 and 10, the data for the analysis includes only individuals with growth of family income falling within one standard deviation window. Specification 1 in Column 2 has only two control variables, change in homeownership status and change in the number of children in the household. Specification 2 in Column 3 additionally includes change in total wealth. Column 4 show Specification 3 with total wealth and indicator for the ratio of the present value of human capital to total wealth. The last three columns show Specifications 5 to 7 which have change in liquid financial assets, change in home equity and change in present value of income over liquid financial wealth. All specifications include changes in age (starting with the 24-to-26 age change and ending with the 83 to 85 age change), and year dummies. The wealth-variable coefficients are the 2-year growth rates.

	(1)	(2)	(3)	(5)	(6)	(7)
owner	0.0137	0.00595	0.0161	0.0292	0.0332	0.0818***
	(0.67)	(0.28)	(0.76)	(1.47)	(0.39)	(3.13)
kids	0.0134	0.0143	0.0113	0.0107	0.00943	0.0107
	(0.93)	(1.02)	(0.81)	(0.78)	(0.65)	(0.74)
ΔlogTW		0.0820***	0.101***			
		(8.95)	(9.45)			
ΔlogLFA				0.0714***	0.0771***	0.0866***
				(10.54)	(10.37)	(10.72)
ΔlogHE					0.00408	
					(0.56)	
dPVYW			0.000408***			0.000131
			(3.03)			(1.61)
N	4387	4342	4333	4387	3795	3786
adj. R^2	0.006	0.039	0.045	0.061	0.070	0.075
F	1.347	2.722	2.983	3.104	3.126	3.387

cluster-robust t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$