

# WHAT DRIVES INVESTORS' PORTFOLIO CHOICES? SEPARATING RISK PREFERENCES FROM FRICTIONS

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## Abstract

We study the role of risk preferences and frictions in portfolio choice, using variation in the default asset allocation of 401(k) plans. We estimate that, absent participation frictions, 94% of investors would prefer holding stocks in their retirement accounts, with an equity share of retirement wealth that declines over the life cycle. We use this variation to estimate a structural life cycle portfolio choice model with Epstein-Zin preferences, finding evidence consistent with relative risk aversion of 2.1 and a portfolio adjustment cost of \$200. Our results suggest that the lack of participation in the stock market is mainly due to participation frictions rather than non-standard preferences (e.g. loss-aversion).

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Many households, including those with significant financial wealth, do not participate in the stock market (Mankiw and Zeldes 1991; Guiso, Haliassos, and Jappelli 2002; Campbell 2006). This limited stock market participation is difficult to reconcile with standard economic theory, which predicts that all investors should hold at least a small amount of stocks in the presence of a positive equity premium (e.g., Merton 1969; Campbell and Viceira 2001).<sup>1</sup> In principle, an investor may choose to not allocate her financial wealth to the stock market for two reasons. First, she may prefer holding safe assets over stocks (e.g., due to loss aversion, ambiguity aversion, or pessimistic beliefs about returns). Alternatively, she may prefer holding stocks over safe assets but not participate due to frictions. These frictions could include the real costs of setting up and maintaining a brokerage account or the cognitive cost of making a financial plan and paying attention. Although these two explanations have similar predictions for the investor's stock market participation, distinguishing between the two mechanisms is important given their different normative implications. For example, interventions designed to encourage more stock market participation may be more desirable if non-participation is due to high participation costs rather than a preference for safe assets.

In this paper, we use variation in the default asset allocation of 401(k) plans to estimate the risk preferences of retirement investors. Using a revealed preference approach, we estimate that, absent participation frictions, 94% of investors would hold stocks in their retirement accounts with an equity share of retirement wealth that declines over the life cycle. We use this variation to estimate a life cycle portfolio choice model with Epstein-Zin preferences and find the evidence is consistent with a coefficient of relative risk aversion of 2.1 and a portfolio adjustment cost of \$200. These results suggest that retirement investors have moderate risk aversion and the lack of participation in the stock market is primarily due to participation frictions rather than first-order risk aversion (e.g., as implied by models of loss aversion or ambiguity aversion).

We begin by illustrating the challenge in separating risk preferences from frictions using cross-sectional data on stock market participation. We show the life cycle profile of participation from the *Survey of Consumer Finances* (SCF) is consistent with two very different calibrations of a standard life cycle portfolio choice model: (i) a model with a risk aversion below 2 and an extremely high adjustment or participation cost or (ii) a model with a risk aversion above 30 and a low adjustment or participation cost. Therefore, identifying investors' risk preferences, in addition to the size and form of participation frictions, requires additional sources of variation.

We next overcome this identification challenge using quasi-experimental variation in the default asset allocation of 401(k) plans. An ideal experiment for distinguishing between preference- and

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<sup>1</sup>With strictly increasing and differentiable utility, agents should be risk-neutral over small risks (Rabin 2000).

friction-based explanations for non-participation would be to randomly give investors not participating in the stock market an investment account with stocks, which would effectively remove any one-time adjustment costs associated with participation. If these investors dislike holding risky assets (for instance, due to loss aversion) or if they face large per-period participation costs, they should sell the stocks and move their holdings toward safer assets. Alternatively, if non-participation is driven by one-time frictions, investors should keep the stocks, switching from stock-market non-participation to participation as a consequence of the treatment.

To approximate this ideal experiment, we rely on account-level data from a large 401(k) plan provider. Such employer-sponsored retirement savings accounts are available to two-thirds of U.S. civilian employees (Myers and Topoleski 2020) and are the main vehicle that American households use to participate in the stock market and invest in financial products.<sup>2</sup> Our identification strategy exploits changes in the default asset allocation of retirement plans. Our treatment group consists of investors hired right after the default asset allocation was changed to a target date fund (TDF), which has significant equity exposure. By default, these investors are participating in the stock market but can choose to opt-out and move their retirement savings toward safer assets. We consider two control groups of investors hired right before the policy change: (i) investors automatically enrolled into a money market fund with no equity exposure and (ii) investors hired under an opt-in regime. Investors in both control groups, by default, have zero equity exposure in their retirement account and must make an active decision to participate.

Empirically, we find that more than 90% of the investors defaulted into stock market participation have a positive equity share of retirement wealth throughout their tenure. In contrast, investors defaulted into a money market fund (or hired under an opt-in regime) progressively increase their equity share away from their zero-stock default. The fact that most investors move away from the default option when it is a safe asset but stay invested in the default when it's equity suggests that, absent any adjustment or one-time participation costs, these investors prefer holding risky assets.

To translate this variation into estimates of preferences, we apply a framework developed by Goldin and Reck (2020). Under a set of assumptions, most importantly that treatment is randomly assigned, we can non-parametrically bound the fraction of investors who would prefer holding stocks within their retirement account absent frictions. In our experiment, 42% of investors who were defaulted into a money market opt out of the default within one year and move towards stock market participation. Intuitively, these investors reveal their preference for stocks by actively

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<sup>2</sup>Among individuals eligible to contribute to a retirement account in the SCF, on average 85% (99.5% at the median) of their financial investment products (defined as stocks, bonds, money and non-money market mutual funds, trusts, and CDs) are held within a retirement account. Only 5% of households participate in the stock market exclusively outside of a retirement account. See Section 2.2 for additional details.

moving away from the money market default, implying at least 42% of investors prefer stock market participation. Conversely, 5% of investors who were defaulted into holding stocks make an active decision to opt-out of stock market participation. This minority of investors revealing their preference for non-participation generates an upper bound for the fraction of investors preferring stock market participation of 95%. If anything, these results underestimate the level of stock-market participation absent frictions for two reasons: (i) we do not observe participation in stocks outside one's retirement account with their current employer and (ii) our quasi-experiment does not remove potential per-period participation costs (e.g., attention costs). We can similarly bound the average preferred stock share of retirement wealth from below at 39%.

Under additional assumptions about the differences in preferences between investors who make active choices and those who do not, we can non-parametrically obtain point estimates for investors' average preferences. We estimate that 94% of investors in our sample prefer stock market participation in their retirement accounts with an average preferred stock share of retirement wealth of 76%. Moreover, the preferences for participation that we estimate are flat over the life cycle, while the average preferred stock share of retirement wealth increases slightly between ages 20 and 30 but decreases after age 30 at a level and rate roughly consistent with textbook normative models of life cycle portfolio choice (e.g., Merton 1969; Cocco, Gomes, and Maenhout 2005). Crucially, our estimates of *preferences* differ substantially from observed *choices*: average participation and stock shares of retirement wealth are substantially lower and increase over the life cycle.

These new quasi-experimental moments offer valuable calibration or estimation targets for both standard and behavioral models of portfolio choice. In order to map our results into estimates of preference parameters, we build a rich life cycle portfolio choice model and estimate it using the variation from our quasi-experiments. This model has three key features that are required to match our quasi-experimental evidence. First, investors can choose different asset allocations for existing wealth and new contributions in their retirement account. Second, investors' decisions are subject to default effects when making both portfolio choice and savings decisions. Finally, investors face uncertainty about future earnings and employment status, which creates value from delaying adjustments to portfolio and savings decisions away from their defaults.

Within this model, we conduct an experiment analogous to the first quasi-experiment in our data by randomizing the default asset allocation of investors when they change jobs. We then estimate investors' structural preference parameters and the magnitude of the frictions that they face by matching the results of the experiment in our structural model to our empirical results. In our estimation, we find the model closely matches our quasi-experimental evidence with a coefficient of relative risk aversion of 2.1 and a portfolio adjustment cost of \$201. This estimate of risk

aversion is lower than most estimates in the life cycle portfolio choice literature (see [Gomes 2020](#), for a review) and is statistically indistinguishable from our estimate of the inverse EIS, suggesting time-separable CRRA preferences provide a good description of investors' behavior in our setting.

We conclude by illustrating the value of using quasi-experimental variation to estimate investors' structural preference parameters. We show that if we target the life cycle of equity shares (a standard moment in this literature), our conclusions regarding investors' preferences change in two ways. First, we estimate a coefficient of relative risk aversion of 8-10, which is around 4-5 times larger than our estimate using quasi-experimental variation. Secondly, we reject CRRA preferences as providing a good description of investors behavior. Collectively, these results highlight how frictions distort the mapping between observed portfolio choices and investors' risk preferences and how quasi-experimental variation can help overcome this identification problem by making estimates less sensitive to model misspecification ([Andrews, Gentzkow, and Shapiro 2017](#); [Catherine, Chaney, Huang, Sraer, and Thesmar 2022](#)).

**Related literature.** This paper makes several contributions to existing literature. First, it relates to the extensive literature on limited household stock market participation by offering a way to distinguish between two leading classes of explanations for this fact. The first category, which we call "preference-based" explanations, argues investors prefer holding safe over risky assets for reasons not captured by standard models. For example, investors' preferences might exhibit first-order risk aversion that makes risky assets unattractive, despite their positive expected return. This occurs in theories of loss-aversion with respect to wealth or news ([Gomes 2005](#); [Pagel 2018](#)), narrow-framing ([Barberis, Huang, and Thaler 2006](#)), rank-dependence ([Chapman and Polkovnichenko 2009](#)), disappointment-aversion ([Chapman and Polkovnichenko 2009](#)), or ambiguity-aversion ([Epstein and Wang 1994](#)). In addition, households may perceive risky assets to have a less attractive return due to background risk ([Benzoni, Collin-Dufresne, and Goldstein 2007](#); [Catherine 2022](#)), disaster risk ([Fagereng, Gottlieb, and Guiso 2017](#)), overly pessimistic beliefs ([Briggs, Cesarini, Lindqvist, and Östling 2021](#); [Galaasen and Raja 2022](#)), or lack of trust in the financial sector ([Guiso, Sapienza, and Zingales 2008](#)).

The second category of explanations for limited stock market participation, which we call "friction-based", argues households prefer risky assets, but do not invest in them because of frictions associated with doing so.<sup>3</sup> Such frictions could be one-time participation costs, adjustment or transaction costs ([Abel, Eberly, and Panageas 2013](#); [Gomes, Fugazza, and Campanale 2015](#)), or per-period participation costs ([Vissing-Jørgensen 2002](#); [Fagereng et al. 2017](#); [Briggs et al. 2021](#);

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<sup>3</sup>We acknowledge the distinction between preferences and frictions is not always obvious. For example, participation costs could capture attention costs, which may be part of investors' preferences. When we refer to frictions, we mean anything that impacts investors' choices that a social planner could set to zero.

Gomes and Smirnova 2021). These costs could be real, such as the cost of opening a brokerage account or paying a financial advisor, or psychological, such as the hassle cost of deviating from a default asset allocation or engaging in financial planning.

A major challenge in this literature is empirically identifying the size of these frictions, as they cannot be measured directly in the data. Our identification strategy allows us to identify the size of these frictions (separately from risk preferences), and our results suggest that choice frictions, rather than preferences or beliefs, are the main reason investors do not hold equity in their retirement accounts. A benefit of our setting relative to those studied by prior literature, such as inheritances (e.g., Andersen and Nielsen 2011) and lottery winnings (e.g., Briggs et al. 2021), is that our empirical variation does not constitute a shock to wealth, which could influence risk preferences directly (as in Meeuwis 2020). Within the class of models with frictions, our results provide support for those with one-time participation or fixed adjustment/transaction costs as opposed to per-period participation costs or time-dependent inaction. In the presence of sufficiently large per-period participation costs, workers automatically enrolled in stocks should opt-out and move their savings away from equity, which is not what we observe. With time-dependent inaction à la Calvo, investors should be equally likely to opt-out regardless of the default, which contrasts with the lower opt-out rate we observe among investors defaulted into stock market participation.

This paper's second contribution is to the literature on life cycle portfolio choice, initiated by Merton (1969) and surveyed by Campbell and Viceira (2001), Gomes (2020), and Gomes, Haliassos, and Ramadorai (2020). On the empirical side, our results are consistent with the literature documenting the effect of default asset allocations on retirement savings behavior (e.g., Mitchell and Utkus 2021; Parker, Schoar, Cole, and Simester 2022). We contribute by using this quasi-experimental variation to distinguish between different theories of investor behavior and estimate structural preference parameters. We view these estimates as particularly relevant for the growing literature on target date funds (e.g., Parker, Schoar, and Sun 2020; Duarte, Fonseca, Parker, and Goodman 2021; Gomes, Michaelides, and Zhang 2021; Massa, Moussawi, and Simonov 2021; Zhang 2022). Estimating the size of portfolio adjustment frictions is key to quantifying the welfare gains associated with TDF adoption, in particular the benefits associated with automatic rebalancing.

Finally, this paper contributes more broadly to the literature on behavioral welfare economics (e.g., Bernheim and Rangel 2009; Allcott and Taubinsky 2015). The framework we apply for inferring preferences in the presence of framing effects was developed and applied by Goldin and Reck (2020) to infer preferences over savings decisions in a cross-sectional setting. We expand on Goldin and Reck (2020) along three dimensions: (i) applying the framework to a different domain,

namely portfolio choice; (ii) illustrating how the use of panel data can provide tests of (some of) the key identifying assumptions; (iii) and, most importantly, showing how the same variation can be used to identify preference parameters in a structural model. In doing so, we highlight not only how choice frictions can break the mapping from observed choices to underlying preferences in structural models, but also how quasi-experimental variation can be useful for sharpening this mapping (see also [Briggs et al. 2021](#); [Choukhmane 2021](#)).

**Outline.** Section 1 illustrates the identification problem in separating preferences and frictions as drivers of limited participation. Section 2 describes our data and quasi-experimental variation, while Section 3 uses this variation to non-parametrically estimate investors' risk preferences. Section 4 describes our life cycle model and our estimation results. Section 5 concludes. The [Appendix](#) contains additional results, the model solution and estimation details, and derivations.

## 1 The Identification Problem

In this section, we discuss the identification of risk preferences and choice frictions. We first discuss the lack of consensus in the existing literature about the value of relative risk aversion in life cycle portfolio choice models. Next, we show the difficulty in separating the two in a standard life cycle portfolio choice model.

### 1.1 Risk Preferences in Life Cycle Portfolio Choice

Risk preferences play a central role in life cycle portfolio choice models. Unfortunately, there is no consensus on the specification and reasonable value for individuals' risk aversion. In [Figure 1](#), we show the values of relative risk aversion calibrated or estimated from papers that solve a dynamic life cycle portfolio choice model with standard preferences.<sup>4</sup>

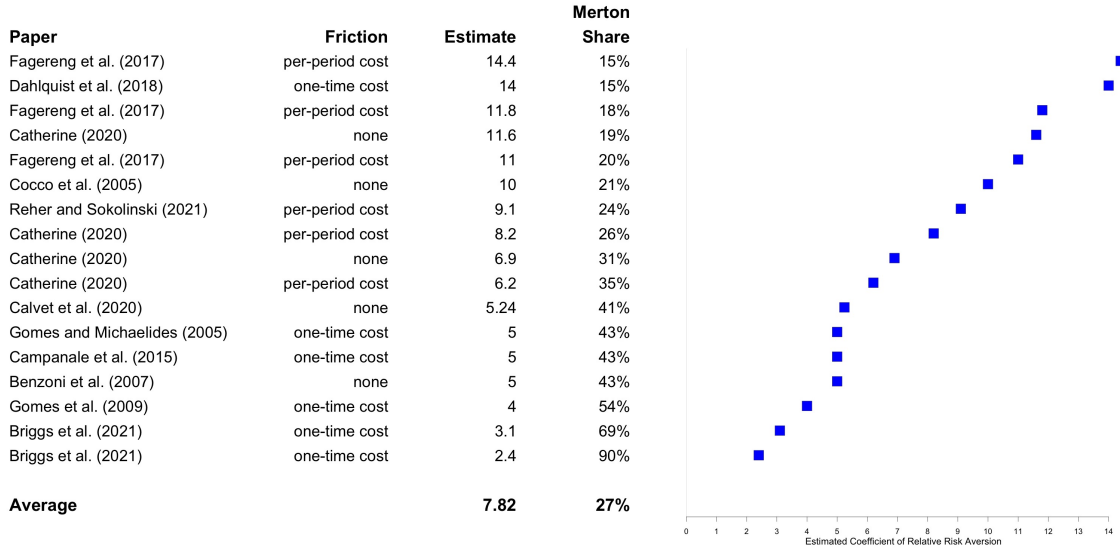
The results in this figure illustrate two points. First, there is substantial variation in estimates of relative risk aversion in life cycle portfolio choice models, from around 3 in [Briggs et al. \(2021\)](#) to around 14 in [Fagereng et al. \(2017\)](#) and [Dahlquist, Setty, and Vestman \(2018\)](#). Secondly, the average value of relative risk aversion in [Figure 1](#) is approximately 8, which is higher than estimates obtained in other literature. For example, evidence on life cycle consumption-savings decisions is consistent with a relative risk aversion of around 2 or 3 ([Gourinchas and Parker 2002](#); [De Nardi,](#)

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<sup>4</sup>We include only papers that use time-separable CRRA or recursive Epstein-Zin preferences because in these models relative risk aversion is independent of wealth.



**Figure 1.** Estimates of Relative Risk Aversion in Life Cycle Portfolio Choice



*Notes:* This figure plots the coefficient of relative risk aversion that is calibrated or estimated in papers that solve dynamic life cycle portfolio choice models with CRRA or Epstein-Zin preferences. We also include the type of the friction associated with stock market participation in the model, distinguishing between one-time and per-period costs. If the paper has multiple estimations, we include the paper’s main estimates. An exception is Calvet, Campbell, Gomes, and Sodini (2019), who estimate risk aversion across investors; we include their average estimate. Merton Share refers to the portfolio share implied by the Merton (1969) model with a risk premium of 5.5% and standard deviation of 16%.

French, and Jones 2016), while the relatively low estimated labor supply elasticities suggest an upper bound of 1 (Chetty 2006).

In sum, the evidence from existing literature suggests that auxiliary assumptions, such as the specification of the size and form of frictions, can lead to widely different estimates of risk preferences in life cycle portfolio choice models. In the next section, we formalize this point using a simple life cycle portfolio choice model.

## 1.2 The Difficulty in Separating Preferences and Frictions

### 1.2.1 Simple Life Cycle Model

We consider a standard life cycle portfolio choice model in the spirit of Cocco et al. (2005), which we describe in more detail in Appendix B. Investors in the model have time-separable preferences with discount factor  $\beta$  and CRRA preferences over flow consumption with risk aversion  $\sigma$ . Each period, investors earn exogenous stochastic labor income while they are working and retirement benefits while retired. In addition to making consumption and savings decisions, investors



choose the fraction of their wealth invested in a risky stock,  $\theta_t$ , with the remaining fraction of their wealth,  $1 - \theta_t$ , invested in a risk-free bond. We assume a risk-free rate of 2% and a equity risk premium of 4.5%; the rest of the parameters are given in Appendix B.

We introduce two frictions into the model that affect investors' portfolio choice decisions. First, there is a per-period participation cost  $p$ , which is incurred as a utility cost if  $\theta_t > 0$  (e.g., Vissing-Jørgensen 2002; Fagereng et al. 2017; Catherine 2022; Briggs et al. 2021). This cost is designed to capture the costs associated with maintaining an account to invest in the risky asset, in addition to any related hassle costs. Secondly, investors must pay a one-time cost to adjust their portfolio (e.g., Haliassos and Michaelides 2003; Gomes and Michaelides 2005; Abel et al. 2013), which is designed to capture the real and psychological costs associated with making an active decision to change one's portfolio allocation. Specifically, investors are required to pay a utility cost  $f$  to choose an asset allocation  $\theta_t \neq \theta_{d,t}$ , where

$$\theta_{d,t} = \theta_{t-1} * \frac{R_t}{(1 - \theta_{t-1})R_f + \theta_{t-1}R_t}. \quad (1)$$

The term  $\theta_{d,t}$  captures the asset allocation absent any adjustment decision (i.e., under passive portfolio rebalancing): it is equal to the asset allocation from the prior period, after adjusting for return realizations. We also assume  $\theta_{d,0} = 0$  to capture the fact that the default for most investors when they begin working is non-participation in the stock market.

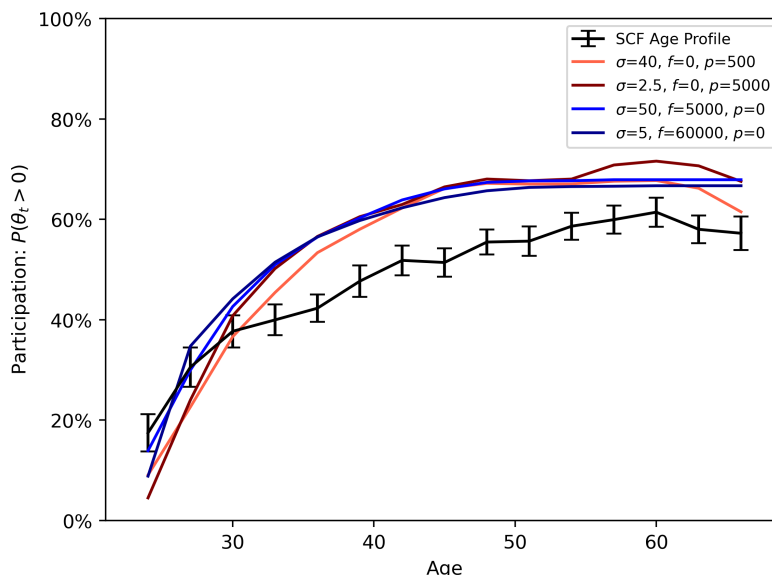
We solve the model numerically for different values of  $\sigma$ ,  $f$ , and  $p$ . Investors' asset allocation decisions are determined by four state variables: age, wealth, income, and  $\theta_{d,t}$ . We simulate the choices of investors and calculate in our simulated sample the stock market participation rate over the life cycle.

### 1.2.2 High Risk Aversion and Large Frictions Produce Observationally Equivalent Patterns of Non-Participation over the Life Cycle

In Figure 2, we plot the life cycle of participation for four different parameterizations of the model: (i) high risk aversion ( $\sigma$ ) and low fixed adjustment cost ( $f$ ), (ii) low risk aversion and high fixed adjustment cost, (iii) high risk aversion and low per-period participation cost ( $p$ ), and (iv) low risk aversion and high per-period participation cost. As illustrated in the figure, these lines are essentially on top of each other. Figure 2 also plots the life cycle of participation from the 1989-2019 Survey of Consumer Finances, estimated using the approach in Deaton and Paxson (1994). Comparing the simulated life cycle of participation from the model with that from the SCF, we

find models with coefficients of relative risk aversion of 2.5 and 50 fit the data equivalently well, depending on the size and form of the choice frictions.<sup>5</sup>

**Figure 2.** Life Cycle of Participation in Simple Model vs. SCF



*Notes:* This figure plots the life cycle of participation for different parameterizations of the model in Appendix B, using a discount factor of  $\beta = 0.96$  in all simulations.  $\sigma$  denotes relative risk aversion,  $f$  denotes the one-time adjustment/participation cost in dollars, and  $p$  denotes the per-period participation cost in dollars. We also plot the age profile of participation from the SCF 1989-2019, identified using the methodology in Deaton and Paxson (1994), with 95% confidence intervals. Each model simulation consists of 10,000 investors.

The results in Figure 2 show that high risk aversion and large frictions generate similar patterns of participation over the life cycle. This illustrates the difficulty in separately identifying the size and specification of both frictions and risk preferences using cross-sectional variation, implying the need for additional sources of variation.

## 2 Data and Quasi-Experimental Variation

Section 1 illustrates the difficulty in separately identifying investors' risk preferences and choice frictions as drivers of limited stock market participation. In this section, we describe the data and quasi-experimental variation that we use to separately identify these two, which we do using a theoretical framework in Section 3.

<sup>5</sup>While these different calibrations generate equivalent patterns of participation over the life cycle, they may imply different patterns of wealth accumulation or conditional equity shares.

## 2.1 The Ideal Experiment

The ideal experiment for identifying preferences in the presence of frictions would be to randomly give some investors an investment account with risky assets. By randomly assigning accounts to investors, we would remove the effects any one-time participation (or adjustment) costs. Ideally, we would also remove any per-period costs associated with participation in the stock market, such as the cost of maintaining a brokerage account.

In this ideal experiment, there are two potential outcomes with respect to stock market participation. First, if investors sell the risky assets, this would suggest they prefer safe assets over risky assets (e.g., due to loss aversion). Second, if investors keep the risky assets, this would indicate a preference for risky assets that is obscured by one-time or per-period participation costs. With respect to stock shares, there are more potential outcomes. However, by observing the fraction of risky assets that investors sell, we would be able to infer their preferred stock share.

## 2.2 Institutional Setting and 401(k) Administrative Data

To approximate the ideal experiment described above, we use panel data from a provider of employer-sponsored retirement savings plans. Nearly two-thirds of U.S. civilian workers (and 75% of full-time private-sector employees) have access to an employer-sponsored retirement savings plans such as a 401(k) or a 403(b) plan (Myers and Topoleski 2020). These accounts are particularly advantageous saving vehicles because assets accumulate tax-free, contributions can be tax-deferred, and 86% of these plans offer an employer matching contribution (Arnoud, Choukhmane, Colmenares, O’Dea, and Parvathaneni 2021).

Our data are provided by a large U.S. 401(k) record-keeper and contain detailed administrative records for 4 million employees in more than 600 401(k) plans between December 2006 to December 2017. For each employee (whom we refer to interchangeably as an investor) in each year, we observe demographic characteristics, participation status in a 401(k) plan, 401(k) balances in dollars, and employee and employer contribution rates. We also observe monthly allocations to different assets by CUSIP, employer plan features, and default asset allocations. While these data offer detailed information on investors’ saving and asset allocation behavior and the details of the plan design, they have two potential limitations.

First, our sample of 401(k) plans is not randomly selected and not necessarily representative of the U.S. workforce. In Table 1, we provide summary statistics on our data. Our estimate of the

median income in our sample increases from \$27,320 in 2006 to \$35,731 in 2017, which is broadly in line with the \$24,892 to \$31,561 increase in median net compensation per worker in the U.S. population reported by the [Social Security Administration](#) (SSA). Additionally, the median age among investors in our sample is 41.6 years old, which is similar to the median age of 41.7 for the U.S. labor force reported by the [Bureau of Labor Statistics](#). Collectively, these results suggest our investors are indeed representative of the broader sample of U.S. retirement investors.

**Table 1.** Summary Statistics

	Our Sample 2006-2017	
	$N = 18,398,750$	
	Mean	Median
Age	41.59	41.00
Wage Income		33,854.40
401(k) Balance	69,658.18	19,758.30
Stock Market Participation in 401(k)	0.68	1.00
Stock Share in 401(k)	0.53	0.73

*Notes:* This table displays summary statistics on the full set of retirement investors and years within our sample. We do not observe income directly in our data but impute it by dividing the retirement contribution amount (in dollars) by the contribution rate (as a percentage of salary). We can impute the compensation only of employees with a positive contribution rate. To obtain an estimate of the median income in our sample, we assume that all non-participating investors have below-median earnings. Note that this implies our median income measure is therefore a lower bound for the actual median income in our sample. When calculating stock shares, we include both U.S. and international stocks. We use the portfolio allocations of the funds provided by the financial institution from which we obtained the data to convert holdings of mutual funds that include mixed allocations into equity shares using the CUSIP of the mutual fund. When calculating the mean and median retirement wealth, we condition on the 401(k) balance being positive.

A second limitation of our data is that we do not observe investors' saving and investment behavior outside of their current employer 401(k) plans. Individuals could have accumulated assets in retirement accounts associated with previous employers that are not observable in our data. In light of this data limitation, the life cycle portfolio choice model we develop in Section 4 has separate accounts for assets held in the retirement account with the current employer, retirement assets accumulated in accounts from previous employers, and non-retirement liquid savings. Nevertheless, we believe that behavior in retirement accounts offers a good indication of individual attitudes toward risky assets. Due to their advantageous tax properties and widespread availability, defined contribution accounts are the main instrument used by American workers to invest in financial products: for individuals eligible to contribute to a retirement savings account in the SCF 2007-2016 waves, on average 85% (99.5% at the median) of their financial investment products (defined as stocks, bonds, money and non-money market mutual funds, trusts, and CDs) are held in a retirement account. Additionally, only 5% of households in the SCF participate in the stock market exclusively outside of a retirement account.

## 2.3 Our Quasi-Experiments: Changes in 401(k) Default Asset Allocations

We use two quasi-experiments motivated by the ideal experiment described above. In the first quasi-experiment, we compare the portfolio choices of investors hired within 12 months before and 12 months after 6 firms change the default asset allocation in their auto-enrollment 401(k) plans. The control group is 1,086 investors hired before the change, who are defaulted into a money market fund (i.e., no stock market exposure), and the treatment group are 1,321 investors hired *at the same firms* after the change, who are defaulted into a TDF (i.e., has stock market exposure). We call this the "money market to TDF" sample.<sup>6</sup> Under the assumption that investors hired before and after the changes are similar (and other assumptions formalized in Section 3), this quasi-experiment provides a close approximation to the ideal experiment: some employees are quasi-randomly assigned a retirement account with positive stock exposure (i.e., the TDF default), while others are quasi-randomly assigned a retirement account with safe assets (i.e., a money market fund). An advantage of this 401(k) setting is that there are no explicit per-period costs associated with maintaining or managing the account, in contrast to a brokerage account. However, this quasi-experiment does not remove the effect of any per-period psychological costs, such as the cost of paying attention to manage a portfolio. As a result, our estimates can isolate the effect of adjustment or one-time costs.

In our second quasi-experiment, we compare the portfolio choices of investors hired within 12 months before and after 191 firms change their 401(k) plans from an opt-in regime to automatic enrollment with a TDF as the default asset allocation. The control group is 40,337 investors hired before the change under the opt-in regime, while the treatment group is 52,400 investors hired after the change and automatically enrolled into a TDF. Figure A3 displays the percent of the total number of firms that change their default in each year, which illustrates this variation is relatively evenly distributed between 2006 and 2017. We call this the "opt-in to TDF" sample.<sup>7</sup>

Relative to the money market to TDF sample, the opt-in to TDF sample has the advantage of being a much larger sample of firms and investors. However, an important difference is that in the opt-in to TDF sample is that the treatment and control groups differ in terms of both the frictions they face to adjust their retirement asset allocation *and* the frictions they face to contribute to the 401(k) plan. This implies that in the opt-in control group, investors face a larger friction to holding stocks in their retirement account (i.e., they need to first select a positive contribution rate and then

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<sup>6</sup>All six of these firms changed their default asset allocation in 2007 following the passage of the Pension Protection Act of 2006.

<sup>7</sup>The menu of funds available is broadly similar before vs. after the adoption of a new default fund. Results are available upon request.

choose an asset allocation with positive equity exposure).

In Panels A and B of Figure 3, we plot the variation that we use in the two quasi-experiments. For the money market to TDF sample, Panel A plots 401(k) participation, money market participation, and stock market participation within 401(k)s for investors in their first year of tenure based on their hiring month relative to the policy change. The investors in the left half of each graph are in the control group (hired before the change), while the investors in the right half are in the treatment group (hired after the change). Consistent with a large literature on default effects (e.g., Madrian and Shea 2001; Blumenstock, Callen, and Ghani 2018; Beshears, Choi, Laibson, Madrian, and Skimmyhorn 2018), we find participation in the money market fund decreases discontinuously while stock market participation within the 401(k) plan increases discontinuously for workers in the treatment group (i.e., hired right after the change in the default). In contrast, 401(k) participation remains unchanged. Panel B shows the analogous plot for the opt-in to TDF sample, in which we observe a discontinuous increase in 401(k) participation and stock market participation within the 401(k) plan for investors in the treatment group.<sup>8</sup>

## 2.4 Results from Quasi-Experiments

### 2.4.1 Investors Defaulted into Non-Participation Re-balance into Equity and Investors Defaulted into TDFs Maintain a High Stock Share

Figure 4 plots the results from our two quasi-experiments in separate panels.<sup>9</sup> In each panel, we plot the fraction of investors participating in the stock market and their average stock share of retirement wealth  $\tau$  years after being hired, where  $\tau = 0$  corresponds to their choice immediately upon being hired. In both samples, we find almost all of the investors in the treatment group ( $\approx 95\%$ ) maintain positive stock market exposure in their 401(k). In contrast, investors in the control groups gradually move away from the default and into holding stocks inside their retirement account. Note that this difference in opt-out rates between the two groups suggests the frictions impacting investors' behavior are not pure time-dependent à la Calvo, which would predict equal opt-out rates in both groups.

In both samples, we also observe that investors in the treatment group maintain a relatively high

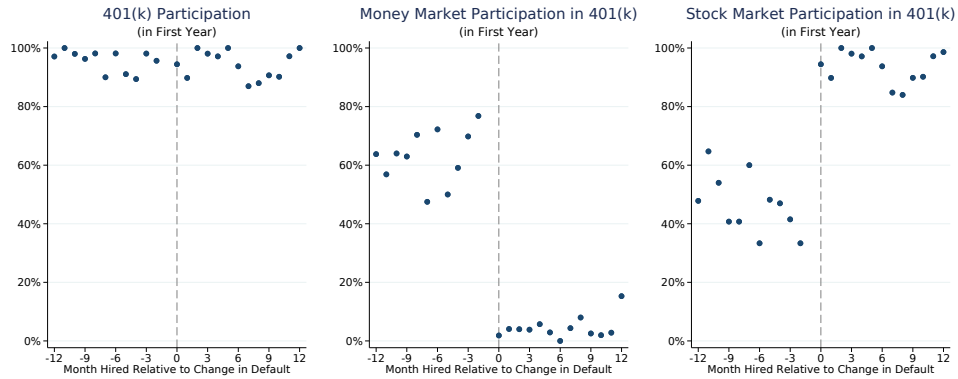
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<sup>8</sup>In Figure A4, we show that the observable characteristics of employees (i.e., age and income) are similar across the control and treatment groups and do not shift around the policy change.

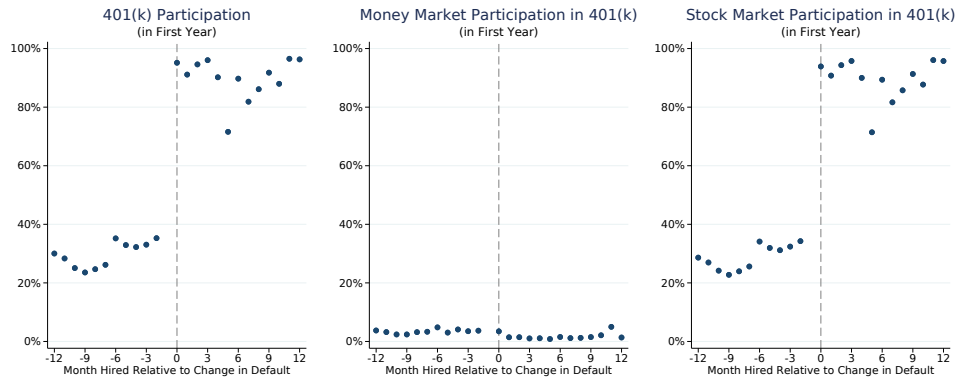
<sup>9</sup>For the rest of the analysis, we focus only on portfolio choices made within 10 years of being hired. We drop choices made after 10 years since few investors remain that long at the firm.

**Figure 3. Identifying Variation**

*Panel A: Money Market to TDF Sample*



*Panel B: Opt-In to TDF Sample*



*Notes:* This figure plots the variation in our two quasi-experiments using data from the end of December for employees with less than 12 months of tenure. In Panel A, we compare the portfolio choices and 401(k) participation of investors hired within 12 months before and 12 months after 6 firms change the default asset allocation in their auto-enrollment 401(k) plans. The control group is 1,086 investors hired before the change, who are defaulted into a money market fund (i.e., no stock market exposure), and the treatment group are 1,321 investors hired *at the same firms* after the change, who are defaulted into a TDF (i.e., has stock market exposure). In Panel B, we compare the portfolio choices and 401(k) participation of investors hired within 12 months before and after 191 firms change their 401(k) plans from an opt-in regime to automatic enrollment with a TDF as the default asset allocation. The control group is 40,337 investors hired before the change under the opt-in regime, while the treatment group is 52,400 investors hired after the change and automatically enrolled into a TDF. In both figures, we observe choices at the end of December for employees with less than 12 months of tenure. We define 401(k) participation based on whether an employee has a positive balance in a 401(k) plan.



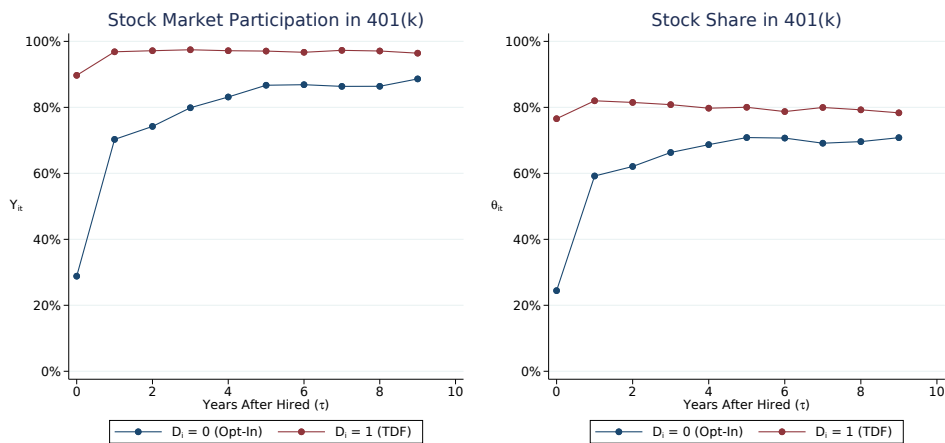
stock share of retirement wealth of approximately 80% while the investors in the control groups start with a lower stock share of retirement wealth and converge toward the level in the treatment group. Table 2 shows the treatment group has a stock market participation rate inside the 401(k) plan that is 19-27 percentage points higher than that in the control group on average, with a stock share of retirement wealth that is 21-24 percentage points higher.

**Figure 4.** Observed Portfolio Choice Response

*Panel A: Money Market to TDF Sample*



*Panel B: Opt-In to TDF Sample*



*Notes:* This figure plots the observed portfolio responses for employees who are defaulted into two groups. In Panel A, we compare employees automatically enrolled into a money market fund and employees automatically enrolled into a TDF. Panel B does the same comparison between investors hired under an opt-in regime and those automatically enrolled into a target date fund.

**Table 2.** Observed Portfolio Choice Response: Regression*Panel A: Money Market to TDF Sample*

	Stock Market Participation in 401(k): $Y_{it}$				Stock Share in 401(k): $\theta_{it}$			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Constant	56.58 (11.61)	56.35 (10.57)	57.81 (8.988)	56.95 (8.600)	37.40 (10.07)	37.21 (9.392)	38.88 (8.329)	38.28 (8.004)
Default Has Stocks: $D_i$	19.92 (5.661)	20.06 (5.596)	19.12 (5.486)	19.68 (5.795)	21.50 (5.229)	21.62 (5.239)	20.55 (5.039)	20.93 (5.215)
Tenure Fixed Effects		✓		✓		✓		✓
Firm Fixed Effects			✓	✓			✓	✓
Firm and Year Clustering	✓	✓	✓	✓	✓	✓	✓	✓
Total Observations	12650	12650	12650	12650	12650	12650	12650	12650
Adjusted R-Squared	0.0898	0.124	0.120	0.149	0.114	0.130	0.133	0.146

*Panel B: Opt In to TDF Sample*

	Stock Market Participation in 401(k): $Y_{it}$				Stock Share in 401(k): $\theta_{it}$			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Constant	65.72 (3.641)	65.28 (3.113)	68.12 (2.122)	66.97 (1.688)	54.63 (3.045)	54.30 (2.648)	56.31 (1.630)	55.46 (1.337)
Default Has Stocks: $D_i$	29.35 (3.692)	30.13 (2.822)	25.10 (2.855)	27.12 (2.798)	25.11 (2.998)	25.70 (2.344)	22.14 (2.292)	23.65 (2.256)
Tenure Fixed Effects		✓		✓		✓		✓
Firm Fixed Effects			✓	✓			✓	✓
Firm and Year Clustering	✓	✓	✓	✓	✓	✓	✓	✓
Total Observations	263061	263061	263061	263061	263061	263061	263061	263061
Adjusted R-Squared	0.145	0.230	0.267	0.323	0.134	0.197	0.248	0.290

*Notes:* This table displays the regression results that complement Figure 4, in which we regress investors' observed choices onto an indicator for whether they are in the treatment group and thus have a default asset allocation with stock market exposure. Panel A displays the results comparing investors defaulted into an automatic enrollment 401(k) plan with a money market fund default and those with a TDF default. Panel B displays analogous results comparing investors defaulted into an opt-in 401(k) plan with those defaulted into an automatic enrollment 401(k) plan with a TDF as the default asset. In both panels, two-way clustered standard errors by firm and year are shown in parentheses.

## 2.4.2 Robustness

We conduct several robustness checks on these results in Appendix G.

**Spillover and peer effects.** A potential concern is that our control groups of employees hired right before the adoption of the TDF default option may also be (indirectly) affected by the policy change. For instance, peer effects from colleagues automatically enrolled into a TDF may lead employees in our control groups to increase the equity share inside their retirement account. Similarly, their employers may start advertising and encouraging higher equity allocation after the policy change. To address this concern, we show in Panel A of Figure A5 that the behavior of employees hired right before the policy change is similar to that of employees in the same firms hired several years before the policy adoption (who are unlikely to be affected by peer effects stemming from a policy adopted several years later).

**Survivorship bias.** We do not observe investors after they separate from their employer. This implies selection into our sample by different tenure levels. A potential concern is that the convergence between the treatment and control groups over tenure may be driven by survivorship bias: those who remain with the firm over a long tenure horizon may be more likely to make similar allocation decisions. In Panel B of Figure A5, we show that the responses of investors in the control group are similar regardless of when the investor separates from her employer, which indicates that the increasing stock share of the control group over time is not driven by a change in the composition of employees remaining at the firm.

**Passive rebalancing.** A third concern is that the evolution (and convergence) of equity shares in the retirement account is driven by passive rebalancing. In Figure A6, we show that the evolution of the asset allocations of new 401(k) contributions over tenure is similar to that of retirement balances shown in Figure 4. The equity share of new contributions reflects only allocation decisions and is not subject to portfolio drift. These results suggest that the dynamic responses of portfolio shares in Figure 4 are primarily driven by investors' active portfolio decisions rather than passive changes in portfolio allocations as returns are realized.

## 2.4.3 Implications for Investors' Preferences

In sum, these results suggest that most investors prefer to participate in the stock market inside their retirement account, given the treatment group maintains its stock market exposure and the control group makes active decisions to move into stocks. The difference in participation between

the treatment and control groups indicates the existence of adjustment (or one-time participation) costs associated with changing one’s asset allocation, which could be real or psychological. To make precise statements about investors’ preferences, we need to place more structure on the responses to different default asset allocations in Figure 4. In the next section, we apply a theoretical framework developed by [Goldin and Reck \(2020\)](#) that allows us to map the results in Figure 4 to estimates of investors’ preferences, taking into account the fact that frictions may affect investors’ choices such that revealed preference fails.

### 3 Identifying Risk Preferences Using 401(k) Default Switches

In this section, we describe and apply a framework developed by [Goldin and Reck \(2020\)](#) to identify investors’ average preferences for stock market participation and stock shares in retirement accounts. For additional details on the framework, in addition to the derivations of the results, see Appendix C.

#### 3.1 Framework

Consider investors  $i$  who are hired by an employer at time  $t = 0$  and make asset allocation choices at  $t = 0, \dots, T$ . Denote  $Y_{it} \in \{0, 1\}$  and  $\theta_{it} \in [0, 1]$  as investor  $i$ ’s participation and stock share of retirement wealth at time  $t$ , respectively, where  $Y_{it} = 1$  corresponds to participating in the stock market. We refer to  $t$  as the investor’s tenure since it captures the length of time since she was hired. Each investor’s participation and stock share decisions are subject to a time-invariant frame denoted by  $D_i \in \{0, 1\}$ , where  $D_i = 1$  corresponds to an investor working for an employer with an auto-enrollment and a TDF as the default asset allocation (i.e., the treatment groups in the two quasi-experiments) and  $D_i = 0$  otherwise (i.e., the control groups). Throughout, we refer to  $D_i$  as the frame or default interchangeably. We also denote  $\theta_i^d(D_i)$  as the default asset allocation faced by investor  $i$ , given frame  $D_i$ .

Each investor’s preferred options at each tenure are denoted by  $Y_{it}^* \in \{0, 1\}$  and  $\theta_{it}^* \in [0, 1]$ , which is not observed, while her choices, denoted by  $Y_{it}$  and  $\theta_{it}$ , are observed. Our ultimate goal is to estimate the average values of these preferences in our sample. Investors are characterized by a set of potential outcomes,  $\{Y_{it}(d), \theta_{it}(d)\}_{d \in \{0, 1\}}$ , which we assume generate their observe choices

according to<sup>10</sup>:

$$Y_{it} = Y_{it}(d), \theta_{it} = \theta_{it}(d) \text{ if } D_i = d.$$

If an investor's participation or stock share decision is independent of the frame, we follow [Goldin and Reck \(2020\)](#) and call that investor *consistent* with respect to that decision. Formally, we denote consistency by  $C_{it}^Y$  and  $C_{it}^\theta$ , where

$$C_{it}^Y = \begin{cases} 1 & \text{if } Y_{it}(0) = Y_{it}(1), \\ 0 & \text{else.} \end{cases}$$

$$C_{it}^\theta = \begin{cases} 1 & \text{if } \theta_{it}(0) = \theta_{it}(1), \\ 0 & \text{else.} \end{cases}$$

Thus, in this framework, there are two possible types of investors for each decision: (i) consistent investors, whose choices are unaffected by frictions associated with the default, and (ii) inconsistent investors, whose preferences *are* affected by frictions associated with the default.

In what follows, we focus on identifying average preferences in the population at different tenures. Denote as  $E(\cdot)$  and  $E_\tau(\cdot) = E(\cdot | t = \tau)$  the expectation across the entire population and the conditional expectation across all investors at tenure  $t = \tau$ , respectively.

## 3.2 Bounding Average Preferences

### 3.2.1 Stock Market Participation in 401(k) Accounts

We begin by making the following assumptions, as in [Goldin and Reck \(2020\)](#).

**Assumption 1** (Frame Separability). *For all  $i$  and  $t$ ,  $(Y_{it}^*, \theta_{it}^*)$  is independent of  $D_i$ .*

**Assumption 2** (Frame Exogeneity).  *$D_i$  is independent of  $(Y_{it}(0), Y_{it}(1), \theta_{it}(0), \theta_{it}(1))$ .*

**Assumption 3** (Frame Monotonicity). *For all  $i$  and  $t$ ,*

$$Y_{it}(1) \geq Y_{it}(0), \quad \theta_{it}(1) \geq \theta_{it}(0).$$

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<sup>10</sup>By writing choices as a function of potential outcomes, we are implicitly making a stable unit treatment value assumption (e.g., [Rubin 1978](#)) that investor  $i$  is not affected by the treatments of investors  $j \neq i$ . This is supported by the evidence in Panel A of Figure A5.

**Assumption 4** (Consistency Principle). *For all  $i$  and  $t$ ,*

$$C_{it}^Y = 1 \implies Y_{it} = Y_{it}^*, \quad C_{it}^\theta = 1 \implies \theta_{it} = \theta_{it}^*.$$

Intuitively, frame separability requires investors' preferences to be independent of which default (or frame) they are given. This assumption rules out the possibility that investors view the default as providing information and prefer to participate more when the default is participation.<sup>11</sup> In our setting, we can examine the plausibility of this assumption by looking at whether the choices of investors that deviate from the default are similar regardless of which default they are given. Figure A9 shows that there is almost no difference between the stock shares chosen by investors who deviate from the money market fund default and the TDF default, consistent with this assumption being a reasonable approximation.

Our second assumption, frame exogeneity, requires the choice of default to be independent of investors' preferences or, equivalently, that the investors in the treatment and control groups have the same preferences. This is a natural assumption in our setting, given that the default is chosen by the firm and heavily influenced by regulation (e.g., [Parker et al. 2022](#)). This assumption is also supported by the evidence in Figure A9.

The third assumption that we require is frame monotonicity. In the case of participation, frame monotonicity requires that there are no investors who always choose the opposite of the default. For stock shares, it requires investors to choose weakly higher stock shares under the TDF default than under the money market default. Both of these assumptions are consistent with most models in which choices are effected by defaults, such as models with fixed adjustment costs, convex adjustment costs, limited attention ([Gabaix 2019](#)), or cognitive uncertainty ([Enke and Graeber 2020](#)). This assumption is analogous to the assumption of monotonicity or no-defiers in the LATE theorem ([Angrist and Pischke 2008](#)).

Our final assumption is the consistency principle, which requires that consistent investors reveal their preferences. For example, if an investor chooses to participate regardless of the default asset allocation, we assume that the investor's preference is indeed to participate. This assumption is our key identifying assumption that allows us to recover the preferences of consistent investors from observed choices.

Under these assumptions, the following result from [Goldin and Reck \(2020\)](#) allows us to bound

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<sup>11</sup>Informally, the partial-identification results that we present below are robust to allowing the frame to affect preferences monotonically. However, once preferences depend on frames, identification of preferences is no longer a well-defined problem because investors do not have an underlying stable preference relation.

the preferences for stock market participation within retirement accounts for the population of investors in our sample.

**Proposition 1.** *Under Assumptions 1–4, the average population preference for stock market participation within retirement accounts among investors with tenure  $t = \tau$  is partially identified:*

$$E_{\tau}(Y_{it}^*) \in [E_{\tau}(Y_{it} | D_i = 0), E_{\tau}(Y_{it} | D_i = 1)]. \quad (2)$$

The intuition for this result is as follows. The average preference for participation is the weighted average of the preferences of consistent and inconsistent investors. Since Assumption 4 implies that the preferences of consistent investors are revealed by their choices, we just need to bound the preferences of inconsistent investors to bound the population average preference. The bounds in (2) come from considering the “worst-case” scenario, in which inconsistent investors’ preferences align with their defaults, in which case the bound is (2).

According to Proposition 1, the results in the left panel of Figure 4 provide the required information to bound the average preferences for stock market participation within retirement accounts. By (2), the average preferences for participation among all investors in our population lie somewhere between the choices of the treatment and control groups, which is illustrated in the left panel of Figure 5 for the Money Market to TDF sample.<sup>12</sup> For example, after investors have been at the firm for 2 years ( $\tau = 2$ ), which is a common tenure in our sample, we can bound the fraction of investors who prefer holding stocks in their 401(k) plan between 78% and 95%. This bound, which is strictly higher than the average participation in our sample of 58% (Table 1), illustrates that one-time adjustment/participation costs drive a wedge between the observed choices and underlying preferences. As tenure increases, more investors in the control group become consistent and reveal their preferences, resulting in a tighter bound.

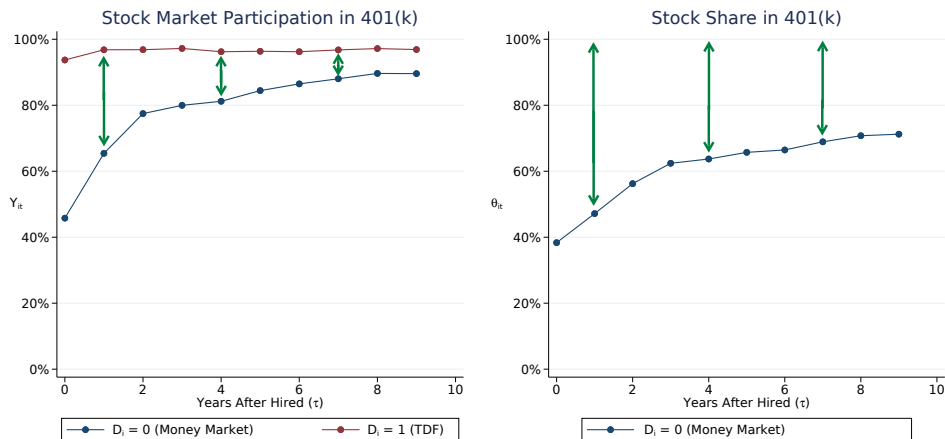
### 3.2.2 Stock Shares in 401(k) Plans

We now turn to identification of investors’ preferences for stock shares of retirement wealth. Unlike in the previous section, Assumptions 1–4 are not sufficient to place meaningful bounds on the average preferences because stock shares are continuous variables. To see why this poses a problem, consider a hypothetical investor with  $0 < \theta_{i\tau}(0) < \theta_{i\tau}(1) < 1$ , for some  $\tau \geq 0$ . This investor is by definition inconsistent at  $\tau$ , implying that we cannot infer anything about her preferences from her observed choices under Assumptions 1–4. For example, this investor may have  $\theta_{i\tau}^* \in (0, \theta_{i\tau}(0))$ .

<sup>12</sup>As is evident from Figure 4, we find similar results across both samples.



**Figure 5.** Bounding Population Preferences: Money Market to TDF Sample



*Notes:* This figure plots the same data as in Figure 4 with the nonparametric bounds on average preferences given in Propositions 1 and 2. The bounds for average preferences for stock market participation within 401(k) plans in our sample are valid under Assumptions 1–4. The lower bound for the average preferred stock share of retirement wealth is valid under Assumptions 1–3 and 5.

The possible presence of such an investor renders the bound analogous to that in Proposition 1 for stock shares invalid since we would have  $E_\tau(\theta_{it}^*) < E_\tau(\theta_{it} \mid D_i = 0)$  in a world with investors of this type.

The prior counterexample illustrates the need to place more structure on the choices of inconsistent investors because investors can be inconsistent in an infinite number of ways with a continuous choice (unlike in the case of participation, which is a binary decision). To address this, we make the following assumption.

**Assumption 5.** For all  $i$ ,  $t$  and  $d$ ,  $\theta_{it}(d) \neq \theta_i^d(d) \implies C_{it}^\theta = 1$ .

This assumption requires that all investors deviating from the default asset allocation are consistent. Economically, this assumption is consistent with a large class of models of default effects in which investors' preferences can be represented as if deviating from a default requires incurring an adjustment cost (see Masatlioglu and Ok 2005, for an axiomatization). However, this assumption is violated in some models, such as those with convex adjustment costs or where default effects are driven by limited attention or cognitive uncertainty (e.g., Gabaix 2019; Enke and Graeber 2020).<sup>13</sup> Under this assumption, the following result shows that we can place a lower bound on population preferences for stock shares of retirement wealth analogously to the lower bound on participation

<sup>13</sup>The lower bound on the average preferred stock share of retirement wealth that we derive below is robust to some relaxations of this assumption. Given that  $\theta_i^d(0) = 0$ , we could allow any model that could be represented as  $\theta_{it}(d) = m\theta_{it}^* + (1-m)\theta_i^d(d)$ .

in Proposition 1.

**Proposition 2.** *Under Assumptions 1–3 and 5, the average population preferred stock share among investors with tenure  $t = \tau$  is bounded from below:*

$$E_{\tau}(\theta_{it}^*) \geq E_{\tau}(\theta_{it} \mid D_i = 0). \quad (3)$$

Proposition 2 shows that the results in the right panel of Figure 4 allow us to bound the average preferences for stock shares, as illustrated in the right panel of Figure 5. After the investors have been at the firm for three years, we can bound the average preferred stock share of retirement wealth among all the investors in our sample from below at 62% (in the Money Market to TDF sample). Note that this lower bound on the average preferred stock share is higher than the average stock share in the SCF of approximately 23% (Table 1) and the average stock share in our sample of 53%, illustrating how frictions can drive a wedge between choices and preferences.

### 3.3 Estimating the Preferences of Consistent Investors

The previous section shows how we can bound the average preferences in the population using our quasi-experimental variation. These average preferences are the weighted average of the preferences of consistent and inconsistent investors. In this section, we recover point estimates of consistent investors' preferences. To do so, we use the following result.

**Proposition 3.** *Under Assumptions 1–4,*

$$E_{\tau}(Y_{it}^* \mid C_{it}^Y = 1) = E_{\tau}(Y_{it} \mid Y_{it} \neq D_i). \quad (4)$$

*Under Assumptions 1–3, and 5,*

$$E_{\tau}(\theta_{it}^* \mid C_{it}^{\theta} = 1) = E_{\tau}(\theta_{it} \mid \theta_{it} \neq \theta_i^d(D_i)). \quad (5)$$

Proposition 3 states that we can recover an estimate of the average preference for participation and stock shares among consistent investors by simply looking at the choices of investors who deviate from the defaults. Intuitively, we can do this because the consistency principle implies that consistent investors' choices reveal their preferences. Although not *all* consistent investors deviate from the default, the fact that  $D_i$  is set by the firm and uncorrelated with investors' preferences (by frame exogeneity) ensures that the preferences of those who do deviate are similar to the

preferences of those of who do not.

Figure 6 plots our estimate of the preferences of consistent investors. In both samples, we find that after three years of tenure, approximately 94% of consistent investors prefer holding stocks within their retirement accounts with an average stock share of retirement wealth of approximately 76%.<sup>14</sup> Consistent with our population bounds, both of these figures are quite high, suggesting that these consistent investors do indeed like stocks but face one-time frictions associated with participation. The fact that our estimates are similar across the two samples provides support for the consistency principle: even though consistent investors face frictions of different sizes in the two samples, when those frictions are overcome, they reveal similar preferences.

We can also use Proposition 3 to estimate the fraction of consistent investors by looking at the fraction of investors who deviate from the default. Figure A7 plots how this varies with age. We find that the fraction of consistent investors is slightly increasing over the life cycle, which is consistent with a one-time real adjustment cost that younger investors (who have less wealth) are less likely to pay.<sup>15</sup> Figure A7 also shows that an investor who is 40 years old (the average age in our sample) is more likely to be consistent in the Money Market to TDF sample than in the Opt In to TDF sample. This is consistent with the fact that the frictions that the control group needs to overcome in the latter sample are likely large due to the need both to change the default asset allocation and opt in to a 401(k) account to begin with. In Figure A8, we plot how the fraction of consistent investors varies by default assignment: investors are less likely to be consistent when they are assigned by default into a TDF.

### 3.4 Estimating Average Preferences

In this section, we estimate the average preferences among investors in the population. Without any additional assumptions, we can derive expressions for the relationship between the preferences of consistent investors and the preferences of the population:

$$E_{\tau}(Y_{it}^*) = E_{\tau}(Y_{it}^* | C_{it}^Y = 1) - \frac{1}{E_{\tau}(C_{it}^Y)} \underbrace{\text{cov}_{\tau}(Y_{it}^*, C_{it}^Y)}_{\text{selection bias}}, \quad (6)$$

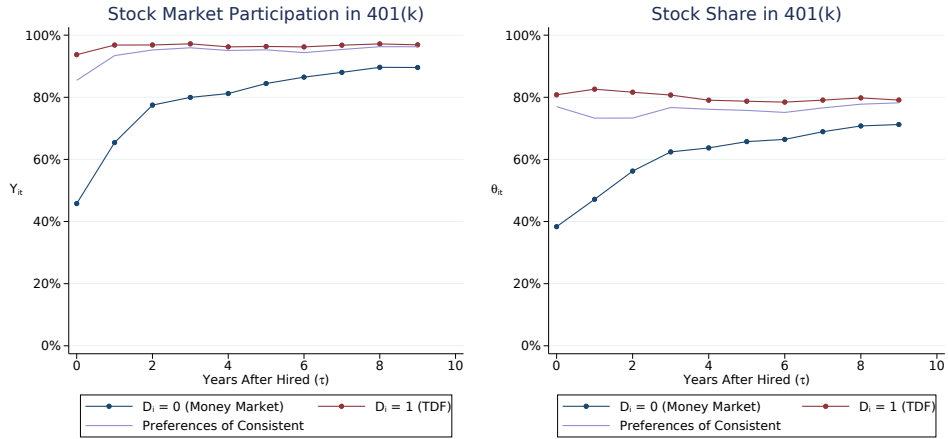
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<sup>14</sup>Figure A9 plots estimates of these preferences based on what default consistent investors are given. For stock shares, we find that consistent investors reveal similar preferences regardless of the default, which supports Assumption 5.

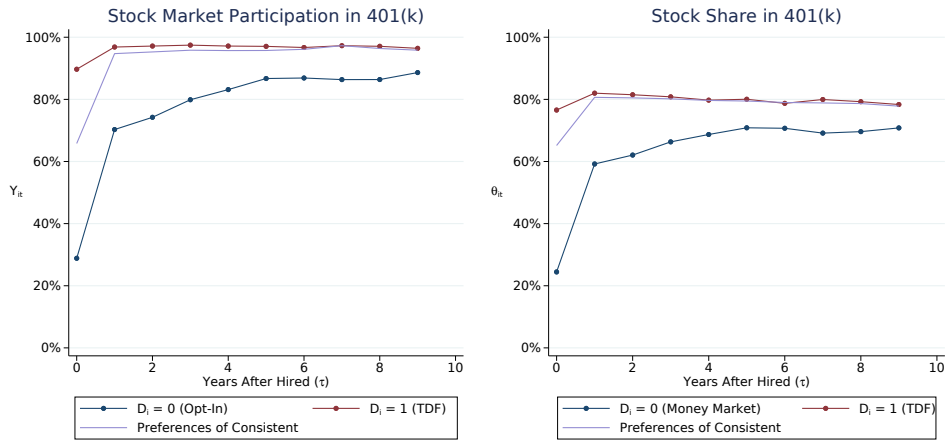
<sup>15</sup>The fact that consistency increases over the life cycle is also consistent with theories of financial literacy accumulation (e.g., Lusardi, Michaud, and Mitchell 2017).

**Figure 6.** Preferences of Consistent Investors

*Panel A: Money Market to TDF Sample*



*Panel B: Opt In to TDF Sample*



*Notes:* This figure plots the same data as in Figure 4 but includes our point estimates for the consistent investors under Assumptions 1–4 for stock market participation within 401(k) plans and Assumptions 1–3 and 5 for the stock share of retirement wealth. Under Assumption 6, these estimates provide an estimate of the preferences of the entire population.

$$E_{\tau}(\theta_{it}^*) = E_{\tau}(\theta_{it}^* | C_{it}^{\theta} = 1) - \frac{1}{E_{\tau}(C_{it}^{\theta})} \underbrace{\text{cov}_{\tau}(\theta_{it}^*, C_{it}^{\theta})}_{\text{selection bias}}. \quad (7)$$

Proposition 3 shows that the first two terms in (6) and (7) are identified, which we estimated in Figure 6. However, the second term in both expressions is not identified. Intuitively, it represents a form of selection bias that arises if consistent investors have preferences different from those of inconsistent investors. In general, this selection bias is unbounded if we place no further restrictions on investor decision-making. For example, in our structural model described in Section 4, we could compute this directly.

To derive point estimates of average population preferences, we begin by making the following identifying assumption.

**Assumption 6.** *For all  $i$  and  $\tau$ ,*

$$\text{cov}_{\tau}(Y_{it}^*, C_{it}^Y) = \text{cov}_{\tau}(\theta_{it}^*, C_{it}^{\theta}) = 0.$$

This assumption states that once we condition on an investor's tenure, whether she is consistent is uncorrelated with her preferences. Under Assumption 6, the preferences of the population at each tenure are given by the preferences of consistent investors in Figure 6: at tenure  $\tau = 3$ , the average preference for stock market participation within retirement accounts is 94%, and the average preferred stock share of retirement wealth is 76%.

Assumption 6 is a strong assumption: it requires that, at a given tenure, consistent (active) and inconsistent (passive) investors have similar preferences over risky assets in their retirement accounts. This assumption cannot be directly tested since we do not observe the preferences of inconsistent individuals. However, we can take advantage of the fact that, over time, more investors make active decisions and reveal their preferences. We can thus obtain an indirect proxy for  $\text{cov}_{\tau}(Y_{it}^*, C_{it}^Y)$  by comparing the allocation decisions of investors who are quick to make active decisions (more consistent) with those of investors who wait several years before deviating from the default (less consistent). In Figure A10, we find that the stock market participation and average stock share within the retirement account are very similar for investors who deviate right away from the default and those who wait up to 8 years to make an active decision, consistent with Assumption 6.

However, in the event that Assumption 6 fails, we can still rely on our bounds for preferences from Section 3.2: at a tenure of 2 years, at least 78% of investors prefer stock market participation

with an average stock share of at least 58%. Additionally, in the structural model that we develop in Section 4, we do not require Assumption 6 since the relationship between preferences and consistency arises endogenously within the model.

### 3.5 Estimating Preferences over the Life Cycle

Assumption 6 is relatively strong in that it rules out the possibility that consistency and preferences might both vary with age (conditional on tenure). This is restrictive given that the stock of human capital, the central driver of portfolio choice in most life cycle models, decreases with age while there are natural reasons to believe that consistency might vary with age as well (e.g., older investors have a lower option value from delaying adjustment). We thus relax Assumption 6 by making the following assumption.

**Assumption 7.** For all  $i$ ,  $\tau$ , and  $A \in \mathcal{A}$ ,

$$\text{cov}_\tau(Y_{it}^*, C_{it}^Y \mid \text{age}_{it} = A) = \text{cov}_\tau(\theta_{it}^*, C_{it}^\theta \mid \text{age}_{it} = A) = 0.$$

Assumption 7 is a weaker version of Assumption 6 in that it conditions on age in addition to tenure. Under Assumption 7, we can identify how preferences vary over the life cycle. In particular, we can apply the law of iterated expectations to (6) and (7) to obtain:

$$\begin{aligned} E_\tau(Y_{it}^* \mid \text{age}_{it} = A) &= E_\tau(Y_{it}^* \mid C_{it}^Y = 1, \text{age}_{it} = A), \\ E_\tau(\theta_{it}^* \mid \text{age}_{it} = A) &= E_\tau(\theta_{it}^* \mid C_{it}^\theta = 1, \text{age}_{it} = A). \end{aligned}$$

Applying Proposition 3 conditionally then gives the following life cycles of preferences for investors of tenure  $t = \tau$ :

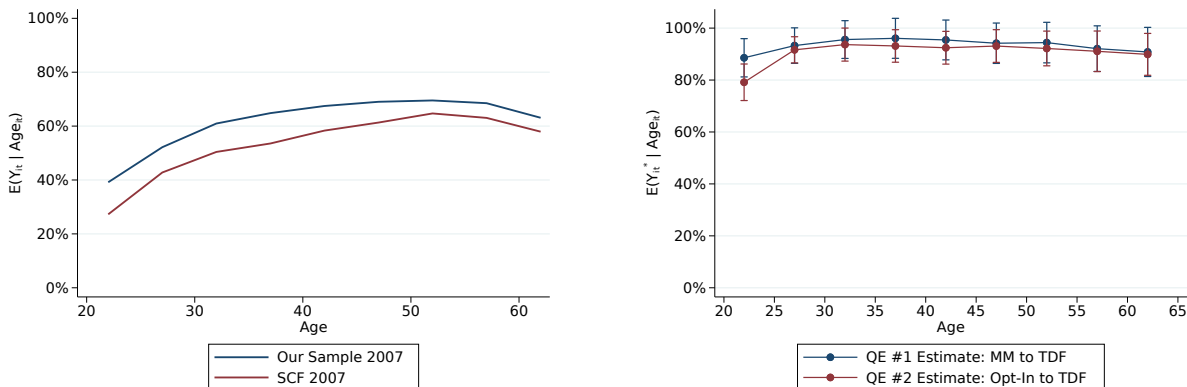
$$E_\tau(Y_{it}^* \mid \text{age}_{it} = A) = E_\tau(Y_{it} \mid Y_{it} \neq D_i, \text{age}_{it} = A), \quad (8)$$

$$E_\tau(\theta_{it}^* \mid \text{age}_{it} = A) = E_\tau(\theta_{it} \mid \theta_{it} \neq \theta_i^d(D_i), \text{age}_{it} = A). \quad (9)$$

The left panel of Figure 7 plots the fraction of investors with a positive stock share both in our sample of retirement assets in 2007 and for total financial wealth in the SCF 2007 wave. Consistent with typical findings in the life cycle portfolio choice literature, we find that participation is upward sloping over the life cycle. The right panel shows our estimate of investors' preferences

for stock market participation using (8), averaging across all tenures.<sup>16</sup> Unlike in the left panel, where *observed* participation is increasing over the life cycle and is strictly below 70%, we estimate that over 90% of investors prefer holding stocks in their 401(k) plan and that this share is relatively flat over the life cycle. Our estimates are statistically indistinguishable across our two quasi-experiments, which provides support for our identifying assumptions.

**Figure 7.** Stock Market Participation in 401(k) Plans over the Life Cycle: Choices vs. Preferences



*Notes:* This figure plots our estimates of investors’ preferences for stock market participation in the right panel in comparison to their observed choices in the left panel. In the left panel, we plot the fraction of investors with a positive stock share in our sample of retirement accounts in 2007 and for total financial wealth in the SCF 2007 wave. Ages are binned into groups of 3 years. The right panel plots our estimate of the average preferences for stock market participation within the retirement account over the life cycle under Assumptions 1–4 and 7. The right panel shows our point estimates from our two quasi-experiments along with the 90% confidence intervals based on standard errors clustered by investor for our first quasi-experiment and by firm for our second quasi-experiment.

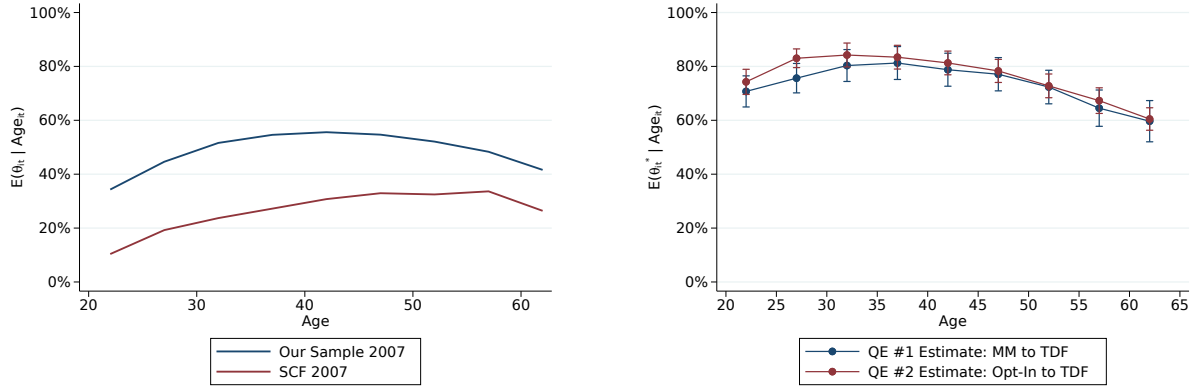
In Figure 8, we show analogous results for stock shares of retirement wealth. The left panel shows that investors’ stock shares of retirement wealth are relatively hump shaped over the life cycle (as in Ameriks and Zeldes 2004) and are strictly below 60%. In contrast, the preferred shares shown in the right panel are significantly higher—above 60% at all ages—and are mostly decreasing over the life cycle. This life cycle of preferences is consistent with standard predictions from life cycle portfolio choice models with risky labor income that is uncorrelated with stock returns (Campbell and Viceira 2001; Cocco et al. 2005). However, we do find some evidence of investors’ preferred stock shares increasing before age 35, consistent with theories of fixed participation costs and some co-integration between stock returns and labor income shocks (Benzoni et al. 2007; Catherine 2022; Gomes and Smirnova 2021). Notably, our estimates of preferences differ from the preference for a TDF, which is flat at 90% before age 35. This preference of younger investors for a lower stock share is also evident from Figure A14: consistent investors assigned by default into a TDF choose lower stock shares at all ages, but this is especially true for younger

<sup>16</sup>Figure A11 shows our estimates of investors’ preferences over the life cycle, conditional on different tenures. We find similar results across different tenures and hence omit these results from the main text.



investors.

**Figure 8.** Stock Share in 401(k) Plans over the Life Cycle: Choices vs. Preferences



*Notes:* This figure plots our estimate of investors’ preferences for stock shares of retirement wealth in the right panel in comparison to their observed choices in the left panel. In the left panel, we plot the average stock share of retirement wealth among all investors in our data in 2007 across different ages, where ages are binned into groups of 3 years. The left panel also plots the analogous results from the 2007 SCF for comparison, where equity shares are calculated based on financial wealth. The right panel plots our estimate of the average preferences for stock shares of retirement wealth over the life cycle under Assumptions 1–4, 5, and 7. The right panel shows our point estimates along with the 90% confidence intervals based on standard errors clustered by investor for our first quasi-experiment and by firm for our second quasi-experiment.

Collectively, these results suggest that in the absence of adjustment or one-time participation costs, the investors in our sample prefer to hold stocks in their retirement accounts with reasonably high stock shares of retirement wealth. The stark difference between observed choices and estimated preferences in Figures 7 and 8, further highlighted in Figure 9, emphasizes the importance of distinguishing between the two in the presence of choice frictions.

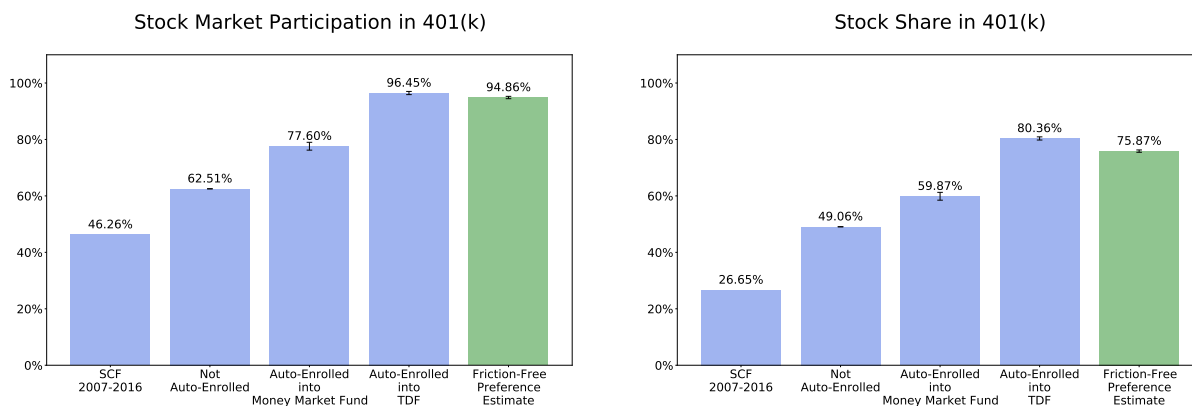
These findings have implications for the large literature on limited household stock market participation. If the investors in our sample had preferences exhibiting first-order risk aversion, had pessimistic beliefs, or faced large per-period participation costs, our estimation would recover a low preference for participation. The fact that, after taking into account choice frictions, we estimate investors prefer positive equity shares provides support for models with real or psychological participation and adjustment costs.<sup>17</sup>

An important caveat to our findings is that they apply specifically to retirement accounts. Although retirement accounts are the primary vehicle for stock market participation (according to the SCF), nonretirement accounts (e.g., brokerage accounts) also constitute a substantial fraction of stock market wealth. There is some evidence that behavior is different in nonretirement accounts. For example, [Galaasen and Raja \(2022\)](#) document that exit from the stock market in nonretirement

<sup>17</sup>As discussed above, to the extent that investors face per-period psychological participation costs, our results understate the importance of choice frictions.

accounts is common in Sweden. Our results suggest this exit is likely driven by larger per-period participation costs in nonretirement accounts. If this exit were driven by beliefs or preferences, we would expect similar exit levels in retirement accounts.<sup>18</sup>

**Figure 9.** Preference Estimates vs. Observed Choices



*Notes:* This figure compares our estimates of preferences to observed choices for retirement wealth stock market participation in the left plot and unconditional stock shares of retirement wealth in the right plot. The first bar, SCF 2007–2016, plots the averages in the SCF 2007, 2010, 2013, and 2016 waves, adjusted for survey weights with each year weighted equally and stock market participation and stock shares calculated based on retirement wealth. Not Auto-Enrolled refers to the averages among the investors in our sample who are not auto-enrolled in a 401(k) plan. Auto-Enrolled into Money Market Fund and Auto-Enrolled into TDF refer to the averages among investors in our sample who are hired under auto-enrollment into a 401(k) plan but assigned by default into a money market fund or target date fund, respectively. The final column represents our estimate of investors’ preferences based on the methodology described in Section 3.5, where the values plotted come from taking weighted averages of the results in Figures 7 and 8 across ages.

### 3.6 Additional Results and Robustness

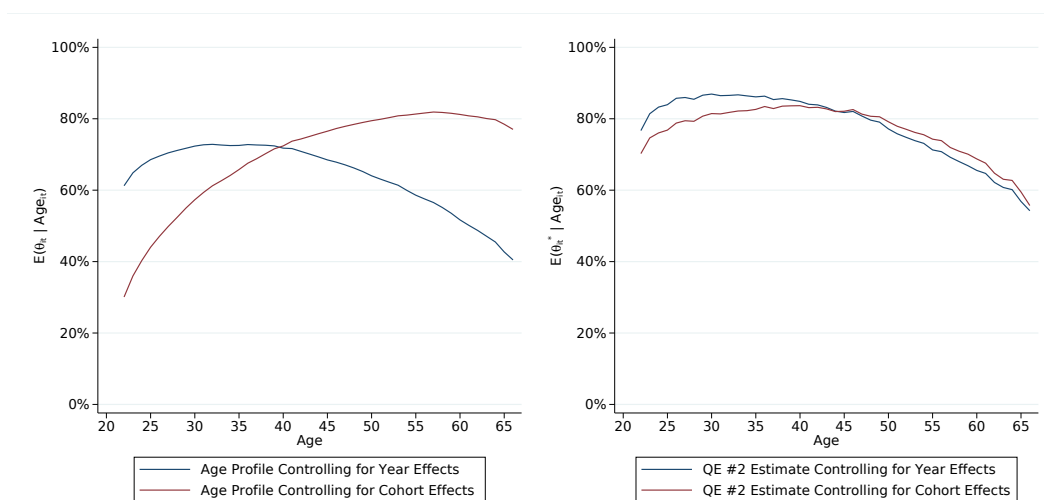
**Year, cohort, and firm effects.** Because age, time and cohort effects are colinear, it is impossible to separately identify the three effects in a linear model (Deaton and Paxson 1994). Using SCF and retirement account data similar to ours, Ameriks and Zeldes (2004) show that the life cycle profile of equity shares is sensitive to the inclusion of either year or cohort effects: it is increasing with age in the presence of cohort dummies and flat or decreasing with age when year dummies are included.<sup>19</sup> In the left panel of Figure 10, we replicate this finding in our data: the life cycle profile of the equity share of retirement wealth is more upward sloping when we include cohort instead of year dummies. In contrast, the right panel of Figure 10 shows that our identification approach, described in Section 3.5, is less sensitive to the inclusion of either time or cohort dum-

<sup>18</sup>A complementary explanation for these two findings would be that pessimistic beliefs drive stock market exit but that investors exit nonretirement accounts first due to their larger per-period participation costs and lack of tax advantages.

<sup>19</sup>Parker et al. (2022) replicate this finding in recent data using rich retirement account data that are also similar to ours.

mies. In particular, our estimated age profile of investors' preferred equity share of retirement wealth is very similar under our baseline specification (with no cohort or time effects) and under the specifications including either year or cohort effects.<sup>20</sup> These results suggest that a substantial fraction of the year and cohort variation in stock years within retirement accounts could come from frictions changing over time, for example, due to changes in 401(k) default options. Additionally, in Figure A13, we show that our estimates of preferences are robust to including firm fixed effects.

**Figure 10.** Cohort and Year Effects in Choices vs. Preferences: Stock Share in 401(k) Plans



*Notes:* The left panel of this figure plots the age profile of stock shares of retirement wealth across all investors and years in our sample for two specifications: one with cohort effects and without year effects and the other without year effects and with cohort effects. The right panel of this figure shows our estimates of investors' preferred stock share of retirement wealth over the life cycle from our second quasi-experiment following the methodology used to make Figure 8 with and without controls for cohort and year effects, respectively. For both panels, we obtain the predicted values by adding the median cohort or year coefficient to each age coefficient.

**Preference heterogeneity.** In Figure A12, we explore preference heterogeneity<sup>21</sup> over the life cycle by plotting the distribution of preferred stock shares among consistent investors for three different age groups: 20–34, 35–49, and over 50. These three groups are approximately evenly spaced terciles. We find that preference heterogeneity increases over the life cycle: most investors in the lowest age group prefer a stock share of over 80%, while there is much more dispersion in the preferred stock shares among the highest age group. Notably, this is qualitatively consistent with the formulation of typical life cycle models, in which heterogeneity increases over the life cycle due to greater cross-sectional variance in the model's state variables.

**Conditioning on income.** In our data, we observe the salary that investors receive from their

<sup>20</sup>In the right panel of Figure 10, we show the evidence using our second quasi-experiment (with the opt-in control group). The results are similar to those of our first quasi-experiment and are available upon request.

<sup>21</sup>We use the term preference heterogeneity loosely, as the results could also reflect heterogeneity in beliefs as in Meeuwis, Parker, Schoar, and Simester (2020) and Giglio, Maggiori, Stroebel, and Utkus (2021).

employer for the subset of investors who contribute to their 401(k) plans. Thus, we can estimate average preferences under a weaker version of Assumption 7, where we assume that consistency and preferences are uncorrelated conditional on age, tenure, *and* income. In Figure A15, we plot the estimates of preferences over the life cycle at different tenures based on this weaker assumption. The results show that our estimates of preferences are unaffected. In Figure A16, we plot our estimates of preferences over the life cycle by income quartile, after integrating over tenure. The results show that our preference estimates are mostly similar across income quartiles, consistent with the results in Figure A15. However, we find some evidence that investors in the bottom income quartile like stocks slightly less than those in the top three quartiles. This could have many explanations, but it is consistent with other evidence that suggests nonhomotheticity in preferences (Brunnermeier and Nagel 2008; Straub 2019; Meeuwis 2020).

## 4 Life Cycle Portfolio Choice Model

In this section, we describe a rich life cycle portfolio choice model and estimate it using the variation from our quasi-experiments. In this model, investors choose a level of consumption, retirement wealth, and liquid wealth and the portfolio allocation in their retirement wealth. This model builds on and extends the consumption–saving model of Choukhmane (2021) to include multiple assets and portfolio choice decisions. The model features three key elements required to match our quasi-experimental evidence. First, investors can choose different asset allocations for existing wealth and new contributions in their retirement account. Second, investors are required to pay separate opt-out costs to deviate from the default contribution rate in their retirement account and the default portfolio allocation. When agents are hired, these defaults are employer specified; in later periods, choices from the prior period are the default in the current period. Finally, investors face uncertainty about future earnings and employment status at their current employer that creates value for investors from delaying adjustments to portfolio and savings decisions from their defaults. Employment uncertainty (with both unemployment and job-to-job transitions) is critical to obtaining reasonable estimates of adjustment costs: a worker who expects to stay in the same job for a lifetime would choose inaction only if she faces a very large adjustment cost. Appendix A provides a summary of the model parameters.

## 4.1 Model Description

### 4.1.1 Demographics and Preferences

Each period corresponds to one year, and working life starts at  $t = 0$  and lasts for  $T_w$  periods. Retirement starts at  $t = T_w$ , and agents can live at most  $T$  periods. Before their certain death in period  $t = T$ , investors face age-dependant mortality risk with survival probability in period  $t + 1$  conditional on survival in period  $t$  denoted by  $m_t$ , which is taken from the SSA life tables. We denote an investor's age as  $a_t = t + a_0$ , where  $a_0$  is the age at which investors are born.

Investors have recursive Epstein–Zin–Weil preferences (Epstein and Zin 1989; Weil 1990) over consumption streams. We denote investors' annualized time discount factor as  $\beta$ , elasticity of intertemporal substitution as  $\sigma^{-1}$ , and relative risk aversion as  $\gamma$ .<sup>22</sup> Per-period consumption at  $t$  is adjusted for an equivalence scale that we take from Lusardi et al. (2017), which we denote by  $n_t$ .

### 4.1.2 Labor Market

There is a continuum of employers indexed by  $e$  for which investors can work. At any point in time, an investor can have one of four employment statuses, denoted  $emp_t$ :  $E$  = employed in the same job in the current as in the prior period,  $JJ$  = employed in a different job in the current period from the job in the prior period,  $U$  = unemployed in the current period, and  $Ret$  = retired.

The fact that investors face uncertainty about their future employment status, in addition to earnings risk, is an important feature of our model for two reasons. First, it introduces deviations in income shocks from normality, which Guvenen, Karahan, Ozkan, and Song (2021) highlight are important empirically. Second, it implies that even a small adjustment cost can cause investors to delay changing their asset allocation or contribution rate since there is a nontrivial probability they will be in a different job (or unemployed) in the next period.

**Employment:**  $emp_t = E$ . While working, investors earn an income  $w_t$  that is stochastic and exogenous. This income consists of a deterministic component that is cubic in age and a stochastic component that follows an AR(1) process with normally distributed innovations:

$$\ln w_t = \delta_0 + \delta_1 a_t + \delta_2 a_t^2 + \delta_3 a_t^3 + \eta_t, \quad \eta_t = \rho \eta_{t-1} + \xi_t^E, \quad (10)$$

---

<sup>22</sup>Formally,  $\sigma^{-1}$  is the elasticity in the CES aggregator, and  $\gamma$  controls the curvature of the certainty-equivalent function. We loosely refer to these as the EIS and the coefficient of relative risk aversion, but strictly speaking,  $\sigma$  and  $\gamma$  do not independently control risk and time preferences (Garcia, Renault, and Semenov 2006).

$$\xi_0^E \sim N(0, \sigma_{\xi_0}^2), \quad \xi_t^E \sim N(0, \sigma_{\xi}^2) \quad \forall t > 0.$$

Investors' tenure status evolves according to  $ten_t = ten_{t-1} + 1$  if they remain employed at the same employer. We assume that the initial distribution of  $\eta_t^E$  is different in the first period ( $t = 0$ ) to account for heterogeneity in the initial period incomes.

**Job transition:**  $emp_t = JJ$ . While in the employed state ( $E$ ), an investor may switch jobs with a probability  $\pi^{JJ}(t, ten_t)$  that depends on both her age and tenure at the current job. We model these transitions separately because retirement accounts are employer specific. After a job-to-job transition, income evolves according to:

$$\ln w_t = \delta_0 + \delta_1 a_t + \delta_2 a_t^2 + \delta_3 a_t^3 + \eta_t, \quad \eta_t = \rho \eta_{t-1} + \xi_t^{JJ}, \quad \xi_t^{JJ} \sim N(\mu^{JJ}, \sigma_{\xi}^2). \quad (11)$$

This earnings process captures a wage premium associated with switching jobs. Investors' tenure is reset to  $ten_t = 0$  following a job-to-job transition.

**Unemployment:**  $emp_t = U$ . While in the employed state ( $E$ ), an investor may become unemployed with a probability  $\pi^{EU}(t, ten_t)$  that depends on both her age and tenure at the current job. When investors are unemployed, they receive unemployment benefits equal to  $ui_t = ui(\eta_t)$ , where  $ui(\eta_t)$  is described below. If investors become employed at  $t + 1$  after being unemployed in period  $t$ , income at  $t + 1$  evolves according to

$$\ln w_{t+1} = \delta_0 + \delta_1 a_{t+1} + \delta_2 a_{t+1}^2 + \delta_3 a_{t+1}^3 + \eta_{t+1}, \quad \eta_{t+1} = \rho \eta_t + \xi_{t+1}^U, \quad \xi_{t+1}^U \sim N(\mu^{UE}, \sigma_{\xi}^2). \quad (12)$$

This earnings process captures the persistent wage reduction associated with experiencing unemployment.

**Retirement:**  $emp_t = Ret$ . In period  $t = T_w$ , all investors retire deterministically. During retirement in periods  $t \in [T_w, T - 1]$ , investors earn public pension benefits denoted by  $ss_t$ , which are described below.

### 4.1.3 Financial Assets

There are three financial assets in the model. First, there is a risk-free bond that has a constant gross return of  $R_t^B = R_f$  per year. Second, there is a risky asset, a stock, that corresponds to a

diversified market index and pays a stochastic IID gross return of  $R_t^S = R_t$  per year, where

$$\ln R_t^S = \ln R_f + \mu_s + \varepsilon_t, \quad \varepsilon_t \sim \mathcal{N}(0, \sigma_s^2). \quad (13)$$

Finally, investors have access to a liquid risk-free asset that has a constant gross return of  $1 + r$  per year. Note that stock returns are uncorrelated with shocks to labor income in our model. If stock returns and income shocks were correlated (as in, e.g., [Benzoni et al. 2007](#); [Catherine 2022](#)), this would make stocks less attractive and thus push down our estimate of relative risk aversion.

#### 4.1.4 Savings Accounts

The asset side of investors' balance sheets is comprised of two savings accounts, which we now describe in turn.

**Liquid savings account.** When investors are born at  $t = 0$ , they are endowed with zero liquid wealth and a liquid savings account. Investors can use this liquid savings account only to invest into a liquid riskless asset. The balance of this account, denoted by  $L_t$ , evolves according to:

$$L_{t+1} = (L_t + s_t^l) [1 + r(1 - \tau_c)], \quad L_0 = 0, \quad (14)$$

where  $s_t^l$  is the net savings that the investor places in this account and  $\tau_c$  is the rate of capital taxation.

**Defined contribution retirement savings accounts.** Each time an investor is matched with an employer for the first time, she is given access to a savings account. This savings account is the counterpart in our model of a defined contribution 401(k) retirement savings plan. Investors use this savings account to buy and sell any combination of the bond and the stock, subject to the restriction of no margin trading (i.e., no leveraged purchases or short-sales). Investors cannot use this account to purchase the liquid risk-free asset or borrow. Returns earned in this account are tax free, unlike those earned in the liquid savings account.

The balance of this savings account, denoted by  $A_t$ , evolves according to:

$$A_{t+1} = A_t \times \sum_{j \in \{B, S\}} \Theta_t^j R_{t+1}^j + w_t \times \mathcal{M}_e(s_{t+1}^{dc}, t, ten_t, emp_t) \times \sum_{j \in \{B, S\}} \theta_t^j R_{t+1}^j, \quad (15)$$

$$\mathcal{M}_e(s, t, ten_t, emp_t) = \begin{cases} s + \Upsilon_e(t, ten_t) \times match_e \times \min\{s, cap_e\} & \text{if } emp_t \in \{E, JJ\}, \\ s & \text{else,} \end{cases}$$



with the initial condition  $A_0 = 0$ . In these expressions,  $s_t^{dc}$  is the rate of net savings (including possible withdrawals) that the investor places in this account;  $\mathcal{M}_e(\cdot)$  is an employer-specific function that determines how savings is mapped to account contributions;  $\{\Theta_t^B, \Theta_t^S\}$  are the portfolio shares of existing assets in stocks and bonds, respectively, chosen at time  $t$ ; and  $\{\theta_t^B, \theta_t^S\}$  are analogous portfolio shares for new contributions. The form of  $\mathcal{M}_e(\cdot)$  captures the fact that when placing  $s$  into the retirement account, investors benefit from employer-specific matching, which is characterized by a match rate,  $match_e$ , and a threshold contribution rate,  $cap_e$ . Additionally, we adjust these employer matches by a factor  $\Upsilon_e(\cdot) \leq 1$  to capture the possible loss of employer matches if investors separate from the employer before vesting is complete.

Importantly, the balance of this savings accounts depends on *two* portfolio choice decisions: (i) the portfolio allocation of existing contributions and (ii) the portfolio allocation of new contributions. This distinction, which matches the institutional features of 401(k) asset allocation decisions, is important in our model because investors are subject to default effects (described in Section 4.1.5). Without the presence of such default effects, these two decisions could be collapsed into one portfolio choice decision. For notational convenience, denote as  $\Xi_t$  the four-dimensional vector of portfolio choices for the two assets.

**Defined contribution account during employment transitions.** Investors have access to a new defined contribution savings account each time they move to a new employer. When investors become unemployed or retired, we assume that they can only withdraw resources but cannot make new contributions to the account, as represented by the constraint  $s_t^{dc} \leq 0$ . We keep track of both the asset allocation in the current employer retirement saving plan and assets previously accumulated in all previous employer retirement accounts. After a job transition, the employer matching function, denoted by  $\mathcal{M}_e(\cdot)$  in (15), and the default asset allocation for new contributions, described in Section 4.1.5, change to those specified by the new employer. For tractability, we assume that when an individual changes the asset allocation of existing assets, it simultaneously affects savings in both the current and previous employer retirement plans. In contrast, a change in the allocation of new contributions affects only the asset allocation within the current employer retirement saving plan.

Denote as  $t_J$  the period in which an individual was hired by her current employer:  $t_J = \sup\{s : s \leq t, emp_s = JJ\}$ . We denote as  $\tilde{\Theta}_t^j$  the investor's portfolio share in asset  $j$  of wealth accumulated at her current employer, which evolves according to

$$\tilde{\Theta}_t^j = \begin{cases} \frac{\Theta_t^j A_t - \Theta_{t_J}^j A_{t_J}}{A_t - A_{t_J}}, & \text{if } emp_t = E, \\ 0 & \text{else.} \end{cases}$$

#### 4.1.5 Default Options and Adjustment Costs

An investor's portfolio allocation and savings decisions in the defined contribution (DC) account are both subject to default effects. We first describe the value of these defaults and then the way in which they impact the investor's choices.

**Default asset allocation for new DC contributions (i.e., flows).** When an investor begins working for employer  $e$  at time  $t$ , the default asset share of contributions to the defined contribution savings account invested in asset  $j$  is  $\bar{\theta}_e^j$ . Later in the worker's tenure, the default asset allocation for contributions corresponds to the allocation chosen in the prior period. Formally, for  $j \in \{B, S\}$ ,

$$\theta_{d,t}^j = \begin{cases} \bar{\theta}_e^j & \text{if } emp_t = JJ, \\ \theta_{t-1}^j & \text{else.} \end{cases} \quad (16)$$

**Default portfolio allocation for existing DC contributions (i.e., stocks).** When the investor chooses the portfolio allocations of existing assets, the default allocation for each asset is equal to the amount of old contributions in that asset, adjusted for realized returns, plus the amount of new contributions allocated to that asset. Formally, for  $j \in \{B, S\}$ ,

$$\Theta_{d,t}^j = \begin{cases} \frac{A_{t-1} \Theta_{t-1}^j R_t^j + \mathcal{M}_e(s_{t-1}^{dc}) \theta_{t-1}^j R_t^j}{A_{t-1} \sum_j \Theta_{t-1}^j R_t^j + \mathcal{M}_e(s_{t-1}^{dc}) \sum_j \theta_{t-1}^j R_t^j} & \text{if } s_{t-1}^{dc} > 0, \\ \frac{A_{t-1} \Theta_{t-1}^j R_t^j}{A_{t-1} \sum_j \Theta_{t-1}^j R_t^j} & \text{else.} \end{cases} \quad (17)$$

Note that the specification embeds the assumption that when investors dis-save out of their DC account, they sell assets in proportion to their current portfolio allocations. Additionally, we set  $\Theta_{d,0}^j = 0$  since investors are born with no assets.

**Default contribution rate in DC account.** When an investor begins working for employer  $e$  at time  $t$ , the default contribution rate in her defined contribution savings account is  $\bar{s}_e^{dc}$ . Later in the worker's tenure, the default contribution rate is equal to the contribution rate from the prior period. Formally,

$$s_{d,t} = \begin{cases} \bar{s}_e^{dc} & \text{if } emp_t = JJ, \\ s_{t-1}^{dc} & \text{else.} \end{cases} \quad (18)$$

**Adjustment costs.** Investors in our model face adjustment costs in changing their asset allocations and savings contribution rate from the default option. Recall that  $\Xi_t$  denotes the vector of the

investor's portfolio allocations in the defined contribution account. If an investor chooses  $\Xi_t \neq \Xi_{d,t}$ , where

$$\Xi_{d,t} = \left( \Theta_{d,t}^B, \Theta_{d,t}^S, \theta_{d,t}^B, \theta_{d,t}^S \right),$$

she incurs a utility cost  $k_\theta$ . This cost is designed to capture any physical or physiological costs associated with making portfolio choice decisions. Similarly, choosing  $s_t^{dc} \neq s_{d,t}$  requires incurring a utility cost of  $k_s$ .<sup>23</sup>

#### 4.1.6 Government

**Income taxes.** Investors face a nonlinear income tax schedule  $tax_i(w_t)$ . Contributions to the DC retirement account are not subject to income taxation, while withdrawals (in either unemployment or retirement) increase taxable income by the withdrawal amount.<sup>24</sup> Capital gains in the liquid savings account are taxed at rate  $\tau_c$ .

**Unemployment benefits.** Investors receive an unemployment benefit of  $ui(\eta_t)$  when their employment ends. This benefit depends on the labor productivity,  $\eta_t$ , from the last period in which the agent was employed. Any withdrawals from the DC retirement account are treated as compensation and thus may offset unemployment benefits.

**Retirement benefits.** After retirement, investors receive benefits modeled on social security, denoted by  $ss_t = ss(ae_{T_w})$ , where  $ae_{T_w}$  is the investor's average lifetime earnings at the time of retirement, which evolves according to:

$$ae_{t+1} = \begin{cases} \frac{w_{t+1} + a_t * ae_t}{a_{t+1}}, & \text{if } t < T_w, \\ ae_{T_w} & \text{else.} \end{cases}$$

**Medicare premiums.** During retirement, investors pay Medicare premiums that are directly deducted from investors' social security benefits.

<sup>23</sup>We model adjustment costs instead of one-time participation costs. This choice reflects the fact that most investors in our sample do not rebalance their portfolios every period, which suggests the presence of adjustment costs rather than one-time participation costs.

<sup>24</sup>The DC account in our model is modeled on the traditional tax-deferred DC model rather than the Roth 401(k) model.

#### 4.1.7 Recursive Formulation

Investors face a dynamic optimization problem with 12 state variables:  $a_t = \text{age}$ ,  $\eta_t = \text{labor productivity}$ ,  $emp_t = \text{employment status}$ ,  $e = \text{employer}$ ,  $ten_t = \text{tenure}$ ,  $ae_t = \text{average lifetime income}$ ,  $A_t = \text{DC retirement savings}$ ,  $L_t = \text{liquid savings}$ ,  $\Xi_{d,t} \in \mathbb{R}^4 = \text{default portfolio shares}$ , and  $s_{d,t} = \text{default contribution to the DC account}$ . Using the fact that the portfolio shares sum to one, we can reduce this to a problem with 10 state variables by dropping the portfolio shares in the bond. Denote the vector of these state variables as  $X_t$ .

In this optimization problem, investors have 7 controls:  $c_t = \text{consumption}$ ,  $\Xi_t \in \mathbb{R}^4 = \text{portfolio shares}$ ,  $s_t^{dc} = \text{defined contribution savings rate}$ , and  $s_t^l = \text{liquid savings}$ . As above, this can be reduced to 4 controls given that the portfolio shares sum to one and that consumption is pinned down by the budget constraint. In choosing these controls, we restrict investors from borrowing and engaging in any margin trading (i.e., short-selling or taking leveraged positions):

$$A_t \geq 0, \quad L_t \geq 0, \quad \Theta_t^j \in [0, 1], \quad \theta_t^j \in [0, 1], \quad \sum_j \Theta_t^j = \sum_j \theta_t^j = 1. \quad (19)$$

We now characterize the value function of an investor,  $V(\cdot)$ , separately for the four states of employment  $emp_t$ . For brevity, we denote  $V(X_t)$  as  $V_t$  and let  $E_t(\cdot)$  denote  $E(\cdot | X_t)$ .

**Retirement:**  $emp_t = Ret$ . There are two sources of uncertainty when decisions are made at time  $t$ : mortality occurring with probability  $m_t$  and asset return shocks,  $\varepsilon_{t+1}$ . An investor's value function is thus characterized by the following recursive equation<sup>25</sup>:

$$V_t = \max_{s_t^{dc}, s_t^l, \Xi_t} \left\{ (1 - \beta) n_t \left[ \frac{c_t - k_\theta * 1 \{ \Xi_t \neq \Xi_{d,t} \}}{n_t} \right]^{1-\sigma} + \beta \left[ m_t E_t V_{t+1}^{1-\gamma} \right]^{\frac{1-\sigma}{1-\gamma}} \right\}^{\frac{1}{1-\sigma}},$$

subject to: (13), (14), (15), (16), (17), (19), and

$$s_t^l = ss_t - s_t^{dc} * w_t - c_t,$$

$$V(a_T, \cdot)^{1-\gamma} = 0,$$

$$s_t^{dc} \leq 0.$$

<sup>25</sup>Following existing literature that uses Epstein–Zin–Weil preferences in life cycle settings, our terminal condition implicitly embeds the assumption that the utility of death is infinite if  $\gamma > 1$ . This is not an innocuous assumption (see [Bommier, Kochov, and Le Grand 2017](#)). We verify that this assumption does not meaningfully affect our preference estimates by estimating a version of the model with nonrecursive preferences ( $\gamma = \sigma$ ), which does not require this assumption.

**Working life:**  $emp_t \in \{E, JJ\}$ . There are five sources of uncertainty when decisions are made at time  $t$ : mortality occurring with probability =  $m_t$ ; asset return shocks,  $\varepsilon_{t+1}$ ; employment risk based on the state transition matrix; labor income shocks based on  $\xi_{t+1}^E$  or  $\xi_{t+1}^{JJ}$ ; and the type of future employer after a job change,  $e$ . An investor's value function is thus characterized by the following recursive equation:

$$V_t = \max_{s_t^{dc}, s_t^l, \Xi_t} \left\{ (1-\beta)n_t \left[ \frac{c_t - k_\theta * 1\{\Xi_t \neq \Xi_{d,t}\} - k_s * 1\{s_t^{dc} \neq s_{d,t}\}}{n_t} \right]^{1-\sigma} + \beta \left[ m_t E_t V_{t+1}^{1-\gamma} \right]^{\frac{1-\sigma}{1-\gamma}} \right\}^{\frac{1}{1-\sigma}},$$

subject to: (10), (11), (13), (14), (15), (16), (17), (19), and

$$s_t^{dc} * w_t + s_t^l = w_t - c_t,$$

$$0 \leq s_t^{dc} \leq limit_{e,t}.$$

**Unemployment:**  $emp_t = U$ . There are five sources of uncertainty when decisions are made at time  $t$ : mortality occurring with probability =  $m_t$ ; asset return shocks,  $\varepsilon_{t+1}$ ; the possibility of becoming employed based on the transition matrix; next-period labor income shocks conditional on becoming employed =  $\eta_{t+1}^U$ ; and the type of future employer after a job change,  $e$ .

$$V_t = \max_{s_t^{dc}, s_t^l, \Xi_t} \left\{ (1-\beta)n_t \left[ \frac{c_t - k_\theta * 1\{\Xi_t \neq \Xi_{d,t}\}}{n_t} \right]^{1-\sigma} + \beta \left[ m_t E_t V_{t+1}^{1-\gamma} \right]^{\frac{1-\sigma}{1-\gamma}} \right\}^{\frac{1}{1-\sigma}},$$

subject to: (12), (13), (14), (16), (17), (18), (19), and

$$s_t^l = ui_t - c_t - s_t^{dc} * w_t * (1 - pen_{e,t}),$$

$$s_t^{dc} \leq 0.$$

We solve this model using standard numerical discrete-time dynamic programming techniques. For additional details, see Appendix D.

## 4.2 Estimation

We estimate the model parameters in two stages, as is common practice in life cycle models (e.g., [Gourinchas and Parker 2002](#); [Cocco et al. 2005](#)). The first stage consists of setting parameters outside of the model based on auxiliary estimation, institutional details, and prior literature. Additional details on this first-stage estimation are provided in Appendix E. The second stage

consists of using the simulated method of moments to estimate the model’s five preference parameters: the intertemporal discount factor ( $\beta$ ), relative risk aversion ( $\gamma$ ), elasticity of intertemporal substitution ( $\sigma^{-1}$ ), and the two adjustment costs ( $k_\theta$  and  $k_s$ ).

#### 4.2.1 First-Stage Parameter Estimation

**Demographics.** We set the length of one period in the model to one year and set  $a_0 = 22$ ,  $T_w = 43$ , and  $T = 68$ , such that workers are born at 22, retire at 64, and live their final year of life at 89. For each age, we take the survival probabilities from the 2015 U.S. Social Security Actuarial Life Tables. We use the equivalence scale estimated in Lusardi et al. (2017) to capture changes in household composition over the life cycle.

**Labor income process.** We use data from the Survey of Income Programs and Participation (SIPP) to estimate parameters of the labor income process and transition probabilities at the annual frequency. This income process has several components. First, we estimate an earnings process for workers staying in the same job, corresponding to (10), which contains a deterministic and stochastic component. We allow for measurement error and use a standard two-step minimum distance approach (as in, e.g., Guvenen 2009). Our estimates (provided in Table A1) are consistent with those in prior literature, in particular our estimate of a relatively high persistence of permanent income shocks. Second, we use data on employment transitions from SIPP to directly estimate the median increase in salary when workers transition to new jobs,  $\mu^{JJ}$ , and the median decrease in salary when workers transition from employment to unemployment,  $-\mu^{EU}$ . Thirdly, we use SIPP microdata to estimate the three transition probabilities across our three employment states. Finally, we set the initial unemployment rate equal to 22%, which is the share in SIPP of unemployed individuals at age 22, and calibrate average annual earnings to be \$37,000, which matches the average net compensation per worker in the 2006 SSA National Average Wage Index.

**Assets returns.** We set the net risk-free rate to be constant at 2% to match the annualized average return of the money market provided by our data provider after subtraction of the expense ratio.<sup>26</sup> We set the equity premium to be 6.4%, which is equal to the average inflation-adjusted return on the CRSP Value-Weighted Index between 1925 and 2006 minus our 2% risk-free rate.<sup>27</sup> We set the volatility of log stock returns to 20%, which matches that of the CRSP Value-Weighted Index. We assume that asset returns are uncorrelated with shocks to labor income and employment transition probabilities. We set the net return on the liquid asset,  $r$ , to be the same as the net risk-free rate.

<sup>26</sup>In reality, the return on this fund is not constant, but its volatility is extremely low. The worst 3-month return since inception is above 0.45%, and the best is below 1.25%.

<sup>27</sup>We adjust for inflation using the CPI.

**Defined contribution savings accounts.** For all employers, we set the employer matching rate,  $match_e$ , equal to 50% and the threshold contribution rate for the maximum employer match,  $cap_e$ , equal to 6%. These values are chosen because they are the most common matching parameters both in our second-stage estimation sample and in nationally representative data of 401(k) and 403(b) plans (Arnoud et al. 2021).

**Vesting schedule.** If an investor separates from her employer before the end of the vesting period, she may lose part (or all) of the employer matching contribution. To account for this, we adjust the level of the employer matching contribution to equal the certainty equivalent given investor age and the tenure-specific separation probabilities. On average, 52% of matching contributions in our estimation sample are vested immediately, and the vested percentage increases with tenure.

**Taxes and benefits system.** Taxable income is defined as the sum of labor earnings, social security, unemployment benefits, and DC withdrawals, less contributions to the DC retirement account. Investors' tax liability is calculated according to the 2006 U.S. federal income tax schedule. We calculate Social Security benefits according to the 2006 formula with a Supplemental Security Income program floor. Unemployment benefits are computed with a replacement rate of 40%, which was the average across U.S. states as of 2018. During retirement, investors pay Medicare Part B and Part D premiums based on the 2006 [Supplementary Medical Insurance](#) formula. These Medicare payments are directly deducted from investors' social security benefits. Capital gains in the liquid savings account are taxed at  $\tau_c$ , which we set equal to 21%.

#### 4.2.2 Second-Stage Parameter Estimation

The five second-stage parameters are estimated with the simulated method of moments (SMM), which minimizes the (weighted) distance between the model-simulated and data moments.

**Empirical moments.** We use 38 empirical moments in total. First, we use the stock market participation rates between tenures of 0 and 6 years for the control and treatment groups in our first quasi-experiment. This gives moments similar to those in Panel A of Figure 4, with the only difference being in this estimation that we restrict the sample to investors between ages 24 and 62. Second, we use two life cycle profiles of average unconditional stock shares: one for those assigned by default into the money market fund and another for those assigned by default into the target date fund. Both of these life cycle profiles are calculated at the end of workers' first years of tenure, conditional on workers having a positive balance in the account. We construct these

profiles from ages 24 to 62 in bins of 5, giving 8 bins per profile for a total of  $8 \times 2 = 16$  moments.

The final set of moments that we use is the distribution of contribution rates among investors in our sample during their first year of tenure. Specifically, we use the 34 401(k) plans in our sample for which the exact date of auto-enrollment is available that have a 3% initial auto-enrollment default contribution rate with no auto-escalation feature and a 50% employer match contribution of up to 6% of income, which matches the structure of the 401(k) plans in our model exactly. We then calculate the fraction of workers who during their first year of tenure contribute one of the following four fractions of their income: 0%, 3%, 6%, or 10% and above. We do this for two samples of investors: investors hired under the opt-in regime within 12 months prior to the change to auto-enrollment and investors hired within 12 months after the change. This gives us a total of  $4 \times 2 = 8$  moments, which (as described below) are necessary to identify time preferences and the contribution adjustment cost.

**Model simulation experiments.** To estimate our five preference parameters with SMM, we need to construct moments within our model that are analogous to the 38 empirical moments that we picked above. We do this by running the following two simulations from our model, which are designed to match our empirical variation as closely as possible. We begin by simulating income processes and job transitions for 7,500 investors (approximately 5 times our sample size) according to the income process estimated in the prior section. Next, for each investor  $i$ , we randomly select one period denoted by  $\tau_i$  from all of the periods in which investor  $i$  experienced a job transition,  $emp_t = JJ$ , or a transition from unemployment to employment,  $emp_{t-1} = U$  and  $emp_t = E$ .

Using these values of  $\tau_i$ , we simulate the choices of each investor  $i$  over her life cycle using the model's policy functions in two different experiments. In both experiments, investors are placed into an opt-in regime prior to  $\tau_i$ , which corresponds to  $\bar{s}_e^{dc} = 0\%$ . However, starting at  $\tau_i$ , we make a change to investors' defined contribution savings accounts. In the first experiment, investors are placed into a 3% auto-enrollment regime with the risk-free as the default asset, which corresponds to  $\bar{s}_e^{dc} = 3\%$ ,  $\bar{\theta}_e^B = 1$ , and  $\bar{\theta}_e^S = 0$ . This corresponds to the control group in our first quasi-experiment above. In the second experiment, investors are placed into a 3% auto-enrollment regime with an age-dependent mixed allocation between the risky and risk-free asset as the default asset, which corresponds to  $\bar{s}_e^{dc} = 3\%$ ,  $\bar{\theta}_e^S = G^\theta(t)$ , and  $\bar{\theta}_e^B = 1 - G^\theta(t)$ . We set  $G^\theta(t)$  to match the glide-path of the TDF provided by our data provider so that this second experiment corresponds to the treatment sample in our first quasi-experiment.<sup>28</sup> In both experiments, we choose a 3% default contribution

<sup>28</sup>The treatment group in the second experiment does not exactly match that in our first quasi-experiment because investors in our model do not have access to a TDF. Modeling such access would require introducing two additional choice and state variables (one for new and one for existing assets), which we avoid doing for computational reasons. However, as discussed below, we target portfolio choices for only six years following the change in default. We view



rate to match the 401(k) plans of the firms that we use to calculate the distribution of contribution rates.<sup>29</sup>

**Model moments.** After running these two simulations from our model, we calculate the share of investors with a positive equity share in the retirement account associated with their current employer in the first and second experiments separately at  $t = \tau_i, \dots, \tau_i + 6$ . This gives us 14 moments analogous to our empirical moments in Panel A of Figure 4. Importantly, for these moments, we calculate stock market participation based on investors' allocation of wealth accumulated with their *current* employer,  $\tilde{\Theta}^S$ , which corresponds to what we observe empirically. We calculate the average unconditional stock shares by age at the end of workers' first year of tenure, just as we do with our empirical moments. Doing this for workers in the treatment and control groups separately gives us 16 moments, which are also calculated with  $\tilde{\Theta}^S$ . Finally, we calculate the distribution of contribution rates across the same four bins that we used for our empirical moments above separately among investors at  $t = \tau_i - 1$  and investors in the second experiment at  $t = \tau_i$ , which gives 8 moments.

**Estimation procedure.** We estimate the five preference parameters in our model using SMM, which corresponds to finding the parameter values that minimize the weighted squared distance between the model and empirical moments described above. We use the inverse covariance matrix of our empirical moments as a weighting matrix, which we calculate by covarying the influence functions of these moments (Erickson and Whited 2002) to avoid the large finite-sample bias associated with bootstrapping weight matrices discussed in Horowitz (2001). For additional details, see Appendix F.

### 4.2.3 Identification of Second-Stage Preference Parameters

The five preference parameters in our model are jointly estimated. In what follows, we provide some brief intuition for which moments help identify the different parameters. Of course, all parameters are jointly identified, but certain moments are particularly sensitive to a given parameter.

**Risk preferences.** Risk preferences in the model are governed by the coefficient of relative risk aversion,  $\gamma$ . Relative risk aversion is primarily identified from the age profile of equity shares of investors in their first year of tenure. Importantly, we target these age profiles in the treatment and control groups separately, which are informative about risk aversion even in the presence of frictions. At the limit of extremely high risk aversion, we would expect investors in the treatment

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it as reasonable to abstract from changes in the equity share of a TDF over this period since they will be small.

<sup>29</sup>Four out of the 6 firms in the Money Market to TDF sample have default contribution rates of 3%.

group to reduce their equity exposure regardless of the size of adjustment costs. Similarly, with low risk aversion, we would expect investors in the control group to increase their equity exposure. The quasi-experimental evidence of participation by tenure in Figure 4 also helps identify risk aversion, but these moments are more informative about portfolio adjustment costs since participation is a binary outcome.

**Time preferences.** Time preferences are governed by two parameters:  $\beta$  and  $\sigma$ . The level of intertemporal discounting,  $\beta$ , is primarily identified from the average contribution among all investors in our experiment. As  $\beta$  increases, the average level of contributions in both the opt-in regime and auto-enrollment regime increases. In general, separately identifying  $\beta$  and the EIS,  $\sigma^{-1}$ , is challenging because they both affect the level of savings. In our setting, the two are separately identified due to a discontinuity in the effective interest rate at a 6% contribution rate, above which the 50% employer match no longer applies. For a given average level of contribution rates that identifies  $\beta$ , the bunching of contributions at 6% relative to other values allows us to identify  $\sigma$  because the EIS directly controls the sensitivity of savings to the interest rate.<sup>30</sup> This identification strategy is motivated by [Best, Cloyne, Ilzetzi, and Kleven \(2019\)](#), who use discontinuities in interest rates from LTV notches to identify the EIS.

**Portfolio adjustment cost.** We identify the portfolio adjustment cost,  $k_\theta$ , by examining the number of investors who deviate from the default asset allocation, in particular how this varies with tenure. In the limit of an infinite adjustment cost, we would expect all investors to stick with the default. In contrast, with no adjustment costs, investors' choices would be independent of the default, which is clearly rejected by Figure 4. In the model, there is an interaction between the portfolio adjustment cost and the tenure-specific job transition risk in the income process. Even with a relatively small adjustment cost, investors may choose not to adjust their portfolio allocation in early years of tenure because they face the risk of switching employers in the next period.

**Contribution adjustment cost.** The contribution adjustment cost,  $k_s$ , is identified by examining the bunching of investors around the contribution rate to which they are assigned by default, as in [Choukhmane \(2021\)](#). Intuitively, if the contribution adjustment cost is zero, the distribution of contribution rates should be identical across the the opt-in and auto-enrollment regimes. Conversely, if the contribution adjustment cost is extremely large, all workers should bunch at the default option (0% for the opt-in group and 3% for the auto-enrollment group). Thus, the extent to which investors bunch at the default contribution rate identifies the size of this adjustment cost.

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<sup>30</sup>Consider the consumption–savings Euler equation in a deterministic environment:  $\log\left(\frac{c_{t+1}}{c_t}\right) = \sigma^{-1} \log(\beta R) = \sigma^{-1} \log \beta + \sigma^{-1} R$ . This shows that the response of consumption growth (i.e., savings) to changes in  $R$  identifies the EIS when we hold fixed the average level of savings by changing  $\beta$ . Intuitively, the discontinuity in  $R$  from the employer match provides precisely this variation.

## 4.3 Estimation Results

### 4.3.1 Baseline Estimation

Column (1) Table 3 presents the results from our baseline estimation. Our estimate of the (annualized) discount factor is  $\beta = 0.964$ . This estimate of  $\beta$  is similar to existing estimates that target life cycle consumption–savings profiles (e.g., [Gourinchas and Parker 2002](#)). However, our estimate is higher than estimates from the literature on life cycle portfolio choice, which typically needs a lower value to slow down the decline in the human-to-financial wealth ratio with age to match the relatively low average equity shares. Column (1) also shows that our estimate of relative risk aversion is 2.03, which is lower than typical estimates in existing literature. This difference provides preliminary evidence of the value of using quasi-experimental variation in panel data to recover risk preferences in the presence of choice frictions, in contrast to targeting cross-sectional averages of investors’ choices that could be driven by preferences or frictions. We explore this further in Section 4.3.4. We estimate a value of the EIS of approximately 0.38, which is consistent with typical estimates in other settings (see [Havránek 2015](#), for a meta-analysis). Notably, the standard errors of our estimates of these three preference parameters are relatively small, consistent with our observation in the previous section that all three parameters are well identified ([Andrews et al. 2017](#)).

Consistent with the presence of frictions impacting portfolio decisions, we estimate a positive portfolio adjustment cost of \$201, which is necessary to explain investors’ tendency to stick with the default asset allocation. This estimate is relatively modest in comparison to typical values of participation costs in life cycle portfolio choice models (e.g., [Gomes 2020](#); [Catherine 2022](#)). Finally, we estimate a contribution adjustment cost of \$540. This contribution cost is larger than the portfolio adjustment cost, which suggests that investors’ nonparticipation in stocks may also be influenced by frictions associated with opting in and opening a defined contribution savings account. Our estimate is around twice as large as that in [Choukhmane \(2021\)](#), consistent with the fact that the value of participating in a retirement account is larger in our model due to the equity premium.

Figure 11 shows how our model fits the results from our first quasi-experiment in Panel A of Figure 4, which were targeted in the estimation. As evident from the figure, our model fits the targeted variation in investors’ portfolio choices on the extensive margin relatively well. The portfolio adjustment cost allows us to match investors’ tendency to slowly rebalance into stocks when the default has no stock market exposure, which most investors prefer given our relatively low

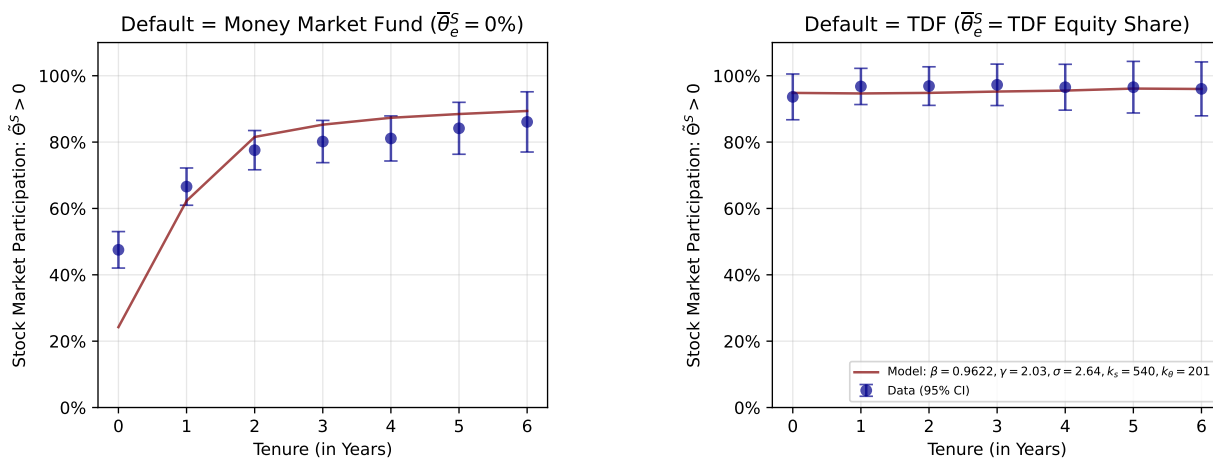
**Table 3.** Second-Stage SMM Preference Parameter Estimates

Preference Parameter		Estimation					
		(1)	(2)	(3)	(4)	(5)	(6)
Discount Factor	$\beta$	0.964 (0.001)	0.962 (0.001)	0.916 (0.005)	0.971 (0.001)	0.600 (0.037)	0.693 (0.004)
Relative Risk Aversion	$\gamma$	2.03 (0.17)	2.23 (0.070)	18.25 (0.841)	1.82 (0.057)	7.80 (0.530)	13.49 (0.587)
Elasticity of Intertemporal Substitution	$\sigma^{-1}$	0.379 (0.031)	. .	0.488 (0.020)	0.935 (0.099)	0.050 (0.006)	. .
Portfolio Adjustment Cost	$k_\theta$	\$201 (\$11.58)	\$213 (\$11.63)	. .	. .	. .	. .
Contribution Adjustment Cost	$k_s$	\$540 (\$19.91)	\$524 (\$14.35)	. .	. .	. .	. .
Model Specification							
Preference Specification		EZW	CRRA	EZW	EZW	EZW	CRRA
No Adjustment Costs				✓	✓	✓	✓
Moments Targeted							
Participation (MM Default)		✓	✓	✓			
Participation (TDF Default)		✓	✓		✓		
Equity Share by Age (MM Default)		✓	✓	✓			
Equity Share by Age (TDF Default)		✓	✓		✓		
SCF Equity Share of Total Wealth						✓	✓
Contribution Rates (Opt-In)		✓	✓	✓		✓	✓
Contribution Rates (AE at 3%)		✓	✓		✓	✓	✓
Total Number of Moments		38	38	19	19	16	16

*Notes:* This table shows the results from different second-stage simulated method of moments estimations, each in separate columns. The upper half of the table shows our preference parameter estimates along with standard errors. Missing values in different columns indicate that the parameter values were restricted in estimation. The bottom half shows the different preference specifications that we employ, where Epstein–Zin–Weil is denoted by EZW and the special case of  $\gamma = \sigma^{-1}$  is denoted by CRRA, in addition to the different moments that we target. In columns (3)–(6), we restrict the adjustment costs to be equal to zero. All estimations are performed with the optimal weighting matrix. When we target the SCF equity share of financial wealth, we use the corresponding total equity held as a fraction of liquid and retirement wealth in our model. The age profile of equity shares from the SCF is adjusted for survey weights and estimated over 1989–2019 following Deaton and Paxson (1994). For additional details on this second-stage estimation, see Appendix F.

estimate of risk aversion. Additionally, the portfolio adjustment cost coupled with our estimate of risk aversion means that relatively few investors rebalance out of stocks when the default asset has stock market exposure.

**Figure 11.** Model Fit: Stock Market Participation in 401(k) from Quasi-Experiment #1



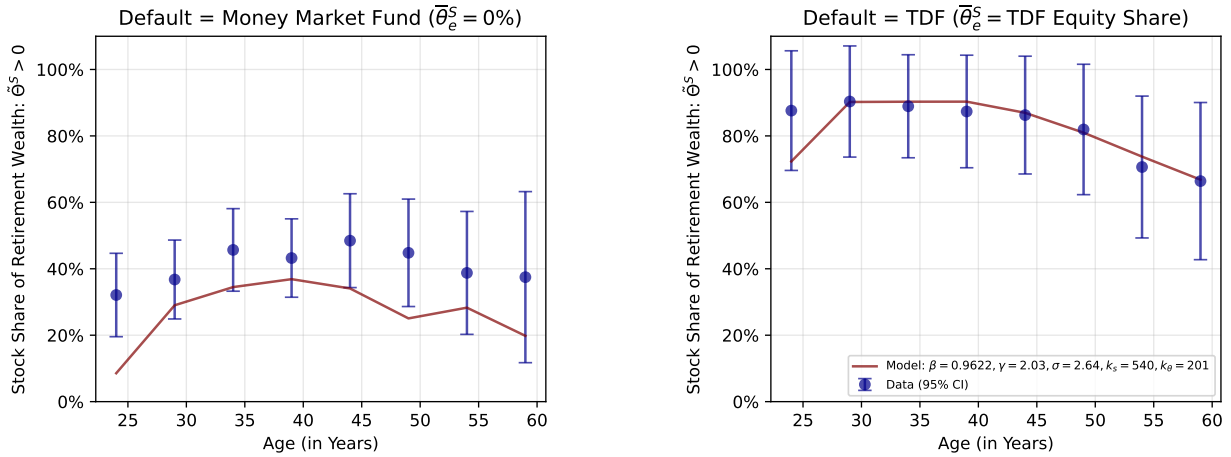
*Notes:* This figure presents the fit of our model on the response of stock market participation within the current employer retirement account for our first quasi-experiment. The data moments in this figure correspond to the moments from our first quasi-experiment in the left half of Figure 4 Panel A for the first six years of tenure along with the 95% confidence intervals. The model moments are from a simulation of this experiment within the model described in the main text at our SMM estimates of preference parameters reported in column (1) of Table 3.

In Figure 12, we show that our model also fits investors' portfolio choices on the *intensive* margin well. Our model replicates the tendency for investors in the control group to increase their equity exposure while most investors in the treatment group stick with their TDF default. In our model, the latter result is driven by the fact that investors' preferred stock shares are relatively close to the share in a TDF so it is not worth paying the adjustment cost to obtain a slightly more optimal portfolio allocation. In contrast, many investors in the control group, especially middle-aged investors, deviate from the default equity share of 0% to obtain greater stock market exposure.

In Figure 13, we show how our model fits the distribution of contribution rates, which were targeted moments to identify time preferences and the contribution adjustment cost. First, our model does a reasonable job in reproducing the substantial bunching at the default contribution rates under both regimes, which is driven by the contribution adjustment cost. Second, our model matches the tendency of investors to contribute 6% instead of 7%–9%, where the 50% employer match no longer applies. This is precisely the variation that identifies the EIS.

Finally, our model matches the average level of contributions well, which is done through adjustment of the time discount factor. However, a notable feature of Figure 13 is that our model fails to generate investors deviating from the default savings rate by a small amount. For example,

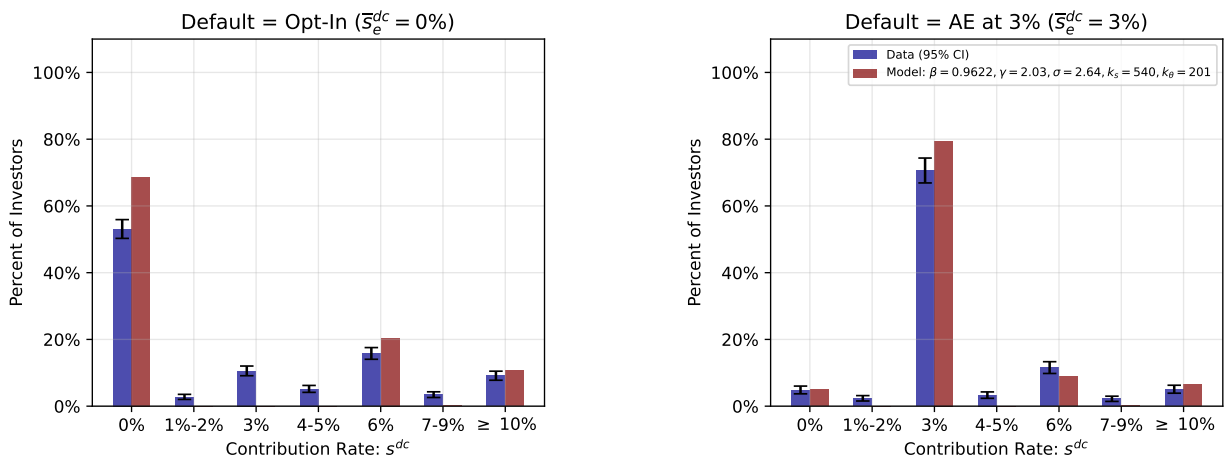
**Figure 12. Model Fit: Stock Shares by Age in First Year of Tenure**



*Notes:* This figure presents the fit of our model on the age profile of equity shares within the current employer retirement account separately for the treatment and control groups in our first quasi-experiment. The data moments are calculated on the same sample that is used in Figure 4 and are shown with their 95% confidence intervals. The model moments are from a simulation of this experiment within the model described in the main text at our SMM estimates of the preference parameters reported in column (1) of Table 3.

under opt-in, our model predicts no investors saving between 1% and 5%. This is driven by the fact that our adjustment cost is a fixed cost, which generates s-S inaction regions. The presence of investors in these regions suggests either preference heterogeneity that is missing from our model or a slightly different form of the contribution adjustment cost.

**Figure 13. Model Fit: Contribution Rates in First Year of Tenure**



*Notes:* This figure presents the fit of our model on the distribution of contribution rates in investors' first year of tenure. The shares of investors contributing 0%, 3%, 6%, and greater than 10% are targeted in the estimations reported in Table 3. The left (right) figure shows contribution rates of investors hired 12 months before (after) the introduction of auto-enrollment for new hires, which we plot directly from the data along with the 95% confidence intervals. The model moments are from a simulation of these shares within the model at our SMM estimates of the preference parameters reported in column (1) of Table 3.

### 4.3.2 Separating Identifying Risk Aversion and the EIS

A unique feature of our setting is our ability to separately identify both  $\sigma$  and  $\gamma$  in the presence of choice frictions. Our baseline results in column (1) cannot reject the null hypothesis of time-separable CRRA preferences—that is, that relative risk aversion equals the inverse elasticity of substitution. In column (2) of Table 3, we perform the same estimation as in the previous section but restricting  $\sigma = \gamma$ . In this case, our estimate of risk aversion (and now the inverse elasticity of substitution) is 2.23, which is quite similar to our estimate in column (1). In Figures A17 to A19, we show that the fit of this model is just as good. We thus conclude that in our setting, time-separable expected utility with CRRA flow utility provides a good description of investors' time and risk preferences. Crucially, this conclusion relies on our use of quasi-experimental variation, which we discuss in Section 4.3.4.

### 4.3.3 The Importance of Choice Frictions

In columns (3) and (4) of Table 3, we estimate our model without choice frictions on two sets of moments. Column (3) uses the stock market participation rates by tenure and life cycle profile of equity shares among individuals in the money market default and contribution rates under an opt-in regime. This corresponds to the retirement savings environment that most retirement investors faced prior to the 2006 Pension Protection Act and that many still face today. As shown in column (3), we estimate a much higher risk aversion of 18.25 for these investors than our baseline estimation in column (1). In other words, through the lens of a model without choice frictions, it's difficult to reconcile the choices of such investors without extreme risk aversion.

Column (4) performs an exercise analogous to that in column (3) but instead using the choices of investors with a TDF default and auto-enrollment at 3%, which corresponds to the retirement savings environment that an increasing number of investors face today. In contrast to the results in column (3), these results suggest that the behavior of investors under an AE-TDF regime is consistent with relatively low risk aversion of approximately 1.82.

Collectively, the results in columns (3) and (4) illustrate the importance of modeling both contribution and portfolio adjustment costs in estimating investors' preferences. Omitting frictions can result in overestimation of investors' risk aversion if the model is estimated from the choices of investors who face large frictions associated with investing in the stock market, in particular investors under an opt-in or money market default regime. Additionally, these results suggest that as the retirement savings environment moves to one in which investors face fewer frictions due to

the adoption of auto-enrollment and target date fund defaults, we should expect investors' choices to appear less risk averse through the lens of standard models. This is likely to have important general equilibrium implications, such as lowering the effective price of risk in the economy and depressing the equity premium, which are explored in [Zhang \(2022\)](#).

#### 4.3.4 The Value of Quasi-Experimental Variation

A primary contribution of our paper is the use of quasi-experimental variation to identify structural preference parameters in the presence of choice frictions. We conclude by examining how our inferences about investors' preferences change if we use standard cross-sectional variation.

Columns (5) and (6) of Table 3 repeat the same estimations as in columns (3) and (4) with adjustment costs restricted to zero, but replacing our quasi-experimental moments with the age profile of equity shares from the SCF, which is the traditional target for identifying risk preferences in life cycle portfolio choice models.<sup>31</sup> The results show that we arrive at dramatically different preference estimates: our estimate of risk aversion increases by a factor of approximately 5, while our estimate of the EIS decreases by a factor of approximately 10. Additionally, the results reject CRRA preferences, which contrasts with the evidence in columns (1) and (2) where CRRA provides an equally good fit as Epstein–Zin to our quasi-experimental variation. More broadly, these findings illustrate how quasi-experimental moments can be useful targets to estimate structural parameters because they reduce sensitivity to model misspecification, as emphasized in [Andrews et al. \(2017\)](#) and [Catherine et al. \(2022\)](#).

## 5 Conclusion

This paper identifies the risk preferences of retirement investors in the presence of choice frictions. Although it is difficult to do so in general, separating preferences from frictions is important for positive reasons, such as distinguishing between competing economic models, but also for normative reasons, such as assessing the impact of interventions designed to increase stock market participation on household welfare. For example, consider the Pension Protection Act of 2006, which led to the rapid growth of target date funds as the default asset in retirement savings plans (see [Parker et al. 2022](#)). If stock market nonparticipation within retirement accounts is primarily driven by frictions, then this trend is likely desirable for households. On the other hand, if nonpar-

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<sup>31</sup>We compute the equity share of total wealth in our model as  $\frac{\Theta_t^S A_t}{A_t + L_t}$ .



ticipation mostly reflects a preference for safe assets, then the welfare implications of this policy evolution is more ambiguous.

This paper has two main results. First, we estimate that absent frictions, 94% of investors would prefer to hold stocks in their retirement account with a stock share of 76%, which declines over the life cycle. Secondly, through the lens of a structural life cycle portfolio choice model, we show that these results are consistent with a coefficient of relative risk aversion of 2.1 and moderately sized adjustment costs. Collectively, our findings suggest that stock market nonparticipation within retirement accounts is driven mainly by (real or behavioral) adjustment costs rather than by a low preference for holding risky assets. In particular, we find limited support in our setting for explanations based on first-order risk aversion, pessimistic beliefs, per-period participation costs, or time-dependent inaction.

More broadly, our analysis illustrates the challenge that choice frictions pose for standard revealed preference approaches. To the extent that frictions are present and impact choices, these frictions obscure the mapping between observed choices and agents' underlying preferences. More constructively, our paper highlights how quasi-experimental variation can help overcome this identification problem and provide better targets for testing different economic theories of investor behavior.

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# INTERNET APPENDIX

This internet appendix contains the following additional materials.

- Appendix [A](#): Table of parameters for the life cycle model presented in Section 4.
- Appendix [B](#): Details on simple life cycle model presented in Section 1.
- Appendix [C](#): Additional details, proofs, and derivations of results in Section 3.
- Appendix [D](#): Details on solution algorithm for the model presented in Section 4.
- Appendix [E](#): Details on first stage estimation of the model presented in Section 4.
- Appendix [F](#): Details on second stage estimation procedure for the model in Section 4.
- Appendix [G](#): Additional results presented in tables and figures.

# Appendix A. Life Cycle Model Parameters

Preference Parameters		Assets	
$\beta$	Discount factor	$1 + r$	Rate of return on liquid assets
$\sigma^{-1}, \gamma$	EIS and RRA	$R_f$	Risk-free rate
$k_s$	Contribution adjustment cost	$R^S(\cdot)$	Return on risky assets
$k_\theta$	Portfolio adjustment cost	$\mu_s$	Log-risk premium
	<b>Utility</b>	$\sigma_s$	S.D. of log risky asset returns
$u_t(\cdot)$	Utility function		<b>Labor Market</b>
$V(\cdot)$	Value function	$\pi^{JJ}(\cdot)$	Job-to-job transition probability
	<b>State Variables</b>	$\pi^{EU}(\cdot)$	Unemployment transition probability
$X$	Vector of all state variables	$\pi^{UE}(\cdot)$	Out-of-unemployment transition probability
$a$	Age	$\{\delta_i\}_{i=0}^3$	Deterministic component of earnings
$emp$	Employment status	$w$	Labor earnings
$ten$	Tenure	$\rho$	Autocorrelation in earnings shocks
$e$	Employer DC plan type	$\xi$	Earnings innovation if continuously employed
$\eta$	Labor productivity	$\sigma_{\xi_0}^2$	Variance of the first earnings innovation
$ae$	Average lifetime earnings	$\sigma_{\xi}^2$	Variance of subsequent innovations
$L$	Liquid assets	$\xi^{JJ}$	Earnings innovation after job-to-job transition
$A$	DC wealth stock	$\mu^{JJ}$	Avg. wage gain after a job-to-job transition
$s_d$	Default contribution rate	$\xi^U$	Earnings innovation out of unemployment
$\Theta_d$	Default allocation existing funds	$\mu^{UE}$	Avg. wage loss out of unemployment
$\theta_d$	Default allocation new contributions	$\iota$	Measurement error in earnings
	<b>Choices</b>	$\sigma_\iota^2$	Variance of measurement error
$c$	Consumption	$\phi$	Earnings innovation plus measurement error
$s^{dc}$	DC contribution rate		<b>Demographics</b>
$s^l$	Savings in liquid assets	$T$	Maximum years of life
$\Theta$	Asset allocation for existing funds	$T_w$	Number of working years
$\theta$	Asset allocation for new contributions	$m_t$	Mortality risk
	<b>Defined Contribution Account</b>	$n_t$	Equivalence scale
$\bar{\theta}_e^j$	Employer-specified default asset allocation		<b>Tax and Benefit System</b>
$\bar{s}_e^{dc}$	Employer-specified default contribution rate	$tax_t(\cdot)$	Tax on income
$\mathcal{M}_e(\cdot)$	Employer DC matching function	$limit_a$	Tax limit on DC contributions
$match_e$	Employer matching rate	$pen_a$	Tax penalty of early DC withdrawals
$cap_e$	Threshold on employer matching	$ui(\cdot)$	Unemployment insurance benefit
$\Upsilon_e(\cdot)$	Vesting risk-adjustment	$ss(\cdot)$	Public pension income
$t_J$	Period of last job transition	$\tau_c$	Capital gains tax in liquid account
$\bar{\Theta}$	Asset allocation for wealth with current employer		



## Appendix B. Simple Life Cycle Model Details

This section provides a description of the simple life cycle model we estimate in Section 1.

### B.1 Demographics

Investors are born at  $t = 0$  and work  $T_w$  periods with their first retirement year at  $t = T_w$ . Each period corresponds to one year. Investors die with certainty at  $t = T$ , at which point all of their resources are bequeathed, such that investor's last period in which they can consume is  $t = T - 1$ . Before their certain death, investors survival probability is time-varying and denoted  $m_t$ , which is taken from the SSA. Denote investor's age as  $a_t = t + a_0$ , where  $a_0$  is the age at which investors are born.

### B.2 Preferences

Investors have time-separable expected utility preferences with a CRRA Bernoulli utility function over consumption. Denote investors' annualized time discount factor as  $\beta$  and their coefficient of relative risk aversion (or equivalently inverse of elasticity of intertemporal substitution) as  $\gamma$ . Per-period flow utility is adjusted for an equivalence scale such that it is equal to

$$u_t(c) = n_t * \frac{(c/n_t)^{1-\gamma}}{1-\gamma},$$

where  $n_t$  is taken from [Lusardi et al. \(2017\)](#).

### B.3 Labor Income

While working, investors supply labor inelastically and earn an income  $w_t$  that is stochastic and exogenous. This income consists of a deterministic component that is cubic in age and a stochastic component that follows an AR(1) process with normal innovations:

$$\ln w_t = \delta_0 + \delta_1 a_t + \delta_2 a_t^2 + \delta_3 a_t^3 + \eta_t, \quad \eta_t = \rho \eta_{t-1} + v_t, \quad v_t \sim N(0, \sigma_v^2). \quad (20)$$

Investors do not receive any labor income at the time of death. Additionally, when investors are born at  $t = 0$ , the distribution of  $\eta$  is different to account for heterogeneity in the initial period income shock.

When  $t \in [T_w, T - 1]$ , investors are retired and earn retirement benefits denoted by  $ss_t$ , which are set equal to 40% of the average annual wage among all working investors. Note that investors do not earn any retirement benefits at the time of death.

## B.4 Financial Assets

There are two assets: (i) a risk-free bond that has a constant gross return of  $R_f$  per year; (ii) a risky asset that pays a stochastic IID gross return of  $R_t$  per year, where

$$\ln R_t = \ln R_f + \mu_s + \varepsilon_t, \quad \varepsilon_t \sim \mathcal{N}(0, \sigma_s^2). \quad (21)$$

## B.5 Savings Account

Investors have access to a liquid savings account in which they can invest any remaining labor income after consuming into any combination of the two available assets. Denote the dollar amount in this account as  $A_t$ . Investors choose the share of their wealth that is invested in the risky asset, denoted by  $\theta_t$ , resulting in  $1 - \theta_t$  allocated to the risk-free bond.

## B.6 Frictions

When making portfolio choice decisions, investors face two costs. First, there is a per-period participation cost  $p$ , which is incurred when  $\theta_t > 0$  as a utility cost. This cost is designed to capture the costs associated with maintaining an account to invest in the risky asset, in addition to any hassle costs.

Secondly, investors must incur a utility cost  $f$  to change their portfolio. Specifically, if investors choose  $\theta_t \neq \theta_{d,t}$ , where

$$\theta_{d,t} = \begin{cases} 0 & \text{if } t = 0, \\ \theta_{t-1} * \frac{R_t}{(1-\theta_{t-1})R_f + \theta_{t-1}R_t} & \text{else.} \end{cases} \quad (22)$$

they are required to pay a cost  $f$  in consumption units that is designed to capture the physical

and opportunity costs associated with altering a portfolio allocation. We assume the default asset allocation in the first period is entirely risk-free bonds to capture the fact that investors are generally not born with exposure to stocks. Default asset allocations in later periods are equal to the asset allocation from the prior period, adjusting for return realizations. Additionally, we assume neither of these costs are incurred at time  $t$  if an investor dies at time  $t$ .

## B.7 Optimization Problem

Investors face a dynamic optimization problem with four state variables:  $a_t = \text{age}$ ;  $w_t = \text{wage}$ ;  $W_t = \text{liquid wealth}$ ;  $\theta_{t-1} = \text{prior-period portfolio share}$ . Denote the vector of these variables as  $X_t$ . There are two controls:  $c_t = \text{consumption}$  and  $\theta_t = \text{stock share}$ . In choosing these controls, investors are restricted from borrowing and engaging in any margin trading (i.e. no short-selling or leveraged positions):

$$W_t \geq 0, \quad \theta_t \in [0, 1]. \quad (23)$$

We now characterize the value function of an investor,  $V(\cdot) : \mathbb{R}_+^4 \rightarrow \mathbb{R}$ , in the two periods of their life. Fr

**Retirement period.** In retirement, there are two sources of uncertainty when decisions are made at time  $t$ :  $\varepsilon_{t+1} = \text{asset return shocks}$ ; mortality occurring with probability  $m_t$ . An investor's value function during retirement is thus characterized by the following recursive equation:

$$V_t = \max_{c_t > 0, \theta_t} \left\{ u_t (c_t - f * 1\{\theta_t \neq \theta_{d,t}\} - p * 1\{\theta_t > 0\}) + (1 - m_t) \beta E[V_{t+1} | X_t] \right\},$$

subject to: (21), (22), (23), and

$$A_t = W_t + ss_t - c_t,$$

$$W_t = A_{t-1} [(1 - \theta_{t-1})R_f + \theta_{t-1}R_t],$$

$$V(a_T, \cdot, \cdot, \cdot) = 0.$$

**Working life.** While working, there are three sources of uncertainty when decisions are made at time  $t$ :  $\eta_{t+1} = \text{labor income shocks}$ ;  $\varepsilon_{t+1} = \text{asset return shocks}$ ; mortality occurring with probability  $m_t$ . An investor's value function during working-life is thus characterized by the following

recursive equation:

$$V_t = \max_{c_t > 0, \theta_t} \left\{ u_t (c_t - f * 1\{\theta_t \neq \theta_{d,t}\} - p * 1\{\theta_t > 0\}) + (1 - m_t) \beta E[V_{t+1} | X_t] \right\},$$

subject to: (20), (21), (22), (23), and

$$A_t = W_t + w_t - c_t,$$

$$W_t = A_{t-1} [(1 - \theta_{t-1})R_f + \theta_{t-1}R_t],$$

$$A_0 = W_0 = 0.$$

## B.8 Parameterization

For the income process parameters ( $\rho$  and  $\sigma_v$ ) we use the parameters estimated in Appendix E for our full model for agents that are in  $emp_t = E$  (i.e. continuously employed). For demographic parameters, we set  $a_0 = 21$ ,  $T_w = 44$  so agents retire deterministically at 65, and  $T = 79$  so agents die at 100. We take  $m_t$  from the SSA as in Appendix E. We use the same parameters for asset returns as in Section 4.

## Appendix C. Additional Details on Non-Parametric Estimation

This section presents derivations of the equations in the main text. We first introduce the formal notation, which follows Goldin and Reck (2020), and then the derivations.

### C.1 Details on Theoretical Framework

Consider a continuum of investors indexed by  $i$  are hired by an employer at time  $t = 0$  and make asset allocation choices at  $t = 0, \dots, T$ . Denote  $Y_{it} \in \{0, 1\}$  and  $\theta_{it} \in [0, 1]$  as investor  $i$ 's participation and stock share of retirement wealth at time  $t$  respectively, where  $Y_{it} = 1$  corresponds to participating in the stock market. We refer to  $t$  as investors' tenure, since it captures the length of time since the investor was hired. Each investor's participation and stock share decisions are subject to a time-invariant frame denoted by  $D_i \in \{0, 1\}$ , where  $D_i = 1$  corresponds to an investor working for an employer with an auto-enrollment and a TDF as the default asset allocation (i.e. the treatment groups in both quasi-experiments) and  $D_i = 0$  otherwise (i.e. the control groups). Throughout, we refer to  $D_i$  as the frame or default interchangeably. We also denote  $\theta_i^d(D_i)$  as the default asset allocation faced by investor  $i$ , given frame  $D_i$ .

Each investor's preferred options at each tenure are denoted by  $Y_{it}^* \in \{0, 1\}$  and  $\theta_{it}^* \in [0, 1]$ , which is not observed, while choices, denoted by  $Y_{it}$  and  $\theta_{it}$ , are observed. Investors are characterized by a set of potential outcomes,  $\{Y_{it}(d), \theta_{it}(d)\}_{d \in \{0, 1\}}$ , which generate their observe choices according to:<sup>32</sup>

$$Y_{it} = Y_{it}(d), \theta_{it} = \theta_{it}(d) \text{ if } D_i = d.$$

The primitives of this environment,  $\{Y_{it}(0), Y_{it}(1), \theta_{it}(0), \theta_{it}(1), Y_{it}^*, \theta_{it}^*, D_i\}$ , are assumed to be drawn from an identical population distribution with unrestricted dependence across  $i$  and  $t$ . As econometricians, we observe a panel of  $(Y_{it}, \theta_{it}, D_i, age_{it})$ , where  $age_{it} \in \mathcal{A}$  denote an age group.

If an investor's participation or stock share decision is independent of the frame, we call that investor *consistent* with respect to that decision. Formally, we denote consistency by  $C_{it}^Y$  and  $C_{it}^\theta$ ,

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<sup>32</sup>By writing choices as a function of potential outcomes, we are implicitly making a stable unit treatment value assumption (e.g. Rubin 1978) that investor  $i$  is not affected by the treatments of investors  $j \neq i$ . This is supported by the evidence in Panel A of Figure A5.

where

$$C_{it}^Y = \begin{cases} 1 & \text{if } Y_{it}(0) = Y_{it}(1), \\ 0 & \text{else.} \end{cases}$$

$$C_{it}^\theta = \begin{cases} 1 & \text{if } \theta_{it}(0) = \theta_{it}(1), \\ 0 & \text{else.} \end{cases}$$

In this framework, there are thus two possible types of investors for each decision: (i) consistent investors, whose choices are unaffected by frictions associated with the default; (ii) *inconsistent* investors, whose preferences *are* affected by frictions associated with the default.

## C.2 Proofs and Derivations

*Proof of Proposition 1.* By the law of iterated expectations, we obtain

$$E_\tau(Y_{it}^*) = E_\tau(Y_{it}^* | C_{it} = 1)P_\tau(C_{it} = 1) + E_\tau(Y_{it}^* | C_{it} = 0)P_\tau(C_{it} = 0).$$

Using the fact that  $Y_{it}^*$  is bounded between zero and one, the previous equation implies

$$E_\tau(Y_{it}^*) \in [E_\tau(Y_{it}^* | C_{it} = 1)P_\tau(C_{it} = 1), E_\tau(Y_{it}^* | C_{it} = 1)P_\tau(C_{it} = 1) + P_\tau(C_{it} = 0)].$$

Note that

$$\begin{aligned} E_\tau(Y_{it} | D_i = 0) &= E_\tau(Y_{it} | D_i = 0, C_{it} = 1)P_\tau(C_{it} = 1 | D_i = 0) + E_\tau(Y_{it} | D_i = 0, C_{it} = 0)P_\tau(C_{it} = 0 | D_i = 0) \\ &= E_\tau(Y_{it} | D_i = 0, C_{it} = 1)P_\tau(C_{it} = 1 | D_i = 0) \\ &= E_\tau(Y_{it} | C_{it} = 1)P_\tau(C_{it} = 1) \\ &= E_\tau(Y_{it}^* | C_{it} = 1)P_\tau(C_{it} = 1), \end{aligned}$$

where the first equality follows from the law of iterated expectations and frame separability, the second equality follows from frame monotonicity, the third equality follows from frame exogeneity, and the fourth equality follows from the consistency principle. Analogously, it follows that

$$E_\tau(Y_{it} | D_i = 1) = E_\tau(Y_{it}^* | C_{it} = 1)P_\tau(C_{it} = 1) + P_\tau(C_{it} = 0).$$

Combining the previous two equations and the bound above deliver the desired result.  $\square$

*Proof of Proposition 2.* Given  $\theta_i^d(0) = 0$ , Assumption 5 combined with the consistency principle implies all investors deviating from the default reveal their preferences. Given we define preferences over the interval  $[0, 1]$ , the lowest possible value for the average preferred stock share would occur when all inconsistent investors have  $\theta_{it}^* = 0$ . This corresponds to the lower bound given in the proposition.  $\square$

*Proof of Proposition 3.* By the consistency principle,

$$E_{\tau}(Y_{it}^* | C_{it}^Y = 1) = E_{\tau}(Y_{it} | C_{it}^Y = 1).$$

By the law of iterated expectations,

$$E_{\tau}(Y_{it} | C_{it}^Y = 1) = E_{\tau}(Y_{it} | C_{it}^Y = 1, Y_{it} = D_i)P_{\tau}(Y_{it} = D_i | C_{it}^Y = 1) + E_{\tau}(Y_{it} | C_{it}^Y = 1, Y_{it} \neq D_i)P_{\tau}(Y_{it} \neq D_i | C_{it}^Y = 1).$$

Frame exogeneity implies the two expectations on the right-hand side of the previous equation are equal to  $E_{\tau}(Y_{it} | C_{it}^Y = 1)$ , which delivers the desired result. An identical argument follows for stock shares.  $\square$

*Derivation of (6) and (7).* These expressions follow from the following identity, which applies when  $W$  is binary:

$$\text{cov}(V, W) = E(VW) - E(V)E(W) = E(W)[E(V|W = 1) - E(V)].$$

$\square$

## Appendix D. Model Solution Details

**Discretization of state variables.** We have eight continuous state variables that need to be placed onto grids: labor productivity, tenure, average lifetime income, DC retirement wealth, liquid wealth, two default portfolio shares, and the default contribution rate. We discretize labor productivity following [Tauchen \(1986\)](#) using 5 elements. We place tenure on a grid with 3 components. We place average lifetime income on a grid with 5 points. We then place liquid assets and retirement assets on grids with 15 points during working life and 30 points during retirement. These wealth grids are spaced according to a power function, where the gaps increase as the values of the variables increase. We place the default portfolio shares and contribution rates on the grids that we choose below for the corresponding choices of each variables. Our grids for these continuous state variables and the choice variables described below are relatively coarse. We have experimented with grids that are up to 2 times larger in each dimension and found that our moments used for estimation changed by no more than an average of 0.95%.<sup>33</sup>

**Discretization of choice variables.** We have 4 continuous choice variables. We place the contribution rate on a grid with 10 evenly spaced values when agents are employed and contributing to a retirement account. When agents are unemployed, we choose a grid for  $-s_t^{dc}$  of  $\{0, 1\%, 2\%, 5\%, 10\%, 15\%, 25\%, 55\%, 75\%, 100\%\}$ . When agents are retired, we choose an evenly spaced grid with 30 grid points between zero and negative one. For stock shares, we choose the following grid  $\{0\%, 30\%, 60\%, 70\%, 80\%, 90\%, 100\%\}$ , following the most common values in a TDF. We choose to place these choice variables on a grid because the portfolio and savings choices of investors in our sample generally correspond to a round number that is included in these grids. Consumption (or equivalently liquid savings) is not placed on a grid and we use a standard golden-section search to find its policy function.

**Solution algorithm.** The model has a finite horizon with a terminal condition and hence can be solved using backward induction in age starting with the terminal condition in the final year of life. In each period, we solve for the policy functions by performing a golden-section search over liquid savings for each possible combination of the other three choice variables on the grids described above. Performing this optimization requires interpolating the next-period value function from the prior and integrating over the distribution of stock returns. We choose to interpolate the value function first and then perform the integration. In complete markets with tradeable human capital, the Epstein-Zin-Weil value function is linear in wealth ([Merton 1969](#)). In our more compli-

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<sup>33</sup>Note that because our value function is concave in wealth and we use linear interpolation, using few grid points leads to an over-estimation of the curvature of the value function and thus an under-estimation of relative risk aversion.



cated model, this value function is approximately linear above low values of liquid wealth, where borrowing constraints don't bind. We thus choose to interpolate using linear interpolation, which provides very good accuracy despite coarse grids due to the approximate linearity of the value function.<sup>34</sup> To integrate over the distribution of stock returns, we use a Gauss-Hermite quadrature with 6 nodes.

**Software and hardware.** The code to solve and estimate the model is compiled in Intel Fortran 2018. We parallelize each model solution across 96 CPUs on the MIT SuperCloud server, which takes around 20 days of CPU time for each solution. When we estimate the model using the second-stage estimation procedure described in Appendix F, we parallelize estimation across 32 nodes using a total of over 3,000 CPUs.

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<sup>34</sup>See Carroll (2012) for additional details, which shows quasi-linear interpolation substantially reduces approximation error with CRRA preferences. The quasi-linear transformation suggested by Carroll (2012) is equivalently the transformation between an Epstein-Zin and CRRA value function in the case when  $\gamma = \sigma$ .

## Appendix E. First-Stage Estimation Details

### E.1 Demographics

**Survival probabilities.** Survival probabilities for each age are calibrated to the U.S. Social Security 2015 Actuarial Life Tables.

**Equivalence scale.** Changes in household composition over the life cycle are captured by an equivalence scale in the utility function. We use the equivalence scale by age estimated by Lusardi et al. (2017). Using PSID data from 1984 to 2005, Lusardi et al. (2017) estimate  $z(j_t, k_t) = (j_t + 0.7k_t)^{0.75}$  where  $j_t$  and  $k_t$  are, respectively, the average number of adults and children (under 18 years old) in a household with a head of age  $t$ . They normalize this measure by  $z(2, 1)$ —the composition of a household with 2 adults and 1 child—to get the equivalence scale at age  $t$  equal to  $n_t = \frac{z(j_t, k_t)}{z(2, 1)}$ . To estimate  $n_t$  we use publicly available replication files from Lusardi et al. (2017) and aggregate the data across education groups.

### E.2 Assets and Savings Accounts

**Assets.** The properties for financial assets are described in the main text. We assume agents cannot borrow at any age.

**Parameters of defined contribution savings account.** For all employers, we set the employer matching rate,  $match_e$ , equal to 50%, and the threshold contribution rate for the maximum employer match,  $cap_e$ , equal to 6%. These values are set to match the parameters of the 401(k) plans used in the sample used to construct the distribution of contribution rates. These are also the most common parameters of the 401(k) plans in the money market to TDF sample, which we use to construct our other target moments.

**Vesting schedule.** An investor who separates from her employer before the end of the vesting period may lose part (or all) of the employer matching contribution. A vesting schedule,  $vst_e(\cdot)$ , determines the percentage of employer contributions that an investor keeps if she separates at a given tenure level. Modeling the vesting schedule explicitly would introduce an additional continuous state variable to the dynamic problem: the amount of non-vested of DC wealth. Instead, we adjust employer contributions by a factor  $\Upsilon_e(t, ten)$  proportional to the risk of losing unvested employer contributions. The adjustment factor  $\Upsilon_e(t, ten)$  is given in equation (24). It depends on

both the cumulative job-separation probability and the vesting schedule. It is smaller than one and increasing in tenure before the end of the vesting period, and equal to one afterward. Importantly, this specification captures the fact that vesting matters more for investors who—based on their age and tenure—are more likely to separate from their employer.

$$\Upsilon_e(t, ten) = 1 - \sum_{j=0}^{T^R-t} \left( \prod_{k=1}^{j-1} \left( 1 - \pi_{t+k, ten+k}^{EU} - \pi_{t+k, ten+k}^{JJ} \right) \right) \left( \pi_{t+j, ten+j}^{EU} + \pi_{t+j, ten+j}^{JJ} \right) (1 - vst_e(ten + j)) \quad (24)$$

We set the vesting schedule,  $vst_e(\cdot)$ , for all firms to the average vesting schedule in the sample 34 401(k) plans that we use to construct the distribution of contribution rates, as in [Choukhmane \(2021\)](#). On average, 52% of matching contribution are vested immediately and this share increases over tenure. The average vested share reaches 70% by the end of the second year of tenure. We assume that all matching contributions are fully vested starting from the 3rd year of tenure.

### E.3 Taxes and Benefit System

**Income taxation.** Taxable income is defined as the sum of labor earnings, social security and unemployment benefits, DC withdrawals, less contributions to the DC account:

$$y_t^{tax} = \begin{cases} w_t - s_t^{dc} * w_t & \text{if } emp_t \in \{E, JJ\} \\ ui_t + s_t^{dc} * w_t & \text{if } emp_t = U \\ ss(ae_{T_w}) + s_t^{dc} * w_t & \text{if } emp_t = Ret \end{cases}$$

Investors' income tax liability is calculated according to the federal income tax schedule of 2006 (the first year of data and the base year for the calibration) for an investor filling as single and claiming the standard deduction. The tax formula has 5 annual income brackets  $\{\tilde{\kappa}_i^\tau\}_{i=1}^5 = \{\$5,150; \$7,550; \$30,650; \$74,200; \$154,800\}$ .<sup>35</sup> Quarterly tax brackets are defined as:  $\kappa_i^\tau = \frac{1}{4} \tilde{\kappa}_i^\tau$ . The quarterly income tax liability is given in the following equation, which we aggregate to an annual frequency by multiplying by four.

<sup>35</sup>Note that the first bracket correspond to the standard deduction amount in 2006.

$$tax_t^i = \begin{cases} 0 & \text{if } y^{tax} \leq \kappa_1^\tau \\ 0.10(y^{tax} - \kappa_1^\tau) & \text{if } \kappa_2^\tau \geq y^{tax} > \kappa_1^\tau \\ 0.10(\kappa_2^\tau - \kappa_1^\tau) + 0.15(y^{tax} - \kappa_2^\tau) & \text{if } \kappa_3^\tau \geq y^{tax} > \kappa_2^\tau \\ 0.10(\kappa_2^\tau - \kappa_1^\tau) + 0.15(\kappa_3^\tau - \kappa_2^\tau) + 0.25(y^{tax} - \kappa_3^\tau) & \text{if } \kappa_4^\tau \geq y^{tax} > \kappa_3^\tau \\ 0.10(\kappa_2^\tau - \kappa_1^\tau) + 0.15(\kappa_3^\tau - \kappa_2^\tau) + 0.25(\kappa_4^\tau - \kappa_3^\tau) + 0.28(y^{tax} - \kappa_4^\tau) & \text{if } \kappa_5^\tau \geq y^{tax} > \kappa_4^\tau \\ 0.10(\kappa_2^\tau - \kappa_1^\tau) + 0.15(\kappa_3^\tau - \kappa_2^\tau) + 0.25(\kappa_4^\tau - \kappa_3^\tau) + 0.28(\kappa_5^\tau - \kappa_4^\tau) + 0.33(y^{tax} - \kappa_5^\tau) & \text{if } y^{tax} > \kappa_5^\tau \end{cases}$$

**Public pension.** The amount of public pension benefit ( $ss$ ) is computed according the 2006 Social Security formula at the full retirement age, with an income floor guaranteed by the Supplemental Security Income program (with a monthly benefit  $si = \$603$ ). Annual public pension benefits are equal to:

$$ss(ae_{T_w}) = 4 \times 3 \times \max\{si; \tilde{ss}(ae_{T_w})\} - med_t$$

where  $\tilde{ss}$ , the monthly social security benefit, is increasing in average lifetime earnings  $ae_{T_w}$  up to a maximum monthly benefit:

$$\tilde{ss} = \begin{cases} 0.90 \times \frac{1}{3} ae_{T_w} & \text{if } \frac{1}{3} ae_{T_w} \leq \$656 \\ 0.90 \times \$656 + 0.32 \times (\frac{1}{3} ae_{T_w} - \$656) & \text{if } \$3,955 > \frac{1}{3} ae_{T_w} > \$656 \\ \min\{0.90 \times \$656 + 0.32 \times \$3,299 + (0.15 \times \frac{1}{3} ae_{T_w} - \$3,299); \$2,053\} & \text{if } \frac{1}{3} ae_{T_w} > \$3,955 \end{cases}$$

and  $med_t$  denotes medicare premiums described below.

**Medicare premiums.** During retirement, investors pay Medicare Part B and Part D premiums, denoted by  $med_t$ , based on the 2006 [Medicare Supplementary Medical Insurance](#) formula. We choose the 2006 Medicare formula to match the calibration of other model elements to 2006. These medicare payments are directly reduced from investors social security benefits, in accordance with rules for Part B premiums. We deduct Part D premiums as well for simplicity. These payments are annualized by multiplying by 12.

**Unemployment benefits.** Unemployment insurance provides a constant replacement rate  $\omega$  of labor earnings implied by the labor productivity level in the last period of employment. Labor productivity  $\eta_t$  stays constant during an unemployment spell. We set  $\omega = 0.40$ , which is the average replacement rate across all U.S. states (U.S. Department of Labor, 2018). For simplicity,

we assume that the employer contribution portion of an early withdrawal is always equal to the employer match rate. This simplifying assumption is valid assuming participants contribute below the matching threshold and contributions are fully vested. Adjusted unemployment benefits for an investor unemployed since period  $t - x$  are given by:

$$ui_t = \max \{0; \omega w_t (\eta_{t-x}) - s_t^{dc} * w_t\}$$

**Asset taxation.** In line with IRS rules for 2006, the maximum contribution limit for tax-deferred retirement contributions ( $limit_a$ ) is set equal to \$15,000 annually for investors younger than 50 years old and \$20,000 after that in 2006 dollars. The tax penalty for early DC withdrawals ( $pen_t$ ) is equal to 10% before age 55 and to zero afterwards<sup>36</sup>

## E.4 Labor Market Parameters

We estimate our labor market parameters using the same data and estimation procedure as in [Choukhmane \(2021\)](#), but perform the estimation at the annual instead of quarterly frequency.

**Data.** We use the Survey of Income and Programs and Participation (SIPP) to estimate of the wage earnings process and labor market transitions probabilities. We use the 1996 panel of the SIPP which contains data from December 1995 to February 2000 and aggregate the data at annual frequency. We focus on an investor’s primary job (defined as the job where he worked the most hours). We restrict the sample to investors aged 22 to 65 years old, and exclude full-time students and business owners. We assign employment status based on investors’ responses in the first week of each quarter. An investor is classified as employed if she reports having a job. We record a job-to-job transition if the identity of an investor’s employer is different in two successive quarters. We record a job separation if an investor is employed in the beginning of a quarter, and not employed in the beginning of the subsequent quarter. Job separations include early retirement decisions, before the age of 65.

**Earnings process.** We estimate the labor earnings process for workers staying in the same job using a standard two-step minimum distance approach similar to [Guvenen \(2009\)](#) and [Low, Meghir, and Pistaferri \(2010\)](#). The empirical income process is given in equation (25), which is the empirical counterpart of the model earning process in equation (10) with one additional term:

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<sup>36</sup>In the model, early withdrawals are only allowed in periods of unemployment. The tax code allows penalty-free 401(k) hardship withdrawals for unemployed people older than 55, which is earlier than the normal 59½ eligibility age for penalty-free withdrawals.

serially uncorrelated measurement error  $u_{i,t} \sim N(0, \sigma_t^2)$ .

$$\ln w_{i,t} = \delta_0 + \delta_1 a_{i,t} + \delta_2 a_{i,t}^2 + \delta_3 a_{i,t}^3 + \underbrace{\phi_{i,t}}_{\eta_{i,t} + u_{i,t}} \quad (25)$$

The estimation has two steps. In the first step, We estimate the parameters of the deterministic component of earnings ( $\{\delta_j\}_{j=0}^3$ )—a cubic in age. In the second step, We use the residual from regression (25) to estimate the five parameters governing the stochastic component of earnings: the coefficient of autocorrelation in earnings shocks ( $\rho$ ), the variances of the first earnings innovation ( $\sigma_{\xi_0}^2$ ), the variance of subsequent innovations ( $\sigma_{\xi}^2$ ), and the variance of measurement error ( $\sigma_t^2$ ). We estimate these five parameters by minimizing the distance between the empirical variance-covariance matrix of earnings residuals and its theoretical counterpart implied by the statistical model. The resulting estimates are provided in Table A1.

**Table A1.** Earnings Process Estimates

This table shows quarterly earnings process estimated using a two-step minimum distance estimator on a panel of workers continuously employed in the same job. Data source: U.S. Survey of Income and Program Participation, aggregated to annual frequency.

Age component				Stochastic component of earnings			
$\delta_0$	$\delta_1$	$\delta_2$	$\delta_3$	$\rho$	$\sigma_{\xi_0}^2$	$\sigma_{\xi}^2$	$\sigma_t^2$
2.813	0.121	-0.00183	$6.91 \times 10^{-6}$	0.9332	0.1749	0.0298	0.0538

**Earnings after a transition.** We estimate the median change in log salary following a job-to-job transition ( $\mu^{JJ}$ ) to be equal to 0.048. We estimate that job transitions following a period of unemployment are associated with a loss in earnings. We estimate the median change in log salary relative to the last salary prior to unemployment ( $\mu^{UE}$ ) to be equal to -0.078.

**Numeraire.** The average net compensation per worker in the U.S. was around \$37,078 in 2006 (from the Social Security Administration national average wage index). This is also almost equal to the median annual salary in the estimation sample (\$37,998 in 2006 dollars). We thus calibrate annual earnings to this numeraire.

**Labor transition probabilities.** We use SIPP micro-data to estimate annual job-to-job ( $\pi^{JJ}$ ) and job to non-employment ( $\pi^{EU}$ ) transition probabilities by age and tenure and job finding rates ( $\pi^{UE}$ ) by age. The initial unemployment rate is set equal to 22%, which is the share not employed at age 22 in SIPP. The probability that an employed investor switches to another job (given in equation (26)) or moves to non-employment (given in equation (27)) is the sum of an age component (i.e. a sixth-order polynomial in age) and a tenure component (a set of dummies for investors in their

first 3 years of tenure):

$$\pi^{JJ}(a, ten) = \sum_{k=1}^6 \alpha_k^{JJ} a^k + \sum_{j=1}^3 \iota_k^{JJ} 1\{(ten = j)\} \quad (26)$$

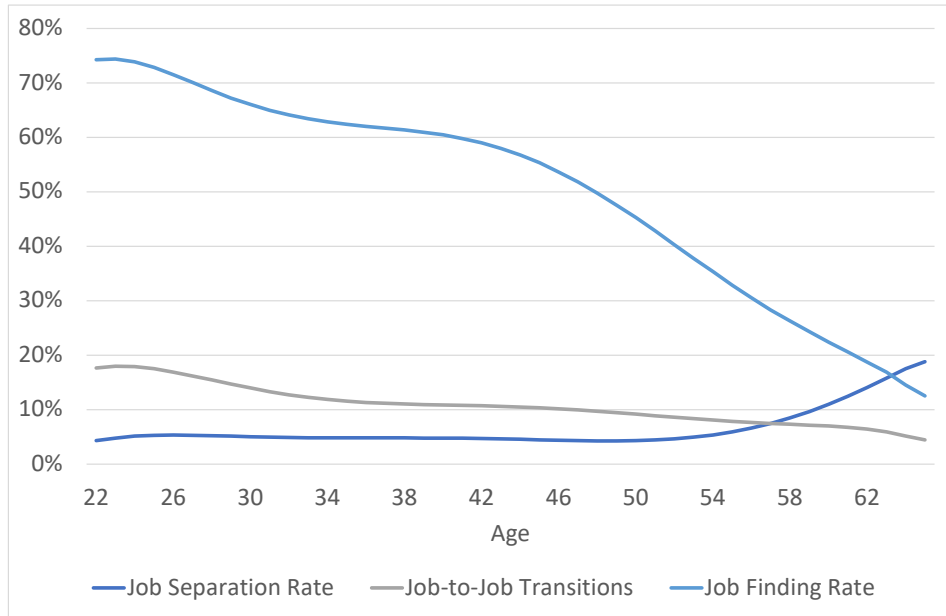
$$\pi^{EU}(a, ten) = \sum_{k=1}^6 \alpha_k^{EU} a^k + \sum_{j=1}^3 \iota_k^{UE} 1\{(ten = j)\} \quad (27)$$

The probability that an unemployed investor finds a job, given in equation (28), is defined as a sixth-order polynomial in age.

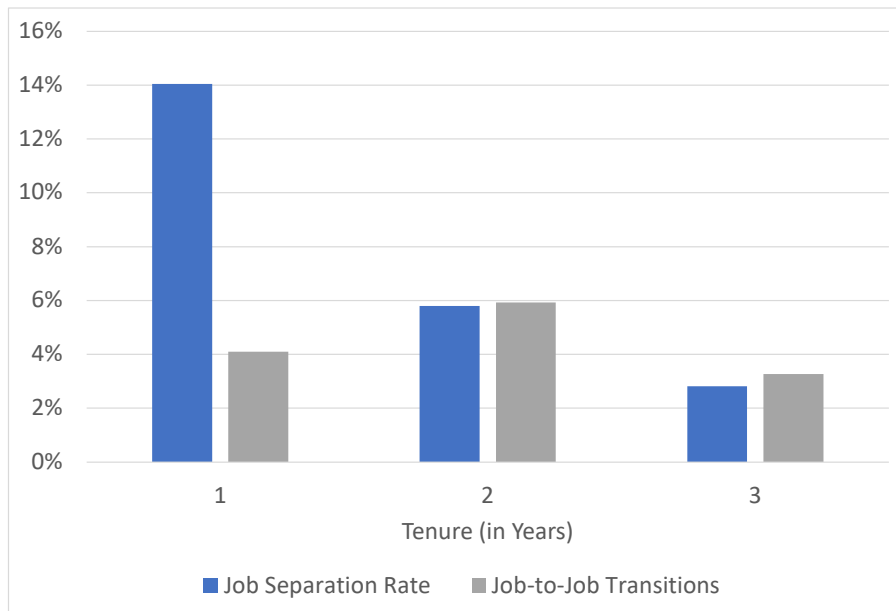
$$\pi^{UE}(a) = \sum_{k=1}^6 \alpha_k^{EU} a^k \quad (28)$$

We estimate equations (26), (27), and (28) using a linear probability regression. Estimates for the age component of labor market transitions are reported in Figure A1. Estimates for the tenure component are reported in Figure A2.

**Figure A1.** Age Component of Annual Labor Market Transitions



**Figure A2.** Tenure Component of Annual Labor Market Transitions





## Appendix F. Second-Stage Estimation Details

This section describes how we estimate our five preference parameters,  $\theta \equiv (\beta, \gamma, \sigma, k_\theta, k_s)$ , in our second stage estimation by selecting the parameter values that generate moments which most closely match their empirical counterparts.

### F.1 Estimator: Simulated Method of Moments

We estimate our preference parameters using the Simulated Method of Moments (SMM). This estimator minimizes the distance between moments from actual data and data simulated from a model. Denote  $m_N$  as the vector of moments from actual data calculated from  $N$  observations, which vary across specifications in the text and are described in the main text. Denote  $\hat{m}(\theta)$  as the moments generated from the model with parameters  $\theta$ . We simulate the model  $S$  times to generate an estimate of  $\hat{m}(\theta)$ , which we calculate by averaging across the  $S$  simulations (specified in the main text) and denote by  $\hat{m}_S(\theta)$ . The SMM criterion function is then

$$Q_{N,S}(\theta) = (m_N - \hat{m}_S(\theta))' W (m_N - \hat{m}_S(\theta)),$$

for some positive definite weighting matrix  $W$ . The SMM estimate of  $\theta$  is then given by

$$\hat{\theta}_{SMM} = \arg \min_{\theta \in \Theta} Q_{N,S}(\theta),$$

where  $\Theta$  is a compact parameter space that we specify.

### F.2 Weighting Matrices

We use optimal weighting matrix, which is the inverse of the empirical covariance matrix, as our weighting matrix. We calculate the covariance matrix of the empirical moments by covarying the influence functions of our empirical moments, following [Erickson and Whited \(2002\)](#). This approach has better finite-sample properties when the covariance matrix is used as a weighting matrix in a second-stage estimation ([Horowitz 2001](#)).

Formally, an influence function for an estimator  $\hat{\theta}$  given data  $X_i$  is defined as a function  $\phi(\cdot)$

such that

$$\sqrt{N}(\hat{\theta} - \theta_0) = \frac{1}{\sqrt{N}} \sum_{i=1}^N \phi(X_i) + o_p(1).$$

Given a moment condition  $Eg(X_i, \theta) = 0$ , standard arguments (a mean value expansion of first-order condition to the GMM objective) imply the influence function for an GMM estimator with an optimal weighting matrix of  $\theta$  is (see e.g. [Newey and McFadden 1994](#), for a derivation)

$$\phi_{GMM}(X_i) = -[G\Omega G']^{-1} G\Omega g(X_i, \theta),$$

where  $G = \frac{\partial g}{\partial \theta}|_{\theta=\theta_0}$  and  $\Omega$  is the optimal weighting matrix. Since all of our moments are straightforward, we can derive these analytically for each of our moments. For each moment  $k$ , denote  $\Phi_k$  as the  $N$ -by-1 vector that stacks the corresponding influence function evaluated at each of the  $N$  data points. Denote  $\Psi$  as the  $N$  by  $k$  vector that stacks the  $\Phi_k$ 's column-wise. The sample covariance matrix of our moments is then  $\Psi'\Psi N^{-2}$ , which we invert to obtain the optimal weighting matrix.

As described in the main text, our estimation moments sometimes come from different samples. When this is the case, we assume the covariance between moments across samples is zero and construct our sample covariance matrix by forming a block-diagonal matrix using the sample covariance matrices calculated for each subset of moments within the same sample using the procedure described above.

### F.3 Optimization Algorithm

We discretize the parameter space,  $\Theta$ , and perform a grid search over values in this space. Our final SMM estimate is the value of  $\theta$  that achieves the lowest value of  $Q_{N,S}(\theta)$  of all parameter combinations over which we searched. We perform this search in three steps. First, we search over a wide grid of values for our preference parameters. Second, we use a narrower grid around the points that minimized the SMM objective function in the first grid search. Finally, we run Nelder-Mead local optimizations from the best points in the second step. We confirm these all converge to similar parameter estimates, from which we take the best point to get our final parameter estimate.

## F.4 Standard Errors

Denote the true value value of the parameters,  $\theta$ , as  $\theta_0 \in \Theta$ . Under standard regularity conditions (see e.g. McFadden 1989; Duffie and Singleton 1993),

$$\sqrt{N}(\hat{\theta}_{SMM} - \theta_0) \xrightarrow{d} N(0, V),$$

where  $\xrightarrow{d}$  denotes convergence in distribution as  $N \rightarrow \infty$  for a fixed  $S$ ,

$$V = \left(1 + \frac{1}{S}\right) [GWG']^{-1} GW\Omega W G' [GWG']^{-1},$$

$G = \frac{\partial \hat{m}(\theta)}{\partial \theta}$ , and  $\Omega$  is the population variance matrix of the empirical moments. By the continuous mapping theorem,  $V$  can be estimated by replacing population quantities with sample analogs. We use our estimate of the covariance matrix of the empirical moments above from influence functions to estimate  $\Omega$ . We compute  $G$  using two-sided finite-differentiation where with step sizes equal to 1% of the parameter value estimated in SMM,  $\hat{\theta}_{SMM}$ , following the recommendation of Judd (1998) (p. 281). Depending on the particular estimation, we use different values of  $W$ . We then calculate standard errors by plugging each of these estimates into the formula above.

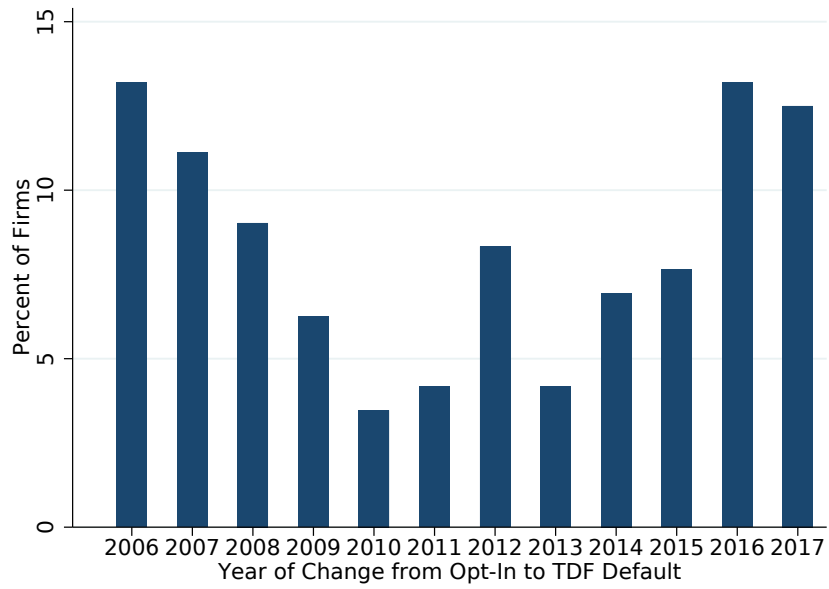
## Appendix G. Additional Results

**Table A2.** Summary Statistics: SCF 2007, 2010, 2013, and 2016

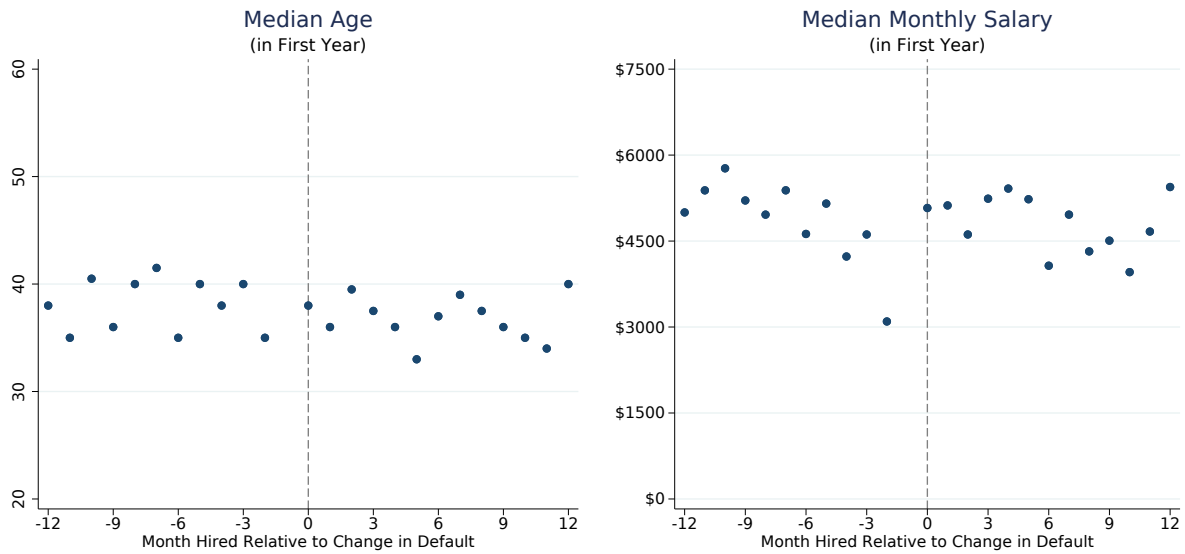
	All Households		Retirement Account Eligible	
	Mean	Median	Mean	Median
Age	49.88	50.00	45.36	46.00
Wage Income	78,032.68	44,577.57	101,397.71	68,548.55
Retirement Wealth	102,806.99	1,234.41	148,518.61	24,249.45
Investable Wealth	219,251.84	5,307.97	264,527.83	30,634.47
Ratio of Retirement to Investable Wealth	0.76	1.00	0.85	1.00
Stock Share of Retirement Wealth	0.27	0.00	0.42	0.40
Ratio of Equity Holdings in Retirement to Total	0.38	0.00	0.62	0.96
Stock Market Participation in Retirement Wealth	0.46	0.00	0.73	1.00
Stock Market Participation Outside Retirement	0.15	0.00	0.16	0.00
Stock Market Participation Only Outside Retirement	0.05	0.00	0.03	0.00

*Notes:* This table provides summary statistics from the 2007, 2010, 2013, and 2016 SCF waves, where we adjust survey weights such that they assign equal weights to each survey wave. We define SCF investors as being eligible for a retirement account if they report having access to a retirement account and/or they report assets in one. Retirement wealth in the SCF is defined as the sum of total quasi-liquid retirement accounts, including IRAs, thrift accounts, future pensions, and currently received benefits. We define investable wealth following Parker et al. (2022) to include money and non-money market mutual funds, all stocks and bonds held within and outside a retirement account, certificates of deposits, and trusts. The ratio of retirement to investable wealth is computed for households with positive investable wealth. Wage income, investable wealth, and retirement wealth from the SCF are divided by the number of adults in the household.

**Figure A3.** Distribution of Treatment and Control Groups by Year: Opt-In to TDF Sample

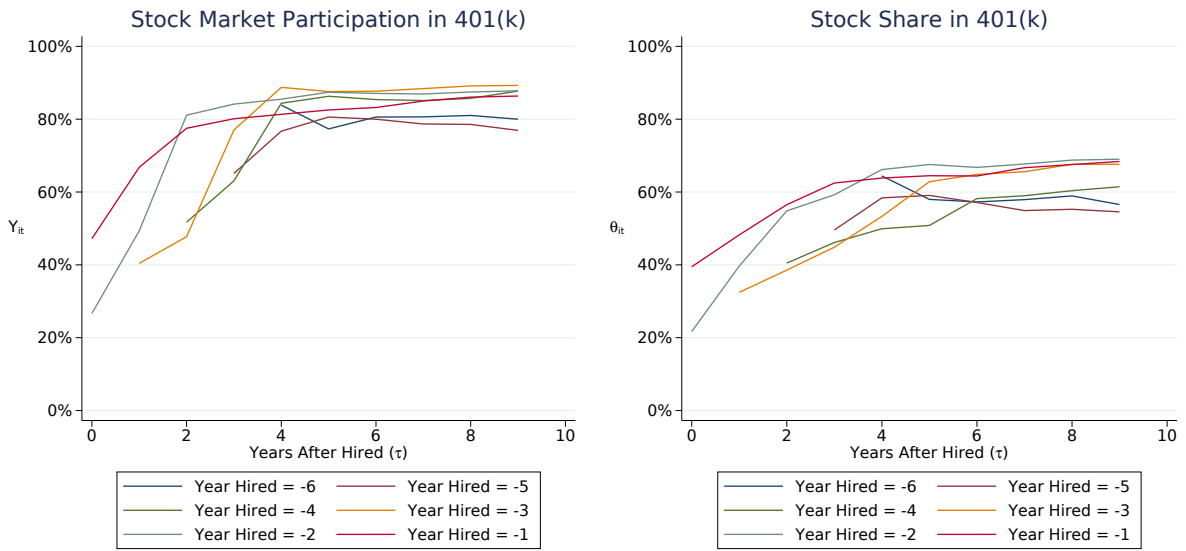


**Figure A4.** Balance Checks: Money Market to TDF Sample



**Figure A5. Robustness of Portfolio Choice Response: Money Market to TDF Sample**

*Panel A: Peer Effects*

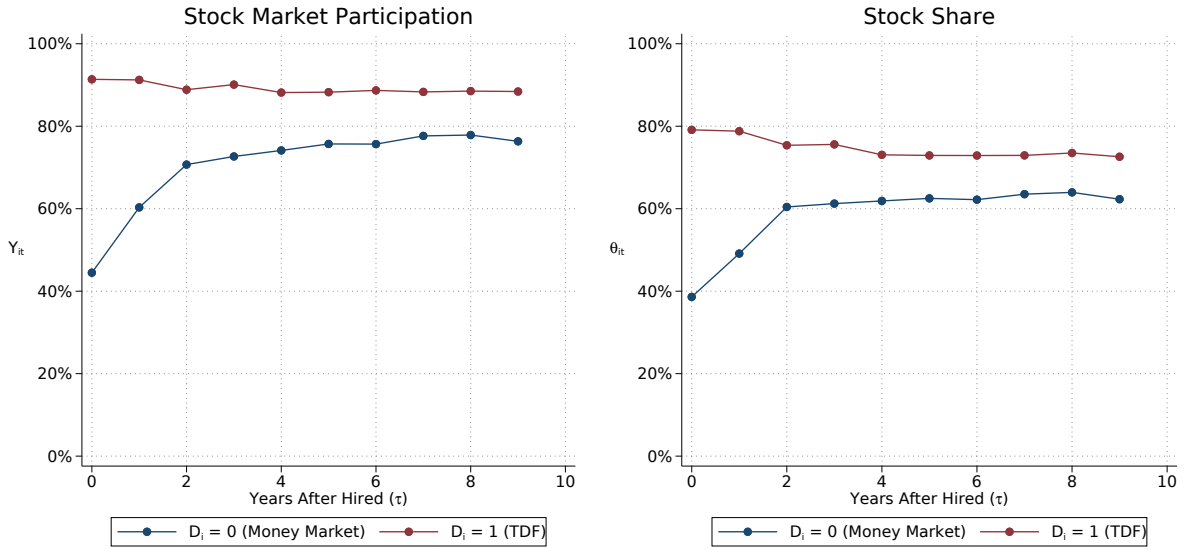


*Panel B: Compositional Change*

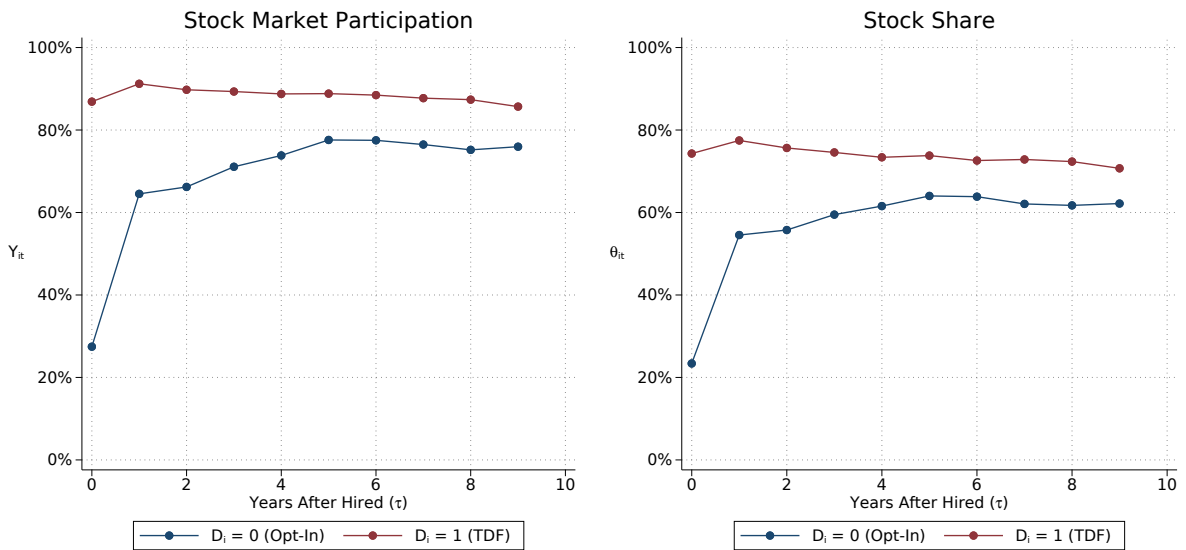


**Figure A6. Robustness of Portfolio Choice Response: Portfolio Choices for New Contributions to 401(k)**

*Panel A: Money Market to TDF Sample*

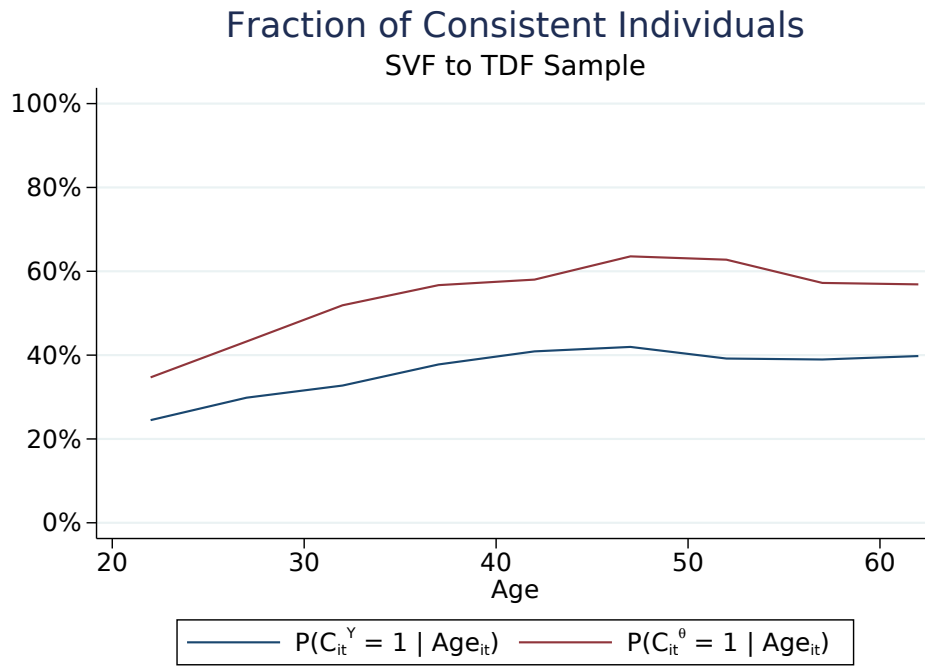


*Panel B: Opt-In to TDF Sample*

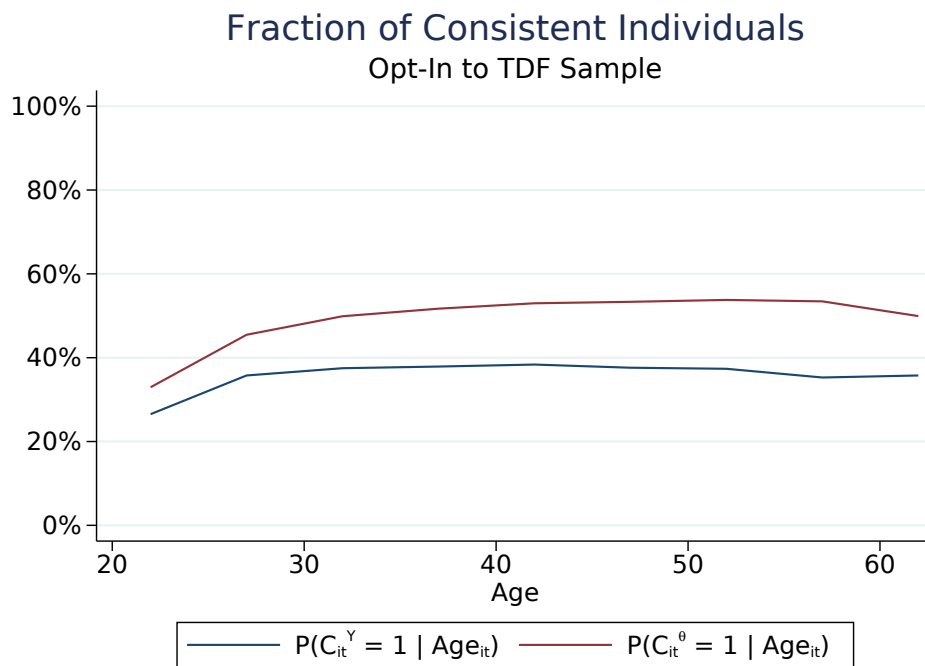


**Figure A7.** Fraction of Consistent Investors by Age

*Panel A: Money Market to TDF Sample*



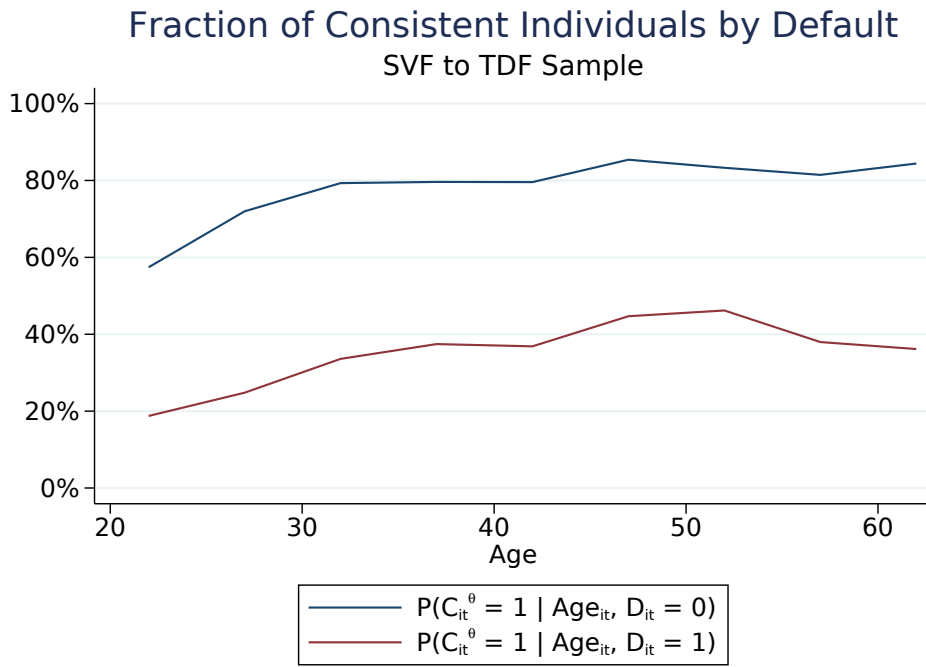
*Panel B: Opt-In to TDF Sample*



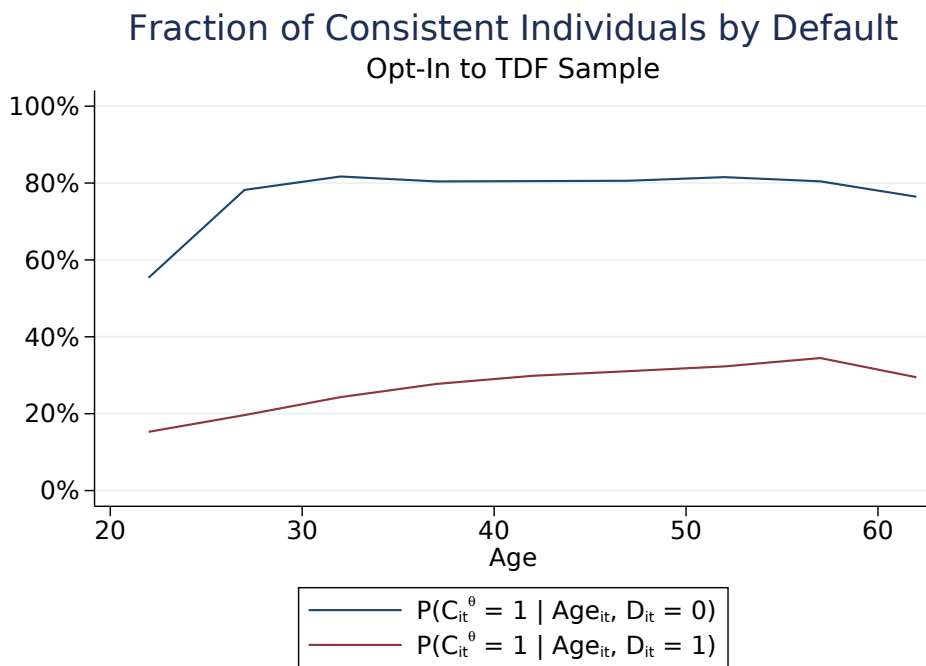


**Figure A8.** Fraction of Consistent Investors by Age and Default

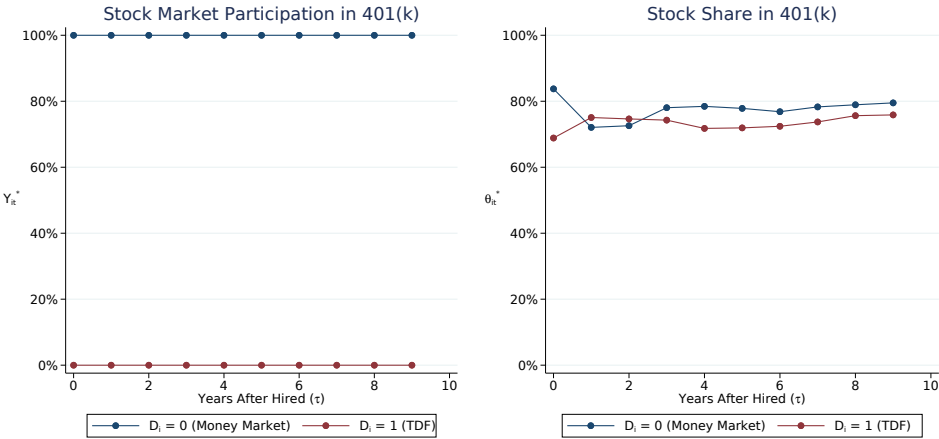
*Panel A: Money Market to TDF Sample*



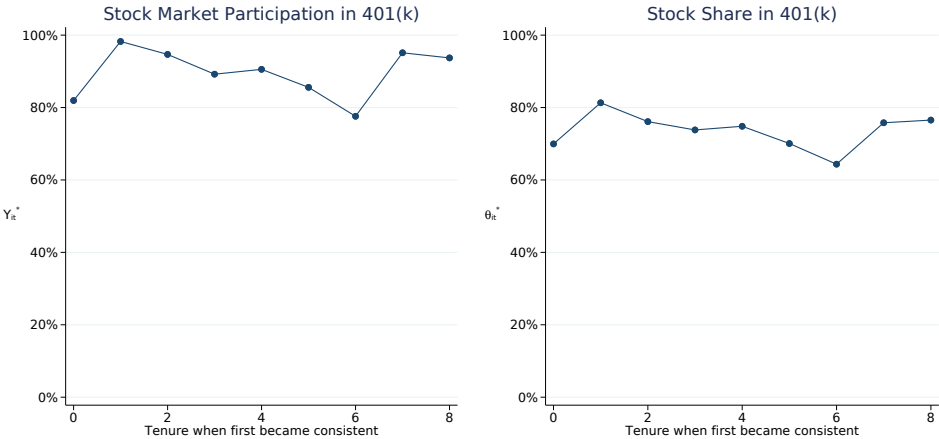
*Panel B: Opt-In to TDF Sample*



**Figure A9.** Preferences of Consistent Investors by Default: Money Market to TDF Sample

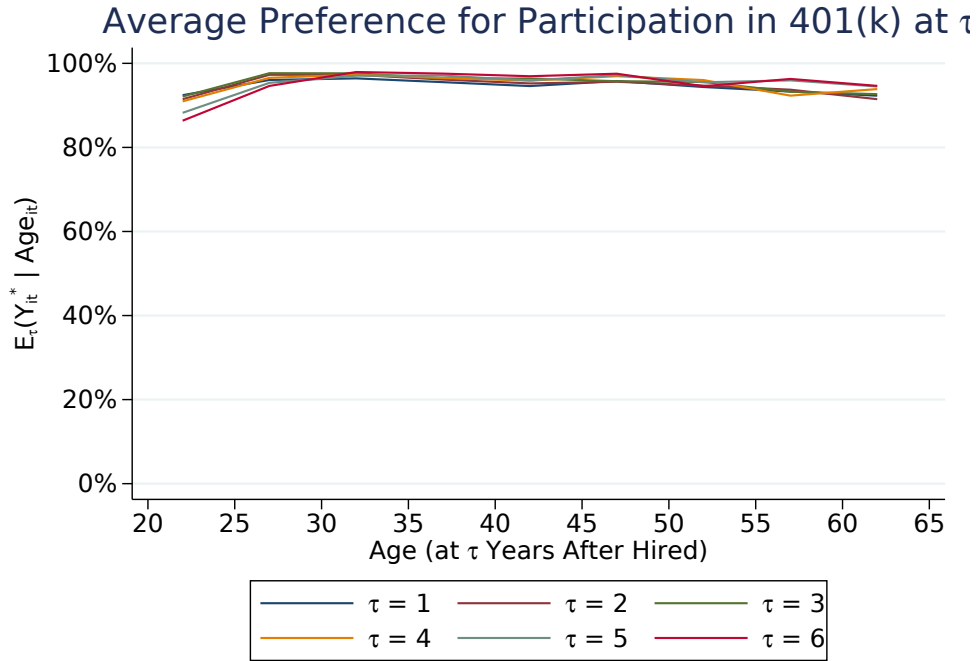


**Figure A10.** Preferences of Consistent Investors by Tenure of Consistency: Opt-In to TDF Sample

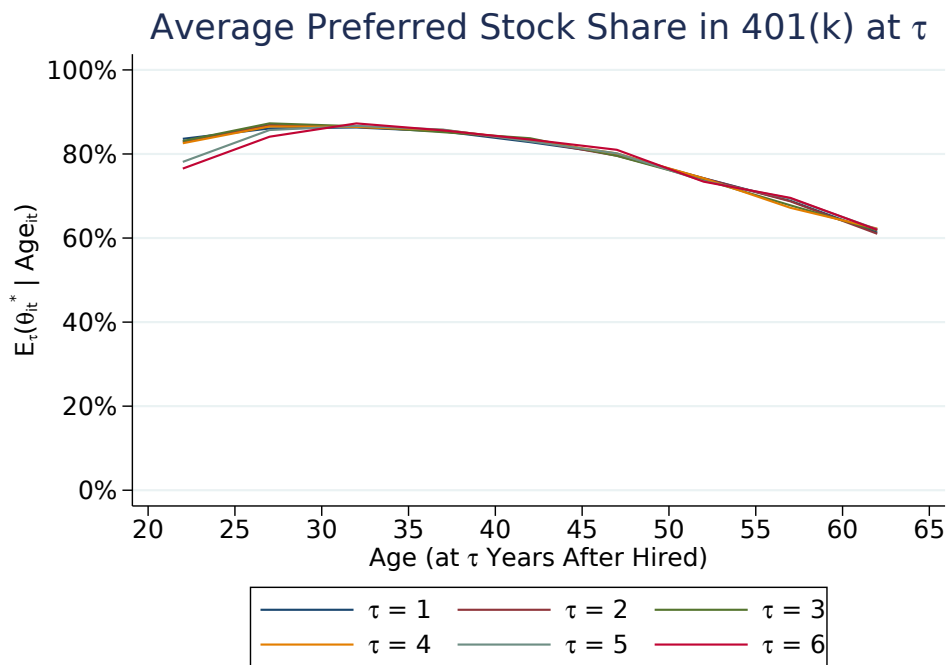


**Figure A11.** Estimated Preferences by Tenure: Opt-In to TDF Sample

*Panel A: Stock Market Participation*

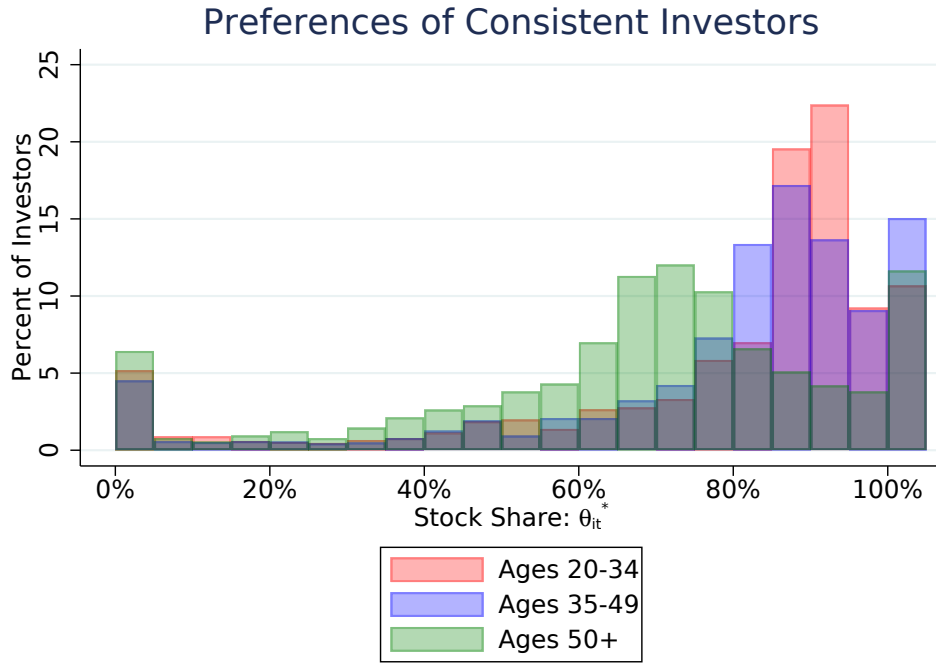


*Panel B: Stock Share of Retirement Wealth*

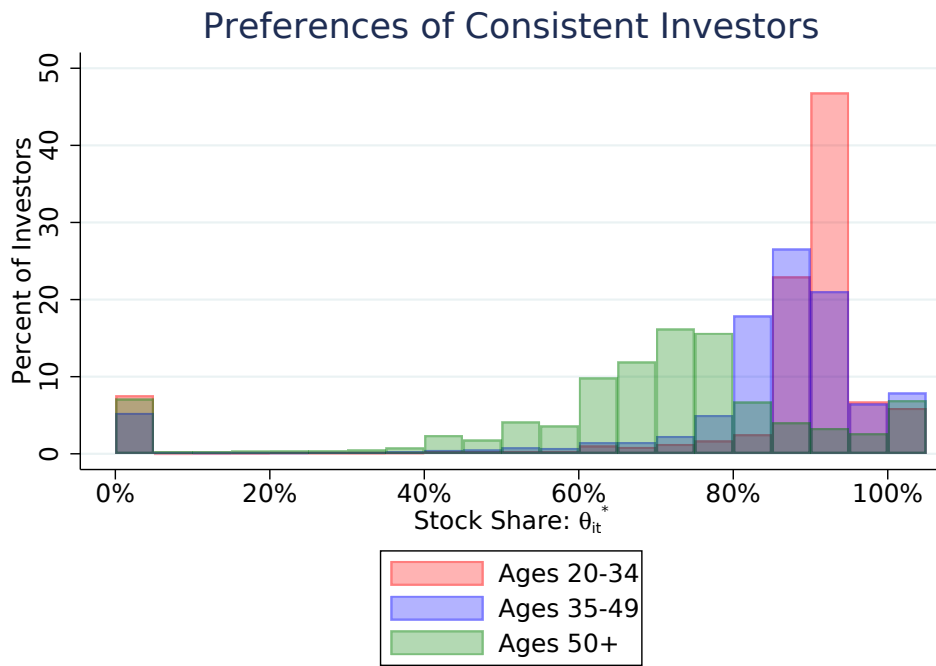


**Figure A12.** Preference Heterogeneity among Consistent Investors

*Panel A: Money Market to TDF Sample*

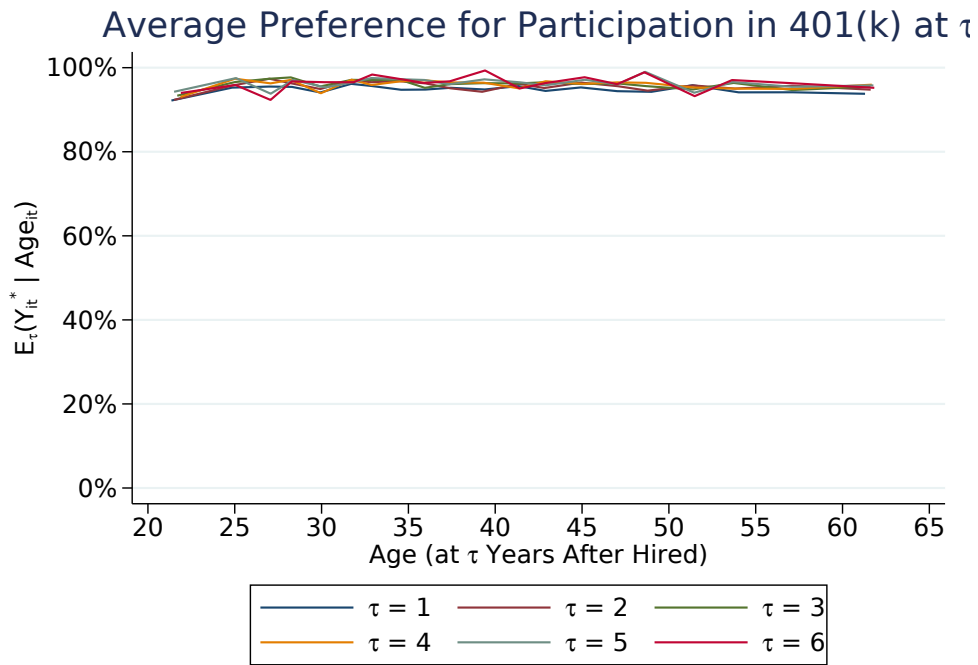


*Panel B: Opt-In to TDF Sample*

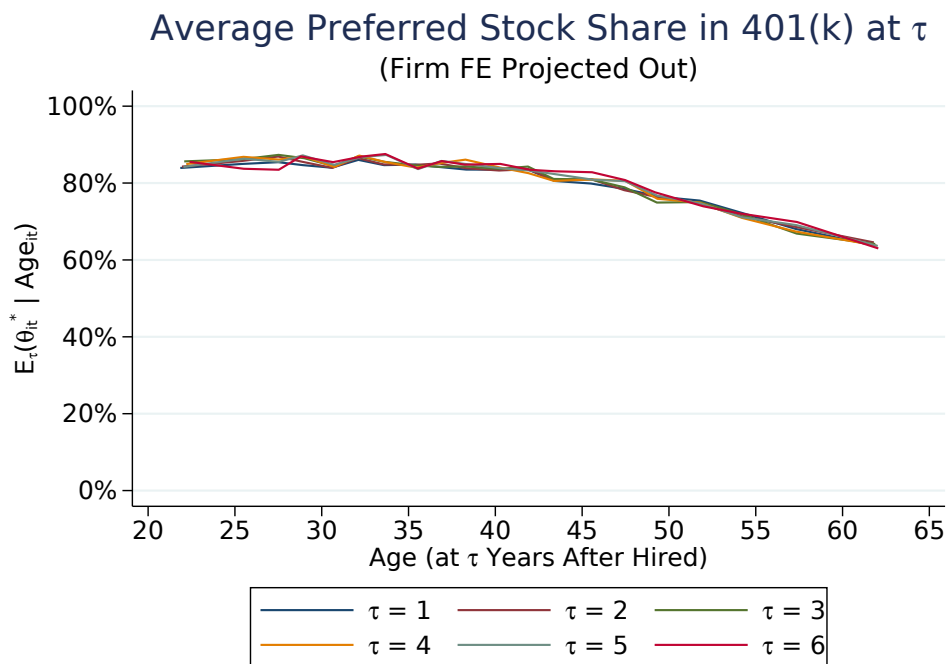


**Figure A13.** Robustness of Preferences over the Life Cycle: Opt-In to TDF Sample

*Panel A: Participation*

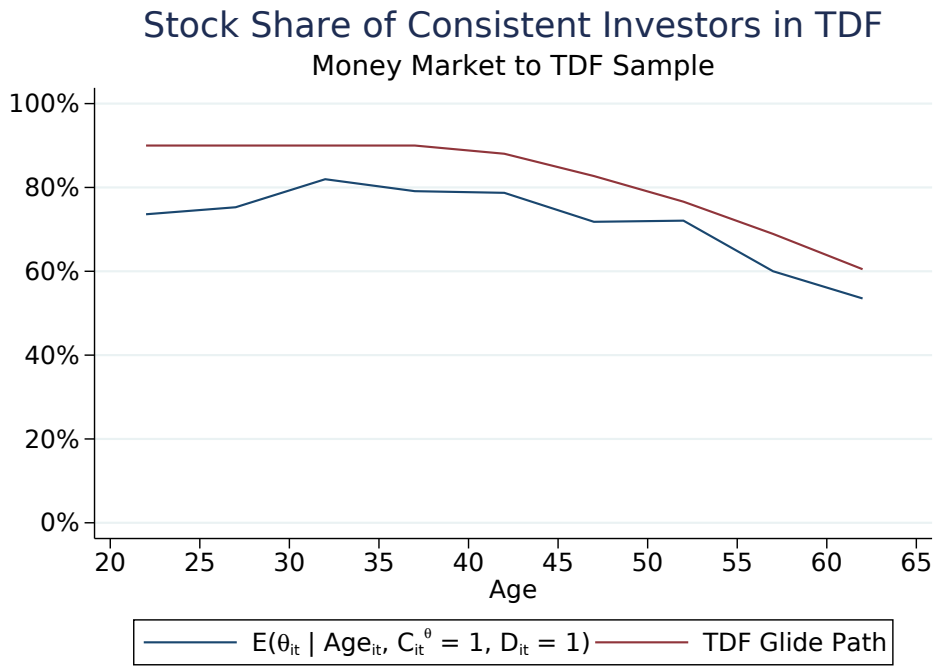


*Panel B: Stock Share of Retirement Wealth*

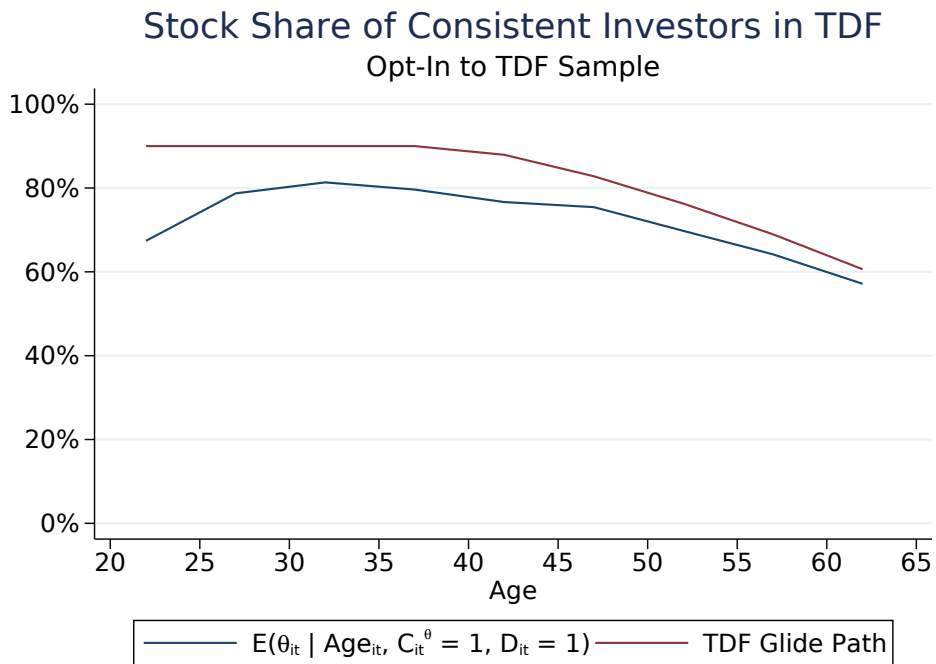


**Figure A14.** Life Cycle Preferences of Consistent Investors Defaulted into TDF

*Panel A: Money Market to TDF Sample*

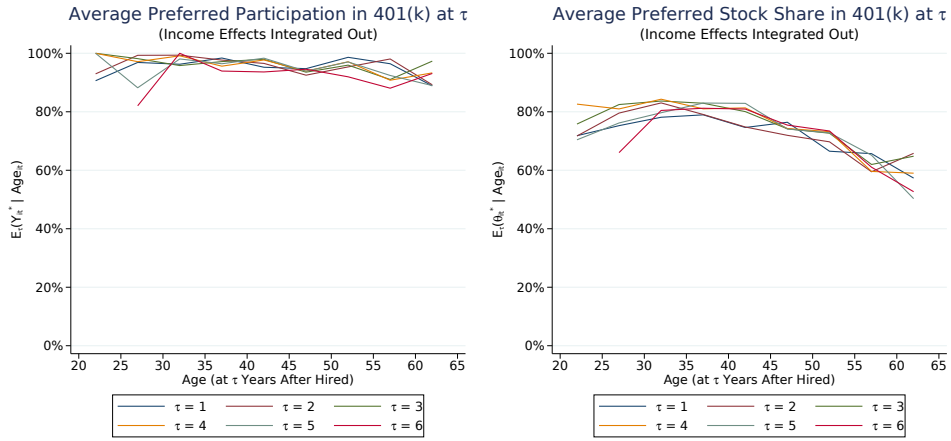


*Panel B: Opt-In to TDF Sample*

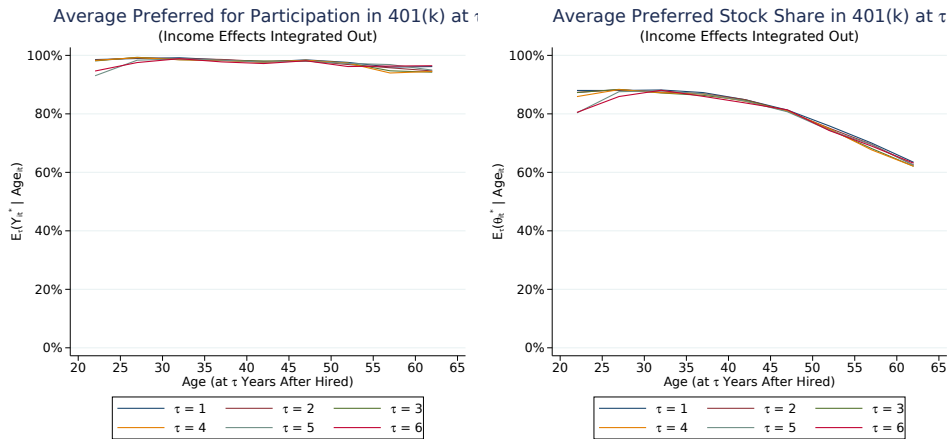


**Figure A15.** Estimated Preferences Under Weaker Identifying Assumption

*Panel A: Money Market to TDF Sample*



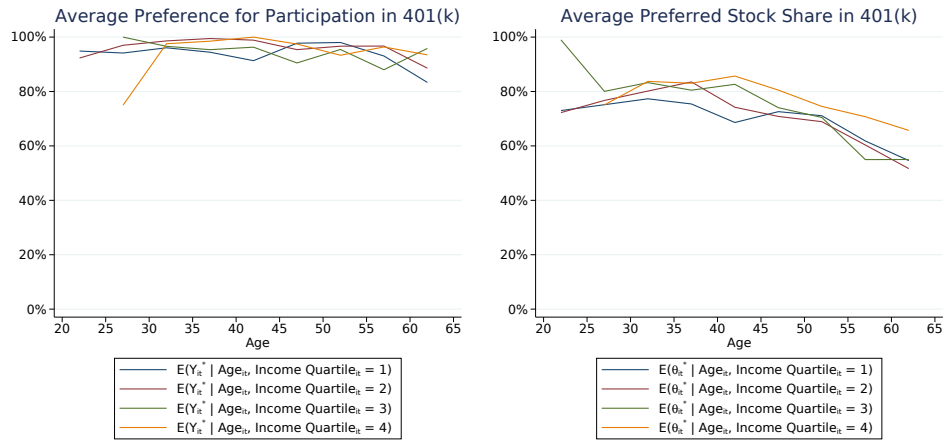
*Panel B: Opt-In to TDF Sample*



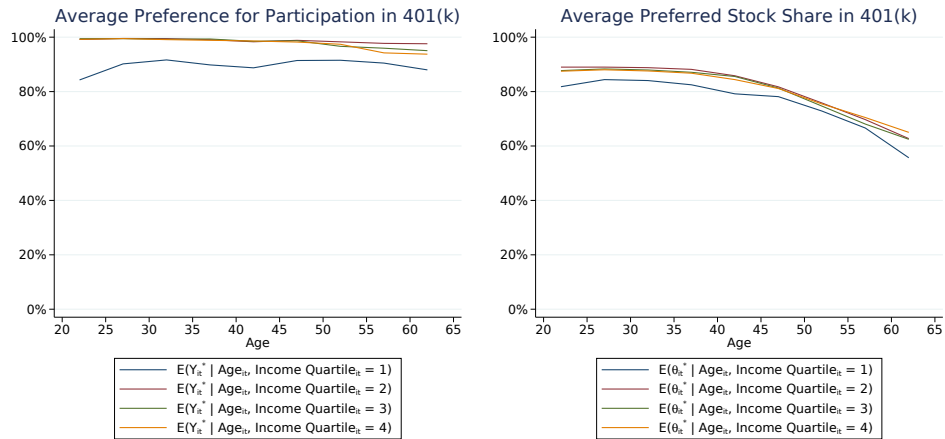


**Figure A16.** Preferences over the Life Cycle by Income Quartiles

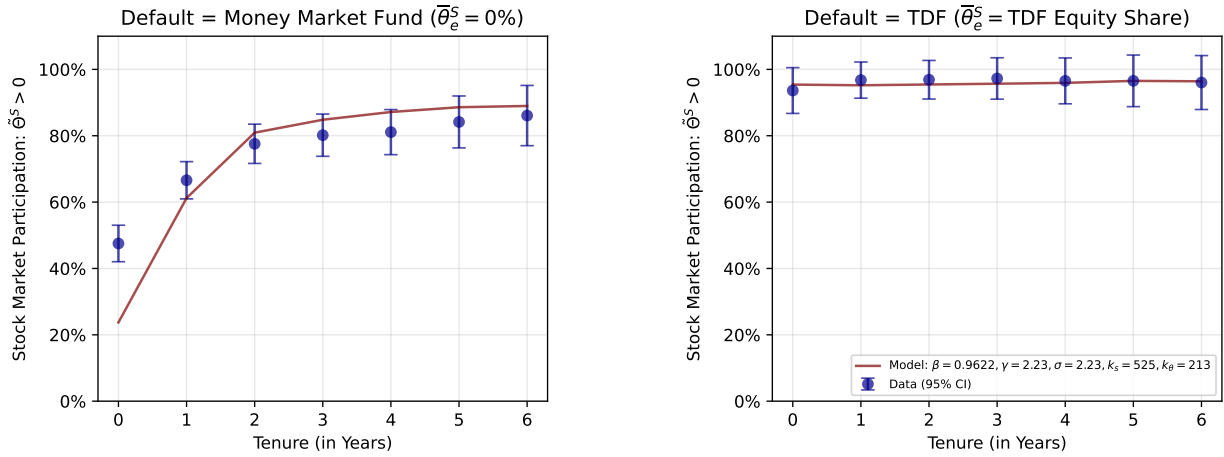
*Panel A: Money Market to TDF Sample*



*Panel B: Opt-In to TDF Sample*

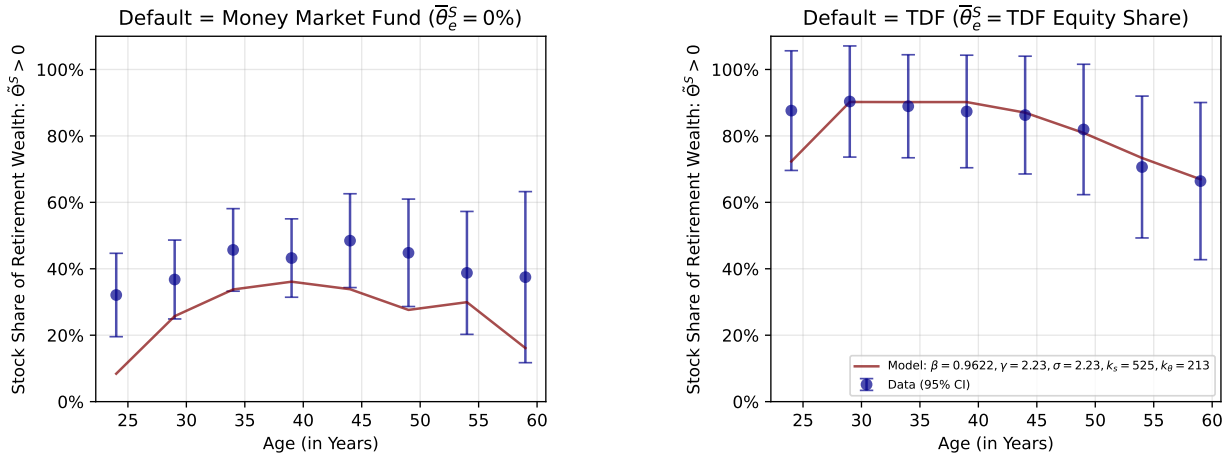


**Figure A17.** CRRA Model Fit: Stock Market Participation in 401(k) from Quasi-Experiment #1



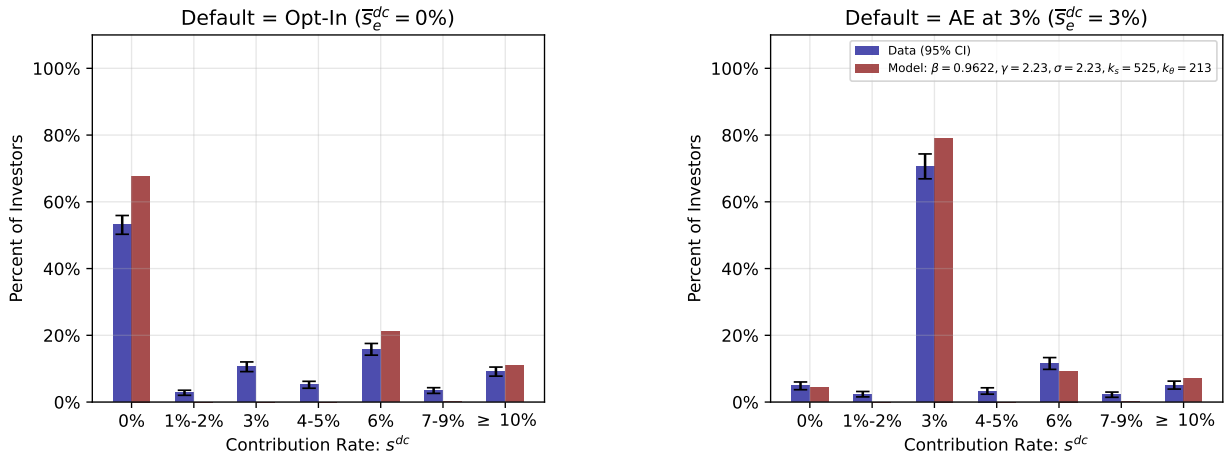
*Notes:* This figure presents the fit of our model on the response of stock market participation inside the current employer retirement account for our first quasi-experiment. The data moments in this figure correspond to the moments from our first quasi-experiment in the left half Figure 4 Panel A for the first six years of tenure along with 95% confidence intervals. The model moments are from a simulation of this experiment within the model described in the main text at our SMM estimates of preference parameters reported in column (2) of Table 3.

**Figure A18.** CRRA Model Fit: Stock Shares by Age in First-Year of Tenure



*Notes:* This figure presents the fit of our model on the age profile of equity shares inside the current employer retirement account for the treatment and control groups in our first quasi-experiment separately. The data moments are calculated on the same sample that is used in Figure 4 and are shown with 95% confidence intervals. The model moments are from a simulation of this experiment within the model described in the main text at our SMM estimates of preference parameters reported in column (2) Table 3.

**Figure A19. CRRA Model Fit: Contribution Rates in First-Year of Tenure**



*Notes:* This figure presents the fit of our model on the distribution of contribution rates in investors' first-year of tenure. The amount of investors at 0%, 3%, 6%, and greater than 10% is targeted in the estimations reported in Table 3. The left (right) figure show contribution rates of investors hired 12 months before (after) the introduction of auto-enrollment for new hires, which we plot directly the data along with 95% confidence intervals. The model moments are from a simulation of this within the model at our SMM estimates of preference parameters reported in column (2) of Table 3.