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

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Abstract

We separately identify the role of risk preferences and frictions in portfolio choice. Individuals may choose not to participate in the stock market because of non-standard preferences (e.g. loss aversion) or frictions impacting their choices (e.g. participation costs). We overcome this identification problem by using variation in the default asset allocation of 401(k) plans and estimate that, absent frictions, 94% of investors would prefer holding stocks in their retirement account with an equity share of retirement wealth that declines over the life cycle, which differs markedly from their observed choices. We use this variation to estimate a structural life cycle portfolio choice model and find the evidence consistent with a relative risk aversion of 3.6. This estimate is significantly lower than most estimates in the life cycle portfolio choice literature and highlights how choice frictions can hamper the identification of risk preferences.

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Many households do not participate in the stock market, including households with significant financial wealth (Mankiw and Zeldes 1991; Guiso, Haliassos, and Jappelli 2002; Campbell 2006). This limited participation in the stock market 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).[1] In principle, an investor may choose to not allocate their financial wealth to the stock market for two reasons. First, this investor may prefer holding safe assets over stocks (e.g. due to loss aversion, ambiguity aversion, or pessimistic beliefs about returns). Alternatively, this investor 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 this investor's participation in the stock market, distinguishing between them has important 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 propose and implement a new empirical approach to recover investor preferences in the presence of frictions. We begin by showing that the life cycle profile of participation in the Survey of Consumer Finances is consistent with very different calibrations of a standard life cycle portfolio choice model: (i) a risk aversion below 2 and an extremely high adjustment or participation cost or (ii) a risk-aversion above 30 and a lower adjustment or participation cost. This illustrates the challenge in separately identifying investors' risk preferences, as well as the size and specification of choice frictions.

Next, we overcome this identification problem using quasi-experimental variation in the default asset allocation of 401(k) plans. An ideal experiment for separating between preference- and friction-based explanations for non-participation would be to randomly give investors who are 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 one-time frictions were responsible for these investors not participating beforehand, we would expect them to keep the stocks, durably 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

[1] With strictly increasing and differentiable utility, agents should be risk-neutral over small risks (Rabin 2000).

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 American households use to participate in the stock market and invest in financial products.[2] 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); (ii) investors hired under an opt-in regime. Investors in both control groups are, by default, not holding any stocks in their retirement account and must make an active decision in order to participate. We find that more than 90% of investors defaulted into stocks maintain a positive equity share of retirement wealth throughout their tenure, whereas investors defaulted into a money market fund (or hired under an opt-in regime) progressively move away from their zero-stock default option and toward higher equity exposure. The fact that most investors move away from the default when it is a safe asset but stay invested in the default when it's equity suggests, 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 inside their retirement account absent frictions. Empirically, 42% of investors who were defaulted into a money market opted out of the default within one year and moved toward stock market participation. Intuitively, these investors have revealed their preference for stocks by actively moving away of the money market default and, therefore, there must be at least 42% of investors who prefer stock market participation. Conversely, 5% of investors who were defaulted into holding stocks made an active decision to opt-out of stock market participation, thus revealing their preference for stock non-participation inside the retirement account. Thus, the upper bound for stock market participation in the retirement account absent any frictions should be 95%. This result is, if anything, an underestimate of stock-market participation absent frictions for two reasons: (i) we do not observe participation in stocks outside of one's retirement account, and (ii) our quasi-experiment does not remove potential per-period participation costs. We can also bound the average preferred stock share of retirement wealth from below at 39%.

[2]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 inside a retirement account. Overall, only 5% of households participate in the stock market exclusively outside of a retirement account. See Section 2.2 for additional details.

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 preferences absent frictions. 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, we estimate preferences for participation 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 30 at a level and rate roughly consistent with 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.

We view these new quasi-experimental moments as valuable calibration or estimation targets for both standard and behavioral models of portfolio choice. On the one hand, models abstracting from adjustment costs could directly target our friction-free estimates of participation and equity shares of retirement wealth over the life cycle to obtain better identified preference estimates. On the other hand, richer models featuring choice frictions could exploit the difference in behavior across the treatment and control group to separately identify the size of the friction from preference estimates. To illustrate these points, 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 are subject to default effects when making portfolio choice and savings decisions. Finally, investors face uncertainty about future earnings and employment status that creates value to delaying adjustments in 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' preferences and the magnitude of the frictions 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 3.6 and a portfolio adjustment cost of $222. This estimate of risk aversion is lower than most estimates in the life cycle portfolio choice literature (see Gomes 2020, for a review). A notable exception is Briggs, Cesarini, Lindqvist, and Östling (2021), who use quasi-experimental variation from lottery-winnings in Sweden and estimate a relative risk aversion of around 2.7.[3] Collectively, these results highlight how frictions distort the mapping between observed portfolio choices and risk

[3]See also Beutel and Weber (2022), who find the portfolio responses of investors to information treatments are consistent with a coefficient of relative risk aversion of 4.1 in a Merton (1969) model with margin constraints.

preferences, and how quasi-experimental variation can help overcome this identification problem.

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 (e.g. due to non-standard preferences or beliefs). 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 et al. 2021), 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. 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; 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 the 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 account. Within the class of models with frictions, we find support for those with one-time participation or fixed adjustment/transaction costs as opposed to per-period participation costs. In the presence of large enough per-period participation costs workers who are automatically enrolled into a stock fund should opt-out and move their savings away from equity, which is not what we observe in the data.

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). We take advantage of quasi-experimental variation to provide estimates for two key parameters governing life cycle portfolio decisions: the coefficient of relative risk-aversion and the size of portfolio adjustment costs. These estimates are 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; Parker, Schoar, Cole, and Simester 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 re-balancing.

Finally, this paper contributes more broadly to the literature on behavioral welfare economics (e.g. Bernheim and Rangel 2009; Allcott and Taubinsky 2015; Choukhmane 2021). Most related is the framework we apply for inferring preferences in the presence of framing effects developed by Goldin and Reck (2020). Our results highlights how choice frictions can break the mapping from observed choices to underlying preferences in the estimation of structural models. More constructively, this paper illustrates how quasi-experimental variation can provide useful variation for distinguishing between different behavioral theories (see also Briggs et al. 2021; Choukhmane 2021).

Outline. Section 1 illustrates the identification problem in separating preferences and frictions as driver 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. An Appendix containing additional results, model solution and estimation details, and derivations.

1 The Identification Problem

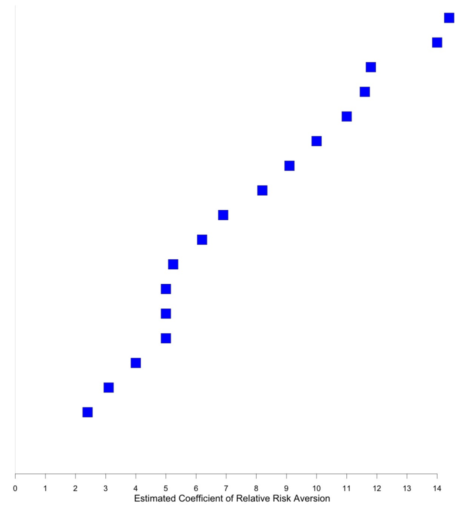
In this section, we discuss the identification of risk preferences and choice frictions. We first discuss the lack of consensus in the existing literature about estimates of risk aversion in life cycle portfolio choice models. Next we show the difficulty in separating the two in a standard life cycle 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.[4]

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

Paper	**Friction**	**Estimate**	**Merton Share**
Fagereng et al. (2017)	per-period cost	14.4	15%
Dahlquist et al. (2018)	one-time cost	14	15%
Fagereng et al. (2017)	per-period cost	11.8	18%
Catherine (2020)	none	11.6	19%
Fagereng et al. (2017)	per-period cost	11	20%
Cocco et al. (2005)	none	10	21%
Reher and Sokolinski (2021)	per-period cost	9.1	24%
Catherine (2020)	per-period cost	8.2	26%
Catherine (2020)	none	6.9	31%
Catherine (2020)	per-period cost	6.2	35%
Calvet et al. (2020)	none	5.24	41%
Gomes and Michaelides (2005)	one-time cost	5	43%
Campanale et al. (2015)	one-time cost	5	43%
Benzoni et al. (2007)	none	5	43%
Gomes et al. (2009)	one-time cost	4	54%
Briggs et al. (2021)	one-time cost	3.1	69%
Briggs et al. (2021)	one-time cost	2.4	90%
Average		**7.82**	**27%**



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%.

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

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

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 β and a CRRA preferences over flow consumption with risk aversion σ. 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, θ_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 in order to choose an asset allocation $\theta_t \neq \theta_{d,t}$, where

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

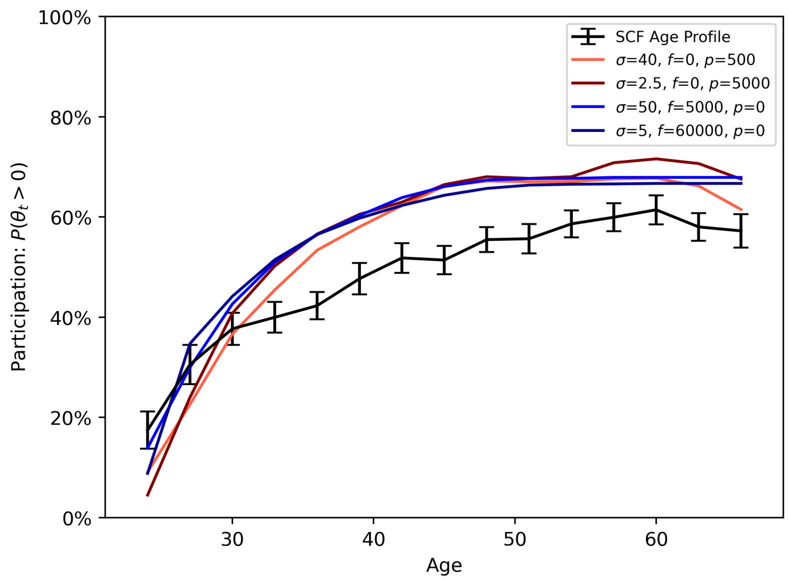
The term $\theta_{d,t}$ captures the asset allocation absent any adjustment decision (i.e.under passive portfolio re-balancing): it is equal to the asset allocation from the prior period, after adjusting for return realizations. We also assume $\theta_{d,0} = 0$ to capture the fact that the default for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

We solve the model numerically for different values of σ, 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 σ and low f; (ii) low σ and high f; (iii) high σ and low p; (iv) low σ and high p. 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 the that from the SCF, we find models with coefficient of relative risk aversion of 2.5 and 50 fit the data equivalently well, depending on the size and form of the choice frictions.[5]

Figure 2. Life Cycle of Participation in Simple Model versus 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. σ 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 illustrate the difficulty to separately identify the size and specification of both frictions and risk preferences. These results that additional sources of variation are need in order to identify the extent to which risk preferences and (different types of) frictions contribute to limited stock market participation.

[5]While these different calibrations generate observationally equivalent patterns of participation over the life cycle, they may imply different patterns of wealth accumulation or conditional equity shares.

2 Data and Quasi-Experimental Variation

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

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 kept the risky assets, this would suggest 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 investors sell, we would be able to infer their preferred stock share.

2.2 Institutional Setting and 401(k) Administrative Data

In order to approximate the ideal experiment described above, we use data from a panel 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 contains detailed administrative records for 4 million employees in more than 600 401(k) plans between December 2006 to December 2017. For each employee (to 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 as well as 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 increased 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 from the Social Security Administration. 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 (which is as a percentage of salary). We can only impute the compensation 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 stock share 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. In light of this data limitation, the life cycle portfolio choice model introduced in Section 4 has separate accounts for assets held inside the current employer's retirement account, retirement assets accumulated at previous employers, and non-retirement liquid savings. Nevertheless, we believe that behavior inside retirement accounts offers a good indication of individuals 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 inside 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.[6] Under the assumption that investors hired before and after the changes are similar (and other assumptions formalized in the 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. 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.[7]

Relative to the money market to TDF sample, the opt-in to TDF sample has the advantage of a

[6] All six of these firms change their default asset allocation in 2007 following the passage of the Pension Protection Act of 2006.

[7] The menu of funds available are broadly similar before vs after the adoption of a new default fund. Results are available upon request.

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 both in terms of the frictions they face to adjust their retirement asset allocation *and* the frictions they face in order to contribute to the 401(k) plan. This implies that in the opt-in control group, investors face a larger friction to hold stocks in their retirement account (i.e. they need to first select a positive contribution rate and then choose an asset allocation with positive equity exposure).

In Panels A and B of Figure 3, we plot the variation we use in both quasi-experiments. For the money market to TDF sample, Panel A plots 401(k) participation, money market participation, and stock market participation inside the 401(k) for investors in their first year of tenure based on their hiring month relative to the policy change. Investors in the left-half of each graph are in the control group (hired before the change), while 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 inside 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 inside the 401(k) plan for investors in the treatment group.[8]

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

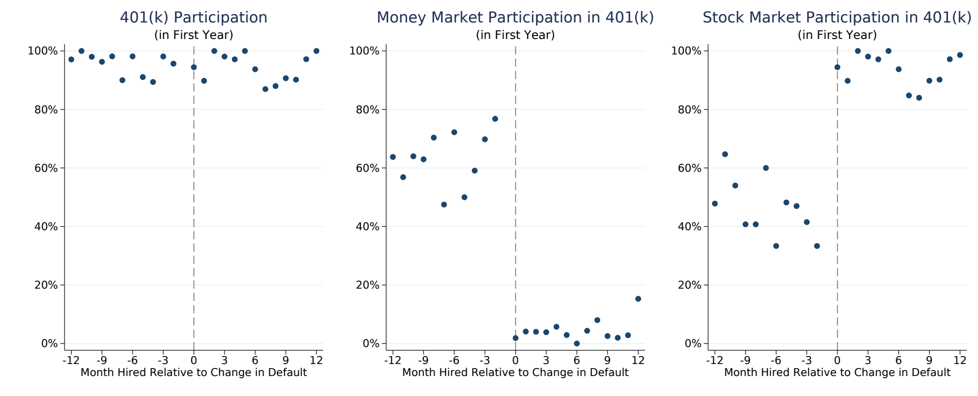
Figure 4 plots the results from our two quasi-experiments in separate panels.[9] In each panel, we plot the fraction of investors participating in the stock market and their average stock share of retirement wealth τ years after they have been hired, where $\tau = 0$ corresponds to their choice immediately 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

[8]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.

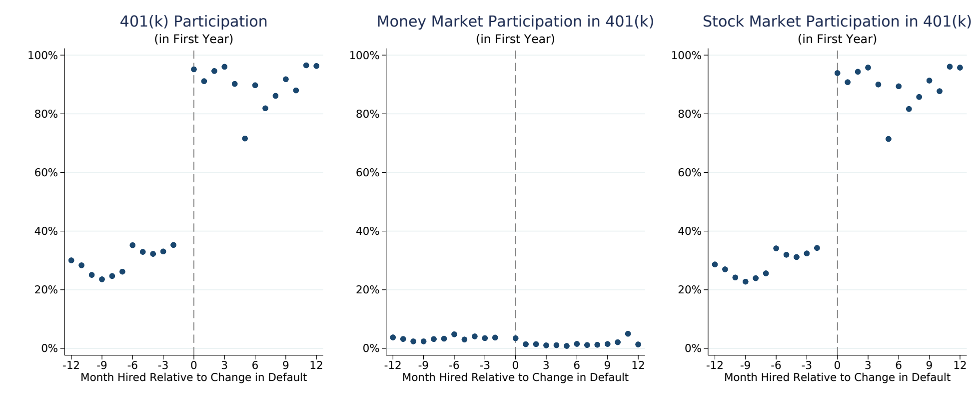
[9]For the rest of the analysis, we only focus on portfolio choices made within 10 years of being hired. We drop choices after that since there are few investors who remain at the firm for that long.

Figure 3. Identifying Variation

Panel A: Money Market to TDF Sample



Panel B: Opt-In to TDF Sample



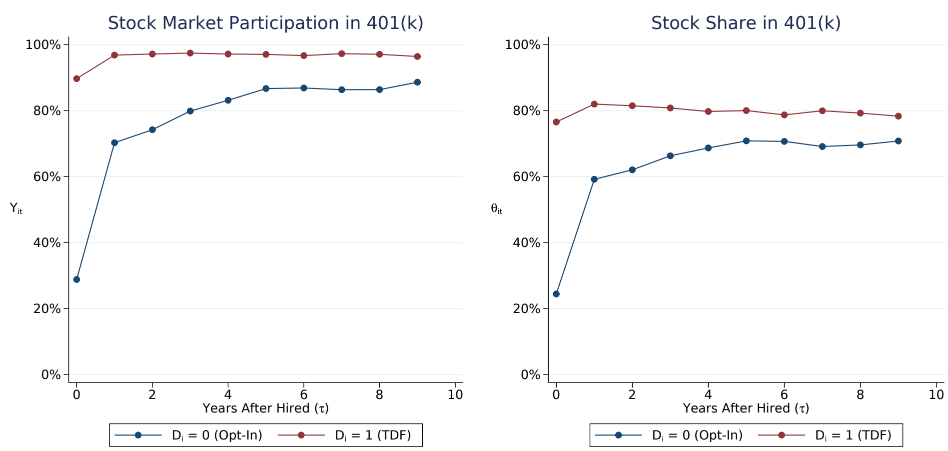
Notes: This figure plots the variation in our two quasi-experiments using data from the end of December for employees with less than 12 months of tenure. In Panel A, we compare the portfolio choices and 401(k) participation of investors hired within 12 months before and 12 months after 6 firms change 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.

account. In both samples, we also observe that investors in the treatment group maintain a relatively high stock share of retirement wealth of around 80%, while the investors in the control groups start with a lower stock share of retirement wealth and converge toward 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 the control group on average, with a stock share of retirement wealth that is between 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 Target Date Fund (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): θ_{it}			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Constant	56.58	56.35	57.81	56.95	37.40	37.21	38.88	38.28
	(11.61)	(10.57)	(8.988)	(8.600)	(10.07)	(9.392)	(8.329)	(8.004)
Default Has Stocks: D_i	19.92	20.06	19.12	19.68	21.50	21.62	20.55	20.93
	(5.661)	(5.596)	(5.486)	(5.795)	(5.229)	(5.239)	(5.039)	(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): θ_{it}			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Constant	65.72	65.28	68.12	66.97	54.63	54.30	56.31	55.46
	(3.641)	(3.113)	(2.122)	(1.688)	(3.045)	(2.648)	(1.630)	(1.337)
Default Has Stocks: D_i	29.35	30.13	25.10	27.12	25.11	25.70	22.14	23.65
	(3.692)	(2.822)	(2.855)	(2.798)	(2.998)	(2.344)	(2.292)	(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 parenthesis.

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, employer 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 likely are not 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 that the selection into our sample is 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 the responses of investors in the control group are similar regardless of when the investor separate from their employer, which indicates that the increased stock market of the control group over time is not driven by a change in the composition of employees remaining at the firm.

Passive re-balancing. A third concern is that the evolution (and convergence) of equity shares in the retirement account are driven by passive re-balancing. 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 only reflects allocation decision 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 most investors like to participate in the stock market inside their retirement account, given the treatment group maintains their stock market exposure and the control group makes active decisions to move into stocks. The difference in participation between the treatment and the control group indicates the existence of adjustment (or one-time participation) costs associated with changing one's asset allocation, which could be real or psychological. In order 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 into 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 inside retirement accounts. For additional details on the framework, in addition to derivations of results, see Appendix C.

3.1 Framework

Consider investors by i that are hired by an employer at time $t = 0$ and make asset allocation choices at $t = 0, \ldots, T$. 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 θ_{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:[10]

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

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}^{θ}, 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) *in*consistent 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 $E(\cdot)$ and $E_{\tau}(\cdot) = E(\cdot \mid t = \tau)$ as the expectation across the entire population and the conditional expectation across all investor at tenure $t = \tau$, respectively.

3.2 Bounding Average Preferences

3.2.1 Stock Market Participation Inside 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,*

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

[10]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 whether which default (or frame) they are given. This assumption results out the possibility that investors view the default as providing information and prefer to participate more when the default is participation.[11] Frame exogeneity requires the choice of default to be independent of investors' preferences, or equivalently that investors in the treatment and control group have the same preferences. This is a natural assumption in our setting, given the default is chosen by the firm. In the case of participation, frame monotonicity requires that there are no investors who always choose the opposite of the default, which we view as reasonable given the literature on default effects. Finally, the consistency principle requires that consistent investors reveal their preferences. For example, if an investor choose to participate regardless of the default asset allocation, we assume the investor's preference is indeed to participate.

Under the previous assumptions, the following result from Goldin and Reck (2020) allows us to bound the preferences for stock market participation inside retirement accounts for the population of investors in our sample.

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

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

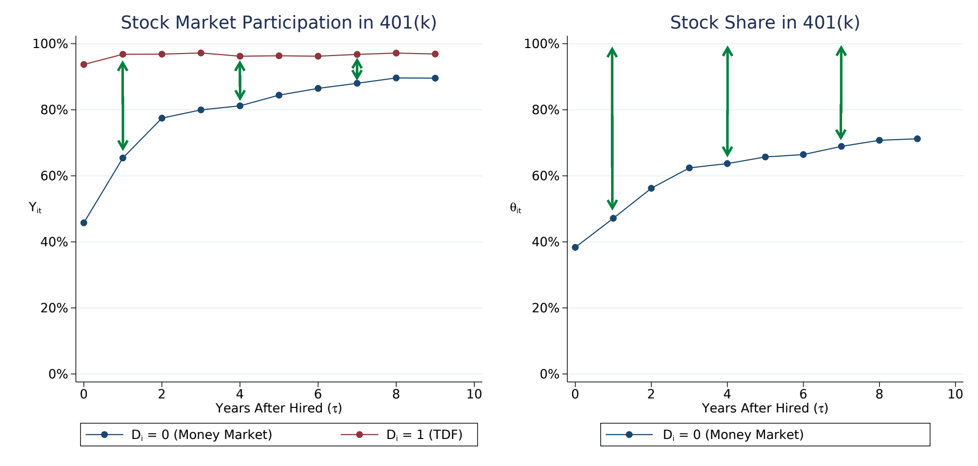
The intuition for this result is as follows. The average preference for participation is the weighted-average of the preferences of consistent and inconsistent investors. Since Assumption 4 implies the preferences of consistent investors are revealed by their choices, we just need to bound the preferences of inconsistent investors to bound the population average preference. The bounds in (2) comes 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 average preferences for stock market participation inside retirement accounts.

[11] Informally, the partial-identification results 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.

By (2), 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.[12] 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 average participation in our sample of 58% (Table 1), illustrates that one-time adjustment/participation costs are driving a wedge between 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.

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



Notes: This figure plots the same data as Figure 4 with the non-parametric 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.

3.2.2 Stock Shares in 401(k) Plans

We now turn to identification of investors' preferences for stock shares of retirement wealth. Unlike 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 τ, implying we cannot infer anything about his preferences from his observed choices under Assumptions 1-4. For example, this investor may have $\theta^*_{i\tau} \in (0, \theta_{i\tau}(0))$.

[12] As evident from Figure 4, we find similar results across both samples.

The possible presence of such an investor renders the analogous bound to 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 counter-example 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).[13] Under this assumption, the following result shows we can place a lower bound on bound population preferences for stock shares of retirement wealth analogously to the participation lower bound 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:*

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

Proposition 2 shows the results in the right panel of Figure 4 allow us to bound average preferences for stock shares, as illustrated in the right panel of Figure 5. After investors have been at the firm for three years, we can bound the average preferred stock share of retirement wealth among all 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 around 23% (Table 1) and the average stock share in our sample of 53%, illustrating how frictions can drive a wedge between choices and preferences.

[13]The lower bound on the average preferred stock share of retirement wealth 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 $\theta_{it}(d) = m\theta_{it}^{*} + (1-m)\theta_i^d(d)$.

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 this, we use the following result.

Proposition 3. *Under Assumptions 1-4,*

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

Under Assumptions 1-3, and 5,

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

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 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 the preferences of those who do deviate are similar to those who don't.

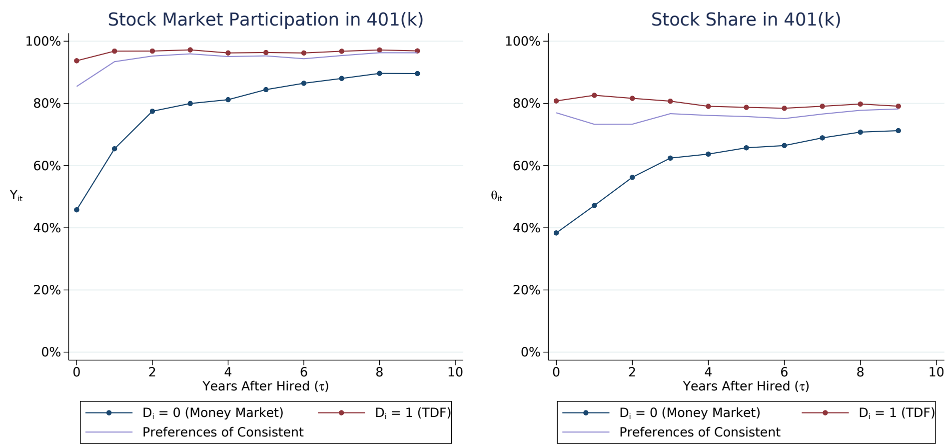
Figure 6 plots our estimate of the preferences of consistent investors. In both samples, after three years of tenure, we find about 94% of consistent investors prefer holding stocks inside their retirement accounts with an average stock share of retirement wealth around 76%.[14] Consistent with our population bounds, these both are quite high, suggesting these consistent investors 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 overcoming 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 the fraction of consistent investors is slightly increasing over the life cycle, which is consistent with a one-time real adjustment cost which younger investors (who have less wealth) are less

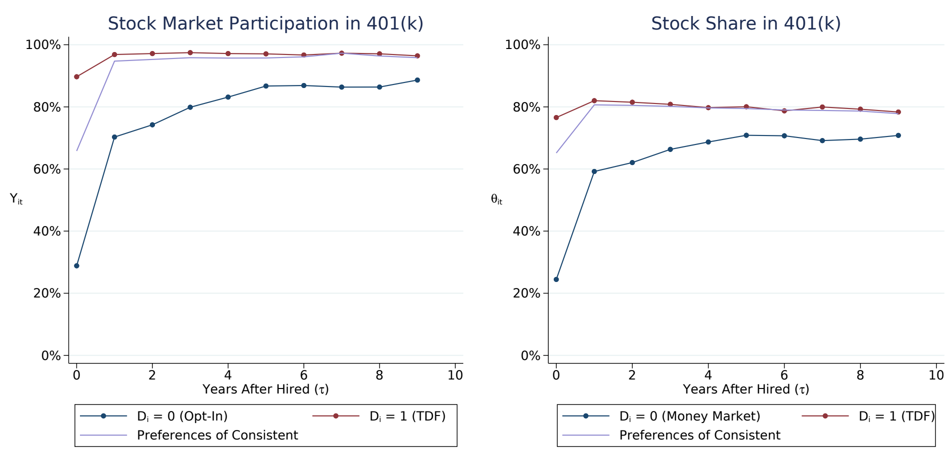
[14] Figure A9 plots estimates of these preferences based on what default consistent investors were given. For stock shares, we find consistent investors reveal similar preferences regardless of the default, which supports Assumption 5.

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 Figure 4, but includes our point estimates for the consistent investors under Assumptions 1-4 for stock market participation inside 401(k) plans and Assumptions 1-3 and 5 for the stock share of retirement wealth. Under Assumption 6, this provides an estimate of the preferences of the entire population.

likely to pay.[15] Figure A7 also shows that a 40 year-old investor (the average 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 the control group needs to overcome in the latter sample are likely large, due to a need to change both 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: investors are less likely to be consistent when they are defaulted 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 consistent investors and the preferences of the population:

$$E_\tau(Y_{it}^*) = E_\tau\left(Y_{it}^* \mid C_{it}^Y = 1\right) - \frac{1}{E_\tau(C_{it}^Y)} \underbrace{cov_\tau\left(Y_{it}^*, C_{it}^Y\right)}_{\text{selection bias}}, \tag{6}$$

$$E_\tau(\theta_{it}^*) = E_\tau\left(\theta_{it}^* \mid C_{it}^\theta = 1\right) - \frac{1}{E_\tau(C_{it}^\theta)} \underbrace{cov_\tau\left(\theta_{it}^*, C_{it}^\theta\right)}_{\text{selection bias}}. \tag{7}$$

Proposition 3 shows 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 different preferences from inconsistent investors. In general, this selection bias is unbounded without placing further restrictions on investor decision-making. For example, in our structural model described in Section 4, we could compute this directly.

To point-estimate average population preferences, we begin by making the following identifying assumption.

Assumption 6. *For all i and τ,*

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

This assumption states that once we condition on an investor's tenure, whether they are consistent is uncorrelated with their preferences. Under Assumption 6, the preferences of the population

[15] 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).

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 in their retirement accounts is 94% and the average preferred stock share of retirement wealth is 76%.

Assumption 6 is a strong assumption: it requires, at a given tenure, consistent (active) and inconsistent (passive) investors to 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 $cov_\tau(Y_{it}^*, C_{it}^Y)$ by comparing the allocation decisions of investors who are quick to make an active decisions (more consistent) to that of investors who waited several years before deviating from the default (less consistent). In Figure A10, we find that the stock market participation and average stock share inside the retirement account are very similar for investors who deviated right away from the default and those who waited up to 8 years to make an active decisions consistent with Assumption 6.

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 the 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 consistency might vary with age as well (e.g. older investors have a lower option value of delaying adjustment). We thus relax Assumption 6 by making the following assumption.

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

$$cov_\tau(Y_{it}^*, C_{it}^Y \mid age_{it} = A) = cov_\tau(\theta_{it}^*, C_{it}^\theta \mid age_{it} = A) = 0.$$

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:

$$E_\tau(Y_{it}^* \mid age_{it} = A) = E_\tau\left(Y_{it}^* \mid C_{it}^Y = 1, age_{it} = A\right),$$
$$E_\tau(\theta_{it}^* \mid age_{it} = A) = E_\tau\left(\theta_{it}^* \mid C_{it}^\theta = 1, age_{it} = A\right).$$

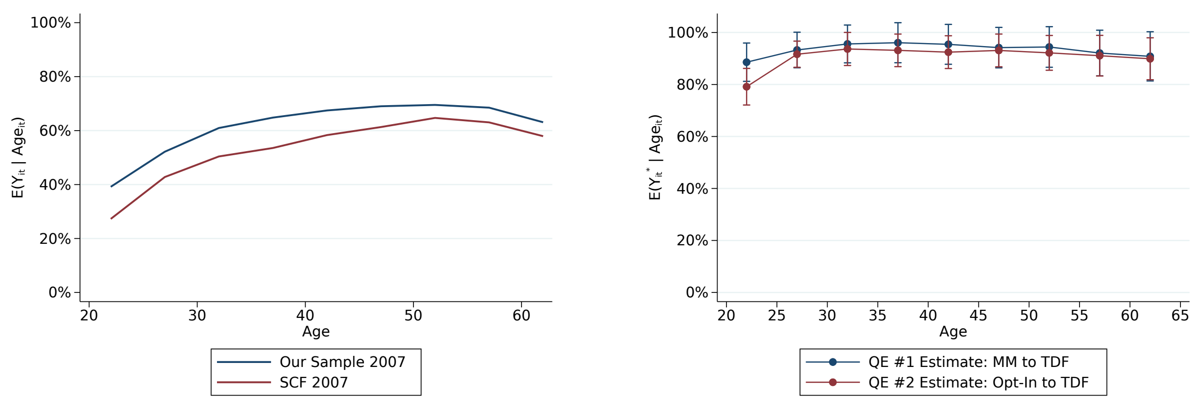
Applying Proposition 3 conditionally then gives the following life cycles of preferences for investors of tenure $t = \tau$:

$$E_\tau(Y^*_{it} \mid age_{it} = A) = E_\tau\left(Y_{it} \mid Y_{it} \neq D_i, age_{it} = A\right), \tag{8}$$

$$E_\tau(\theta^*_{it} \mid age_{it} = A) = E_\tau\left(\theta_{it} \mid \theta_{it} \neq \theta^d_i(D_i), age_{it} = A\right). \tag{9}$$

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 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.[16] In contrast to the left panel, where *observed* participation is increasing over the life cycle and is strictly below 70%, we estimate over 90% of investors prefer holding stocks in their 401(k) plan and 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



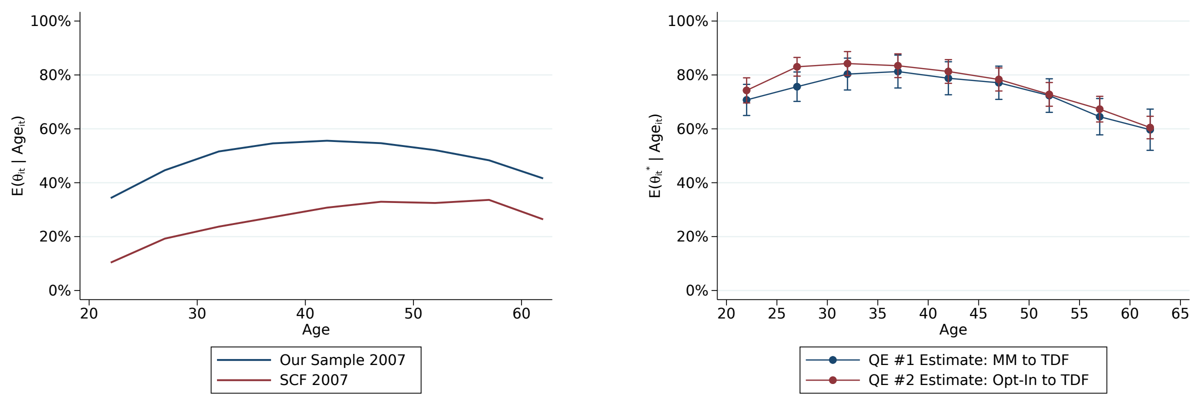
Notes: This figure plots our estimate of investors' preferences for stock market participation in the right panel in comparison to their observed choices in the left panel. In the left panel, we plot the fraction of investors with a positive stock share in our sample of retirement accounts in 2007 and 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 inside 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 90% confidence intervals based on standard errors clustered by investors 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 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 right panel shows is significantly higher, above 60% at all ages, and is mostly decreasing over the life cycle. This life

[16]Figure A11 shows our estimates of investors' preferences of the life cycle, conditional on different tenures. We find similar results across different tenures and hence omit these results from the main text.

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 that of 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 defaulted into a TDF choose a lower stock shares at all ages, but this is especially true for younger investors.

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

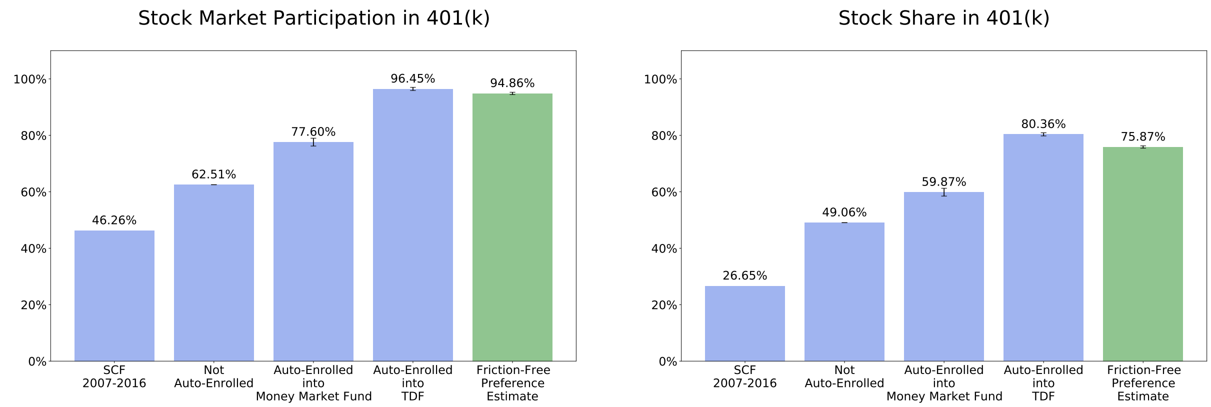


Notes: This figure plots our estimate of investors' preferences for stock shares of retirement wealth in the right panel in comparison to their observed choices in the left panel. In the left panel, we plot the average stock share of retirement wealth among all investors in our data in 2007 across different 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 from our two quasi-experiments along with 90% confidence intervals based on standard errors clustered by investors 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, 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 studying limited household stock market participation. If investors in our sample had preferences that exhibited first-order risk-aversion, had pessimistic beliefs, or faced large per-period participation costs, our estimation would have recovered 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.[17]

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 and weighing each year equally and calculating stock market participation and stock shares based on retirement wealth. Not-Auto-Enrolled refers to the averages among the investors in our sample who are not auto-enrolled into a 401(k) plan. Auto-Enrolled into Money Market Fund and TDF refers to the averages among investors in our sample that are hired under auto-enrollment into a 401(k) plan, but defaulted into a money market fund or target date fund, respectively. The final column represents our estimate of investors' preferences using 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

Preference heterogeneity. In Figure A12, we explore preference heterogeneity[18] over the life cycle by plotting the distribution of preferred stock shares by consistent investors for three different age groups: 20-34, 35-49, and over 50. These three groups are roughly evenly-spaced terciles. We find 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 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.

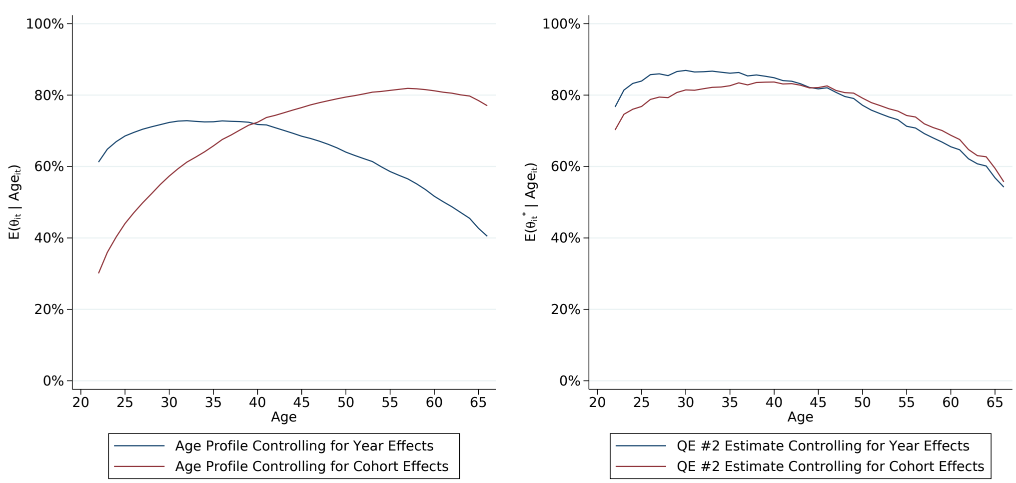
Year, cohort, and firm effects. Because age, time and cohort effects are co-linear, it is impossible to separately identify the three effects in a linear model (Deaton and Paxson 1994). Using the SCF and retirement account data similar to ours, Ameriks and Zeldes (2004) show the life cycle

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

[18] We use the term preference heterogeneity loosely, as these could also reflect heterogeneity in beliefs as in Meeuwis, Parker, Schoar, and Simester (2020) and Giglio, Maggiori, Stroebel, and Utkus (2021).

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.[19] In the left panel 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 including year 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 dummies. 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.[20] Additionally, in Figure A13 we show 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 controlling for cohort and year effects respectively. For both panels, we obtain the predicted values by adding the median cohort and year coefficient, respectively, to each age coefficient.

Conditioning on income. In our data, we observe the salary investors receive from their 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 estimates of preferences over the life cycle at different tenures using this weaker assumption. The results show that our estimates of preferences are unaffected. In Figure A16, we plot our esti-

[19] Parker et al. (2022) replicate this finding in recent data using rich retirement account data also similar to ours.

[20] In Figure 10 right panel, we show the evidence using our second quasi-experiment (with the opt-in control group). Results are similar our first quasi-experiment and available upon request.

mates of preferences over the life cycle by income quartiles, after integrating over tenure. The results show our estimates our preferences 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 be driven by many explanations, but it is consistent with other evidence that suggests non-homotheticity 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, liquid wealth, and the portfolio allocation in their retirement wealth. This model, which builds on Choukhmane (2021), 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 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 current period's default. Finally, investors face uncertainty about future earnings and employment status at their current employer that creates value for investors to delaying portfolio adjustments and savings decisions from their defaults. Appendix A provides a summary of the model parameters.

4.1 Model Description

4.1.1 Demographics and Preferences

Investors are born at $t = 0$ and work T^w periods with their first retirement period at $t = T^w$. Each period corresponds to one year. Investors die with certainty at $t = \overline{T}$, at which point all of their resources are bequested, such that investor's last period in which they can consume is $t = \overline{T} - 1$. 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.

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

$$u_t(c) = n_t * \frac{\left(c/n_t\right)^{1-\sigma}}{1-\sigma}.$$

4.1.2 Labor Income

There is a continuum of employers indexed by e for which investors can work. At any point in time, an investor's employment status, denoted emp_t, is in one of four states: E = employed in the current and prior period; JJ = employed in a different job in the current period from prior period; U = unemployed in the current period; Ret = retired. When investors are employed, we also keep track of their tenure, denoted by ten_t.

The current state of employment determines the income process investors receive in the current period in addition to the transition probabilities across states in the next period. We now describe these different income processes in turn.

Employment: $emp_t = E$**.** While working, investors supply one unit of 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:

$$\begin{gathered} \ln w_t = \delta_0 + \delta_1 a_t + \delta_2 a_t^2 + \delta_3 a_t^3 + \eta_t, \quad \eta_t = \rho\eta_{t-1} + \xi_t^E, \\ \xi_0^E \sim N(0, \sigma_{\xi_0}^2), \quad \xi_t^E \sim N(0, \sigma_\xi^2)\ \forall t > 0. \end{gathered} \tag{10}$$

Investors' tenure status evolves according to $ten_t = ten_{t-1} + 1$. Investors do not receive any labor income in the event that they die in the current period. Additionally, when investors are born at $t = 0$, the distribution of η_t^E is different to account for heterogeneity in the initial period income shock.

Job transition: $emp_t = JJ$**.** In each period, investors can switch jobs. We model these transitions separately because of the fact that retirements are employer-specific, so we need to account for when investors change jobs. If they do so, their income evolves according to :

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

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

Unemployment: $emp_t = U$**.** 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

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

This earnings process captures a wage reduction from switching jobs. Investors' tenure is irrelevant in this state.

Retirement: $emp_t = Ret$**.** When $t \in [T^w, \overline{T}-1]$, investors are retired and earn retirement benefits denoted by ss_t, which are described below. Note that investors do not earn any retirement benefits at the time of death. Investors' tenure is irrelevant in this state.

State transitions. Investors' employment status, emp_t, evolves according to a first-order Markov chain. States are ordered as follows: E, JJ, U, Ret. The state transition matrix, which is tenure and age-dependent, is:[21]

$$\begin{pmatrix} 1-\pi^{JJ}(t,ten_t)-\pi^{EU}(t,ten_t) & \pi^{JJ}(t,ten_t) & \pi^{EU}(t,ten_t) & 0 \\ 1-\pi^{JJ}(t,ten_t)-\pi^{EU}(t,ten_t) & \pi^{JJ}(t,ten_t) & \pi^{EU}(t,ten_t) & 0 \\ 0 & \pi^{UE}(t) & 1-\pi^{UE}(t) & 0 \\ 0 & 0 & 0 & 1 \end{pmatrix}.$$

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

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

Finally, investors have access to a liquid risk-free asset that has a constant gross return of $1+r$ per year. This corresponds to the interest paid on short-term checking and savings accounts.

[21] Entry i-j of this matrix corresponds to the probability of transitioning from the i-th state at t to the j-th state at $t+1$

4.1.4 Savings Accounts

The asset side of investors' balance sheets are 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 only use this liquid savings account to invest into a liquid riskless asset. The balance of this account, denoted by L_t, evolves according to:

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

where s_t^l is the net savings the investor places in this account.[22]

Defined-contribution retirement savings accounts. Each time an investor is matched with an employer for the first time, they are given access to a savings account. This savings account is the counterpart in our model to 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.

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

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

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

with the initial condition $A_0 = 0$. In these expressions, s_t^{dc} is the net savings rate (including possible withdrawals) the investor places in this account, $\mathcal{M}_e(\cdot)$ is an employer-specific function that determines how savings is mapped into account contributions, $\left\{\Theta_t^B, \Theta_t^S\right\}$ are the portfolio shares of existing assets in stocks and bonds respectively chosen at time t, and $\left\{\theta_t^B, \theta_t^S\right\}$ 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

[22] Since in the estimation below we set the net return on the liquid riskless asset is zero, we ignore capital taxation.

investors separate from the employer before vesting is complete.

Importantly, the balance of this savings accounts depends on *two* portfolio choice decisions: (i) their portfolio allocation of existing contributions and (ii) their portfolio allocation of new contributions. This distinction, which matches the institutional features of 401k 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 Ξ_t as 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 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 the asset allocation in both 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 only affect the asset allocation inside the current employer retirement saving plan.

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

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

Default asset allocation for new DC contributions. 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 $\overline{\theta}_e^j$. Later in the worker's tenure, the default asset allocation for contributions corresponds to the allocation chosen in the prior period. Formally, for $j \in \{B, S\}$,

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

Default portfolio allocation for existing DC contributions. When choosing 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 $j \in \{B, S\}$,

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

Note that 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 their defined-contribution savings account is $\overline{s}_e^{dc}$. Later in the worker's tenure, the default contribution rate is equal to the contribution rate from the prior period. Formally,

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

Effect of defaults. Investors in our model are subject to default effects when making portfolio choice decisions and savings decisions in the defined-contribution account. Recall Ξ_t denotes the vector of investor's portfolio allocations in the defined-contribution account. If an investor chooses $\Xi_t \neq \Xi_{d,t}$, where

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

the investor incurs a utility cost k_θ. 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.[23]

4.1.6 Government

Income taxes. Investors face a non-linear 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.[24]

Unemployment benefits. Investors receive an unemployment benefit of $ui(\eta_t)$ when uncompleted. This benefit depends on labor productivity, η_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 after 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 denoted that are directly reduced from investors' social security benefits.

4.1.7 Recursive Formulation

Investors face a dynamic optimization problem with 12 state variables: a_t = age; η_t = labor productivity, emp_t = employment status; e = employer; ten_t = tenure; ae_t = average lifetime income; A_t = DC retirement savings; L_t = liquid savings; $\Xi_{d,t} \in \mathbb{R}^4$ = default portfolio shares; $s_{d,t}$ = default contribution to DC account. Using the fact that portfolio shares sum to one, this can be reduced 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.

[23] 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.

[24] The DC account in our model is modeled after the traditional tax-deferred DC model rather than the Roth-401(k) model.

In this optimization problem, investors have 7 controls: c_t = consumption; $\Xi_t \in \mathbb{R}^4$ = portfolio shares; s_t^{dc} = defined-contribution savings rate; s_t^l = liquid savings. As above, this can be reduced to 4 controls given portfolio shares sum to one and consumption is pinned down by the budget constraint. In choosing these controls, investors are restricted from borrowing and engaging in any margin trading (i.e. no short-selling or leveraged positions):

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

We now characterize the value function of an investor, $V(\cdot)$, separately for the four states of employment emp_t.

Retirement: $emp_t = Ret$**.** There are two sources of uncertainty when decisions are made at time t: mortality occurring with probability m_{t+1}; asset return shocks, ε_{t+1}. An investor's value function is thus characterized by the following recursive equation:

$$V(X_t) = \max_{s_t^{dc}, s_t^l, \Xi_t} \left\{ u_t\left(c_t - k_\theta * 1\left\{\Xi_t \neq \Xi_{d,t}\right\}\right) + (1 - m_{t+1})\beta E\left[V(X_{t+1}) \mid X_t\right] \right\},$$

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

$$s_t^l = ss_t - s_t^{dc} * w_t - c_t,$$
$$V(a_{\overline{T}}, \cdot) = 0,$$
$$s_t^{dc} \leq 0.$$

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

$$V(X_t) = \max_{s_t^{dc}, s_t^l, \Xi_t} \left\{ u_t\left(c_t - k_\theta * 1\left\{\Xi_t \neq \Xi_{d,t}\right\} - k_s * 1\left\{s_t^{dc} \neq s_{d,t}\right\}\right) + (1 - m_{t+1})\beta E\left[V(X_{t+1}) \mid X_t\right] \right\},$$

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 $= m_{t+1}$; asset return shocks, ε_{t+1}; possibility of becoming employed based on transition matrix; next-period labor income shocks conditional on becoming employed $= \eta^U_{t+1}$; the type of future employer after a job change, e.

$$V(X_t) = \max_{s_t^{dc}, s_t^l, \Xi_t} \left\{ u_t \left(c_t - k_\theta * 1\left\{ \Xi_t \neq \Xi_{d,t} \right\} \right) + (1 - m_{t+1}) \beta E \left[V(X_{t+1}) \mid X_t \right] \right\},$$

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 Simulated Method of Moments to estimate the model's four preference parameters: the intertemporal discount factor (β), risk-aversion (σ), and the two adjustment costs (k_θ 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 $\overline{T} = 68$, such that workers are born at 22, retire at 64, and live their final year of life at 89. For each age, we take 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, which corresponds to (10), which contains a deterministic and stochastic component. We allow for measurement error and use a standard two-step minimum distance approach (e.g. Guvenen 2009). Our estimates (provided in Table A1) are consistent with prior literature, in particular our estimate of a relatively high persistence of permanent income shocks. Secondly, we use data on employment transitions from SIPP to directly estimate the median increase in salary when transitioning to new jobs, μ^{JJ}, and the median decrease in salary when transitioning from employment to unemployment, $-\mu^{EU}$. Thirdly, we use SIPP micro-data to estimate the three transition probabilities across our three employment states. Finally, we set the initial unemployment rate equal to 22%, which is share of unemployed individuals in SIPP 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 risk-free rate, R_f, to be constant at 2% to match the annualized average return of the money market provided by our data provider after subtracting the expense ratio.[25] We set the equity premium, $R_t^S - R_f$, of 4.5%, which is the average of the calibrations in Cocco et al. (2005) and Catherine (2022). Following Catherine (2022), we use a standard deviation of log returns, σ_s, of 19%. We assume asset returns are uncorrelated with shocks to labor income and employment transition probabilities. We set the net return on the liquid asset, r, equal to zero.

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 employer matching contribution to equal the certainty equivalent given an investor age and 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 benefit 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 using a replacement rate of 40%,

[25] In reality, the return on this fund is not constant, but it's volatility is extremely low. The worst 3-month return since inception is above 0.45% and the best is below 1.25%.

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 reduced from investors' social security benefits.

4.2.2 Second-Stage Parameter Estimation

The four second-stage parameters are estimated using the Simulated Method of Moments (SMM), which minimizes the (weighted) distance between model-simulated and data moments.

Empirical moments. In our baseline estimation, we use 22 empirical moments in total. First, we use the stock market participation rates inside retirement accounts between tenures of 0 and 6 years for the control and treatment groups in our first quasi-experiment. This gives the 14 moments from Panel A of Figure 4. Second, we use 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 up to 6% of income, which matches the structure of 401(k) plans in our model exactly. We then calculate the fraction of workers that 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 4×2=8 moments, which (as described below) is necessary to identify time preferences and the contribution adjustment cost.

Model simulation experiments. In order to estimate our four preference parameters with SMM, we need to construct moments within our model that are analogous to the 22 empirical moments 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 1500 investors according to the income process estimated in the prior section.[26] Next, for each investor i, we randomly select one period denoted by τ_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 τ_i, we simulate the choices of each investor i over their life cycle using the model's policy functions in two different experiments. In both experiments, investors are placed

[26] We choose a simulation size of 1500 to match the sample size of our first quasi-experiment.

into an opt-in regime prior to τ_i, which corresponds to $\overline{s}_e^{dc} = 0\%$. However, starting at τ_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 $\overline{s}_e^{dc} = 3\%$, $\overline{\theta}_e^B = 1$, and $\overline{\theta}_e^S = 0$. 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 $\overline{s}_e^{dc} = 3\%$, $\overline{\theta}_e^S = G^\theta(t)$, and $\overline{\theta}_e^B = 1 - G^\theta(t)$. 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.[27] In both experiments, we choose a 3% default contribution rate to match the 401(k) plans of firms that we use to calculate the distribution of contribution rates.[28]

Model moments. After running these two simulations from our model, we calculate the share of investors with a positive equity share in their current employer's retirement account in the first and second experiments separately at $t = \tau_i, \ldots, \tau_i + 6$. This gives 14 moments analogous to our empirical moments in Panel A of Figure 4. Importantly, for these moments we calculate stock market participation using investors' based on investors' allocation of wealth accumulated with their *current* employer, $\tilde{\Theta}^S$, which corresponds to what we observe empirically. We then calculate the distribution of contribution rates across the same four bins as we did 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 four 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 diagonal of the empirical covariance matrix as a weighting matrix in our baseline estimation due to its preferable finite sample properties (Altonji and Segal 1996). We calculate the covariance matrix of our empirical moments 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).[29] For additional details, see Appendix F.

[27] The second experiment does not exactly match the treatment group in our first quasi-experiment because investors in our model don't have access to a TDF. Doing so would require introducing two additional choice and state variables (one for new and existing assets), which we avoid doing for computational reasons. However, as discussed below, we only target portfolio choices for six years following the change in default. We view it as reasonable to abstract from changes in the equity share of a TDF over this period since they will be small.

[28] Four out of the 6 firms in the money market to TDF sample have default contribution rates of 3%.

[29] We assume the covariance between the 8 moments that characterize the distribution of contribution rates and the remaining moments are zero, as these moments are calculated from a different sample.

4.2.3 Identification of Second-Stage Preference Parameters

The four preference parameters in our model are jointly estimated. In what follows we provide some brief intuition for which moments help identify the different parameters.

Risk preferences. Risk preferences in the model are governed by the coefficient of relative risk aversion, σ. Relative risk aversion is identified from the levels of participation in treatment and control groups within our quasi-experiment. In the limit of extremely high risk-aversion, we would expect few investors to participate in the stock market in either groups .

Portfolio adjustment cost. The portfolio adjustment cost, k_θ, is identified 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. Importantly, 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 next period.

Intertemporal discount factor. We estimate the level of intertemporal discounting, β, by targeting the distribution of contribution rates in the two regimes. The average level of contribution helps identify the level of patience in our population.

Contribution adjustment cost. The contribution adjustment cost, k_s, is identified by examining the bunching of investors around the contribution rate into which they are defaulted, 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 regime. 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.

4.3 Estimation Results

Table 3 presents results from our baseline estimation. Our estimate of the (annualized) discount factor is $\beta = 0.9675$. This estimate of β similar to existing estimates that targets life cycle consumption-savings profiles (e.g. Gourinchas and Parker 2002). However, this estimate is higher than estimates from the literature on life cycle portfolio choice, which typically needs a lower value to slow down the decline of the human-to-financial wealth ratio with age in order to match the relatively low equity shares of financial wealth.

Table 3 also shows our estimate of relative risk aversion is 3.6, which is lower than typical estimates in existing literature (see Figure 1). This estimate highlights the value of quasi-experimental variation using 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. Consistent with the presence of frictions impact portfolio decisions, we find estimate a portfolio adjustment cost of $222, which is necessary to explain investors' tendency to stick with the default asset allocation. This estimate is relatively modest compared to typical calibrated values in life cycle portfolio models (e.g. Gomes 2020; Catherine 2022).

Finally, we estimate a contribution adjustment cost of $444. This contribution cost is similar to the portfolio adjustment cost, which suggests investors' non-participation in stocks may also be influenced by frictions associated with opting-in and opening a defined-contribution savings account.

Table 3. Baseline Estimation Results

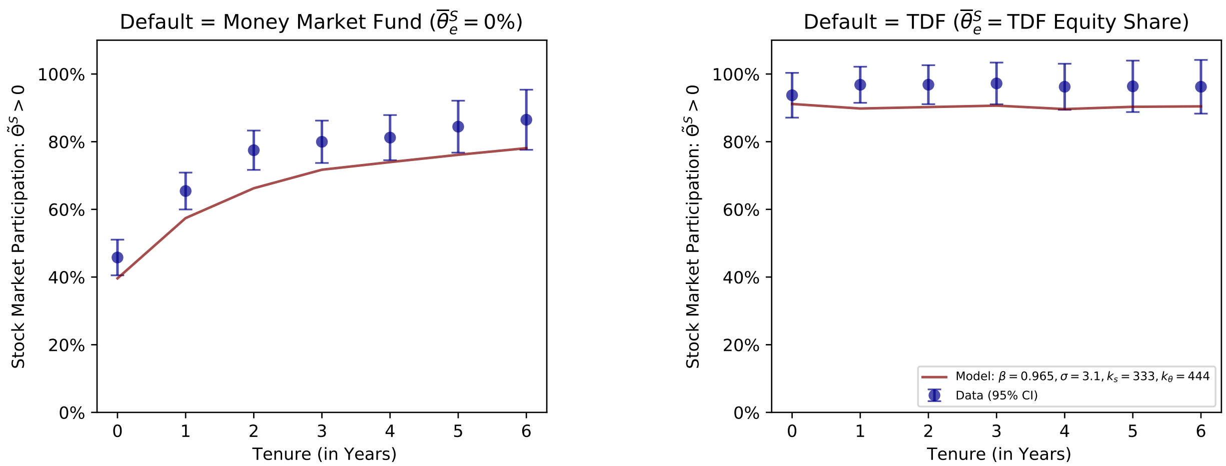
	Discount Factor β	Relative Risk Aversion σ	Portfolio Adj. Cost k_θ	Contribution Adj. Cost k_s
Parameter Estimate	0.9675	3.6	$222	$444
Standard Error	(0.001)	(0.045)	($39.96)	($9.25)

Notes: This table presents results from an SMM estimation of our four preference parameters in which we target the quasi-experimental moments in Panel A of Figure 4 and the distribution of contribution rates under two regimes, described in the main text. The table shows our estimates in addition to standard errors. This estimation is performed using the inverse of the diagonal of the empirical covariance matrix as a weighting matrix. The fit of the model on the 22 target moments is presented in Figures 11 and 12 and **??**. For additional details on our estimation procedure, see Appendix F.

4.4 Model Fit

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 non-trivial portfolio adjustment cost allows us to match investors tendency to slowly re-balance into stocks when the default has no stock market exposure, which most investors prefer given our relatively low estimate of risk aversion. Additionally, the portfolio adjustment cost coupled with our estimate of risk aversion mean that relatively few investors re-balance 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



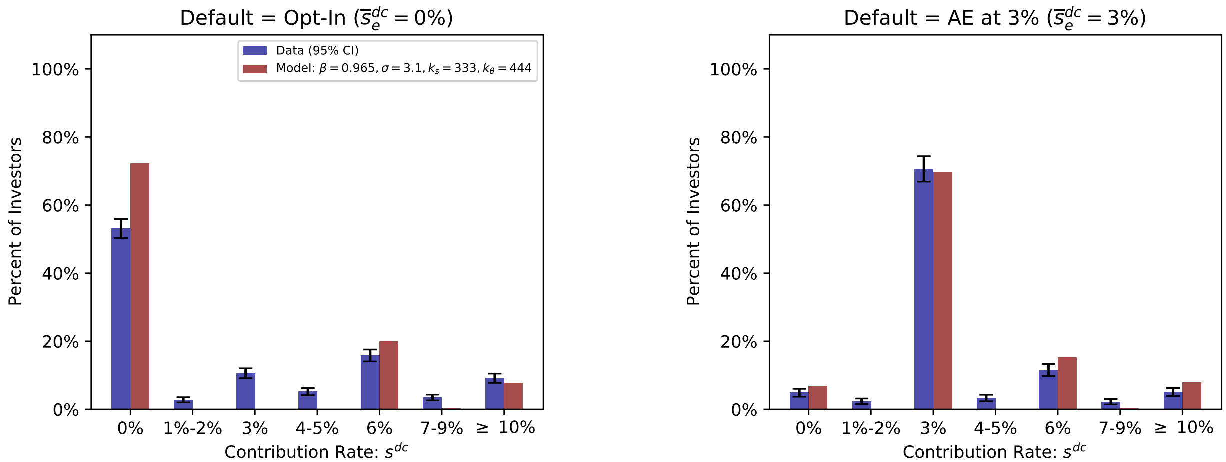
Notes: This figure presents the fit of our model on the response of stock market participation inside the current employer retirement account for our first quasi-experiment. The data moments in this figure correspond to the moments from our first quasi-experiment in the left half Figure 4 Panel A for 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 Table 3.

In Figure 12, we show how our model fits the distribution of contribution rates, which were targeted moments in order to identify time preferences and the contribution adjustment cost. The presence of a contribution adjustment cost allows our model to generate bunching in savings rate at the default in both the opt-in and auto-enrollment regimes that is consistent with the data. Conditional on deviating from the default, our model is able to roughly match the distribution of contribution rates through adjusting the discount factor.

Stock share of total wealth. Existing evidence suggests equity shares in retirement accounts tend to be higher than outside of retirement accounts (Gomes et al. 2020; Parker et al. 2022). Since our estimate of relative risk aversion is lower than typical estimates, a natural question is whether this is driven by the fact that our model was estimated by targeting equity shares in retirement accounts, which tend to be higher. In Table 4, we show how the average stock share of total wealth in our model compares to the SCF 2007-2016.[30] Despite our relatively low estimate of relative risk aversion, our model generates values for unconditional and conditional stock shares of total wealth that are relatively close to the SCF. Notably, the model generates lower equity shares of total wealth than the equity shares of retirement wealth. This is because the retirement account in our model is illiquid, so investors build up buffer stocks of liquid savings outside of their retirement

[30]We calculate stock shares in the SCF using financial wealth. The average stock share and conditional stock share of net worth (for households with positive net worth) are almost identical: they are 24.33% and 43.57% respectively.

Figure 12. Model Fit: Contribution Rates in 401(k)



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 estimation reported in Table 3 in order to identify time preferences and the contribution adjustment cost. 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 Table 3.

account, which lowers the equity share of total wealth.

Table 4. Stock Shares of Total Wealth: Model vs. SCF

	Stock Share of Total Wealth	Conditional Stock Share of Total Wealth
Model	39.25%	46.95%
SCF 2007-2016	23.26%	44.62%

Notes: This table shows how the stock share of total wealth within our model compares to that in the SCF. The stock share of total wealth in the model is defined as $\frac{\Theta_t^E A_t}{A_t + L_t}$. The values from the SCF correspond to the average value of equity holdings divided by total financial wealth calculated across the 2007, 2010, 2013, and 2016 waves. For the SCF averages, we use survey weights adjusted such that they assign equal weights to each survey wave. The model moments are from a simulation of this within the model at our SMM estimates of preference parameters reported in Table 3.

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 non-participation inside retirement accounts is primarily driven by frictions, then this trend is likely desirable for households. On the other hand, if non-participation 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 holding 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 these results are consistent with a coefficient of relative risk aversion of 3.6 and moderately-sized adjustment costs. Collectively, our findings suggest stock-market non-participation inside retirement accounts is mainly driven by (real or behavioral) adjustment costs rather than 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, or per-period participation costs.

More broadly, our analysis illustrates the challenge choice frictions pose for standard revealed preference approaches. To the extent that frictions are present and impact choices, these frictions will 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**
β	Discount factor	$1+r$	Rate of return on liquid assets
σ	Relative Risk Aversion	R_f	Risk-free rate
k_s	Contribution adjustment cost	$R^S(\cdot)$	Return on risky assets
k_θ	Portfolio adjustment cost	μ_s	Log-risk premium
	Utility	σ_s	S.D. of log risky asset returns
$u_t(\cdot)$	Utility function		**Labor Market**
$V(\cdot)$	Value function	$\pi^{JJ}(\cdot)$	Job-to-job transition probability
	State Variables	$\pi^{EU}(\cdot)$	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	ρ	Autocorrelation in earnings shocks
e	Employer DC plan type	ξ	Earnings innovation if continuously employed
η	Labor productivity	$\sigma^2_{\xi_0}$	Variance of the first earnings innovation
ae	Average lifetime earnings	σ^2_{ξ}	Variance of subsequent innovations
L	Liquid assets	ξ^{JJ}	Earnings innovation after job-to-job transition
A	DC wealth stock	μ^{JJ}	Avg. wage gain after a job-to-job transition
s_d	Default contribution rate	ξ^{U}	Earnings innovation out of unemployment
Θ_d	Default allocation existing funds	μ^{UE}	Avg. wage loss out of unemployment
θ_d	Default allocation new contributions	ι	Measurement error in earnings
	Choices	σ^2_ι	Variance of measurement error
c	Consumption	ϕ	Earnings innovation plus measurement error
s^{dc}	DC contribution rate		**Demographics**
s^{l}	Savings in liquid assets	$\overline{T}$	Maximum years of life
Θ	Asset allocation for existing funds	T^{w}	Number of working years
θ	Asset allocation for new contributions	m_t	Mortality risk
	Defined Contribution Account	n_t	Equivalence scale
$\overline{\theta}_e^{j}$	Employer-specified default asset allocation		**Tax and Benefit System**
$\overline{s}_e^{dc}$	Employer-specified default contribution rate	$tax_i(\cdot)$	Tax on income
$\mathcal{M}_e(\,)$	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		
$\tilde{\Theta}$	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 $t = \overline{T}$, at which point all of their resources are bequested, such that investor's last period in which they can consume is $t = \overline{T} - 1$. 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 β and their coefficient of relative risk aversion (or equivalently inverse of elasticity of intertemporal substitution) as σ. Per-period flow utility is adjusted for an equivalence scale such that it is equal to

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

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:

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

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

When $t \in [T^w, \overline{T} - 1]$, 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

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

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 θ_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

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

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 = age; w_t = wage; W_t = liquid wealth; θ_{t-1} = prior-period portfolio share. Denote the vector of these variables as X_t. There are two controls: c_t = consumption and θ_t = 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):

$$W_t \geq 0, \quad \theta_t \in [0,1]. \tag{23}$$

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

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

$$V(X_t) = \max_{c_t > 0, \theta_t} \left\{ u_t \left(c_t - f * 1\{\theta_t \neq \theta_{d,t}\} - p * 1\{\theta_t > 0\} \right) + (1 - m_{t+1}) \beta E \left[V(X_{t+1}) \mid X_t \right] \right\},$$

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

$$A_t = W_t + ss_t - c_t,$$
$$W_t = A_{t-1} \left[(1 - \theta_{t-1}) R_f + \theta_{t-1} R_t \right],$$
$$V(a_{\overline{T}}, \cdot, \cdot, \cdot) = 0.$$

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

$$V(X_t) = \max_{c_t>0,\theta_t} \left\{ u_t\left(c_t - f * 1\{\theta_t \neq \theta_{d,t}\} - p * 1\{\theta_t > 0\}\right) + (1 - m_{t+1})\beta E\left[V(X_{t+1}) \mid X_t\right] \right\},$$

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

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

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

$$A_0 = W_0 = 0.$$

B.8 Parameterization

For the income process parameters (ρ and σ_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 $\overline{T} = 79$ 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 $t = 0, ..., T$. 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 θ_{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:[31]

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

The primitives of this environment, $\left\{Y_{it}(0), Y_{it}(1), \theta_{it}(0), \theta_{it}(1), Y_{it}^*, \theta_{it}^*, D_i\right\}$, 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}^θ,

[31] 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) *in*consistent 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

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

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

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

Note that

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

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

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

Combining the previous two equation and the bound above deliver the desired result. □

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,

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

By the law of iterated expectations,

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

Frame exogeneity implies the two expectations on the right-hand side of the previous equation are equal to $E_\tau(Y_{it} \mid C_{it}^Y = 1)$, 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:

$$cov(V,W) = E(VW) - E(V)E(W) = E(W)\left[E(V|W=1) - E(V)\right].$$

$\square$

Appendix D. Model Solution Details

Discretization of state variables. We have eight continuous state variables that need to be place 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 then place liquid assets and retirement assets on a grid that 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.

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 it's 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. We use the quasi-linear interpolation scheme of the value function proposed by Carroll (2012) to interpolate. This method substantially reduces the interpolation approximation error (as shown by Carroll 2012), despite fairly coarse grids. To integrate over the distribution of stock returns, we use a Gauss-Hermite quadrature with 7 nodes.

Software and hardware. The code to solve and estimate the model is compiled in Intel Fortran 2018. We parallelize each model solution across 14 CPUs on the MIT Sloan Engaging Cluster, which takes around 10 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 360 nodes using a total of over 5,000 CPUs.

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.

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

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:

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

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 $\left\{\tilde{\kappa}_i^\tau\right\}_{i=1}^5 = \{\$5,150; \$7,550; \$30,650; \$74,200; \$154,800\}$.[32] 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.

[32]Note that the first bracket correspond to the standard deduction amount in 2006.

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

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:

$$
ss\,(ae_{T^w}) = 4 \times 3 \times \max\left\{si\,;\, \tilde{ss}\,(ae_{T^w})\right\} - med_t
$$

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

$$
\tilde{ss} = \begin{cases} 0.90 \times \frac{1}{3} ae_{T^w} & if\, \frac{1}{3} ae_{T^w} \le \$656 \\ 0.90 \times \$656 + 0.32 \times (\frac{1}{3} ae_{T^w} - \$656) & if\, \$3,955 > \frac{1}{3} ae_{T^w} > \$655 \\ \min\left\{0.90 \times \$656 + 0.32 \times \$3,299 + \left(0.15 \times \frac{1}{3} ae_{T^w} - \$3,299\right)\,;\, \$2,053\right\} & if\, \frac{1}{3} ae_{T^w} > \$3,955 \end{cases}
$$

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 ω of labor earnings implied by the labor productivity level in the last period of employment. Labor productivity η_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:

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

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[33]

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:

[33] 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 $\iota_{i,t} \sim N\left(0, \sigma_\iota^2\right)$.

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

The estimation has two steps. In the first step, We estimate the parameters of the deterministic component of earnings $\left(\left\{\delta_j\right\}_{j=0}^3\right)$—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 (ρ), the variances of the first earnings innovation ($\sigma_{\xi_0}^2$), the variance of subsequent innovations (σ_ξ^2), and the variance of measurement error (σ_ι^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**			
δ_0	δ_1	δ_2	δ_3	ρ	$\sigma_{\xi_0}^2$	σ_ξ^2	σ_ι^2
2.813	0.121	−0.00183	6.91×10^{-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 (μ^{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 (μ^{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 (π^{JJ}) and job to non-employment (π^{EU}) transition probabilities by age and tenure and job finding rates (π^{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):

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

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

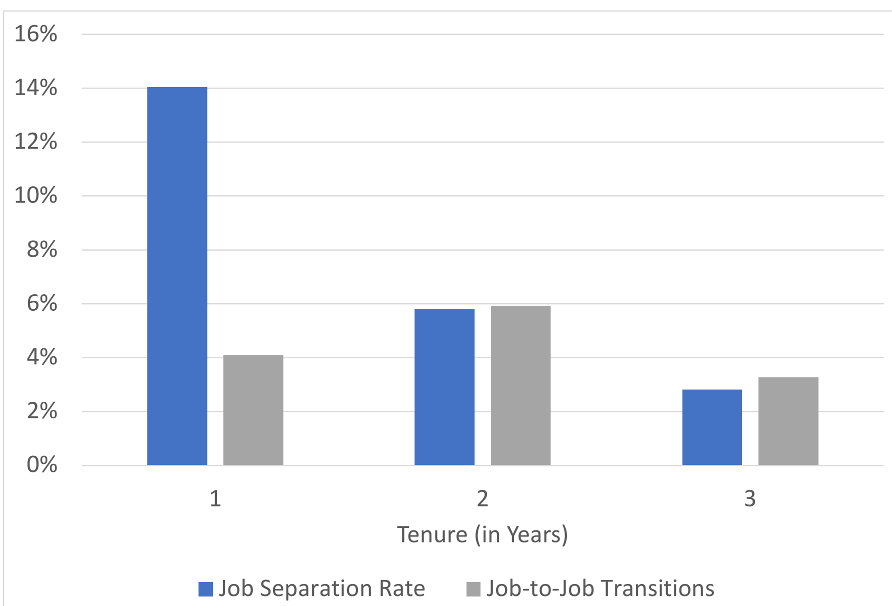
The probability that an unemployed investor finds a job, given in equation (28), is defined as a sixth-order polynomial in age.

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

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 four preference parameters, $\theta \equiv (\beta, \sigma, k_\theta, k_s)$, 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 θ. 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 θ is then given by

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

where Θ is a compact parameter space that we specify.

F.2 Weighting Matrices

We use both the identity matrix and the inverse diagonal of the empirical covariance matrix as weighting matrices in our estimation, due to their better finite sample properties Altonji and Segal (1996). When we use the identity matrix, we scale $m_N - \hat{m}_S(\theta)$ by m_N so that the moments are scale-independent. 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 (mean value expansion of first-order condition) imply the influence function for an GMM estimator with an optimal weighting matrix of θ is (see e.g. Newey and McFadden 1994, for a derivation)

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

where $G = \frac{\partial g}{\partial \theta}|_{\theta=\theta_0}$ and Ω 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 Φ_k as the N-by-1 vector that stacks the corresponding influence function evaluated at each of the N data points. Denote Ψ as the N by k vector that stacks the Φ_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, Θ, and perform a grid search over values in this space. Our final SMM estimate is the value of θ that achieves the lowest value of $Q_{N,S}(\theta)$ of all parameter combinations over which we searched. We perform this search in two steps. First, we search over a wide grid of values for our preference parameters. Second, we use a narrower grid around the point that minimized the SMM objective function in the first grid search. In our current estimation results, none of the parameter values chosen we're close to the grid over which we searched.

F.4 Standard Errors

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

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

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

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

$G = \frac{\partial \hat{m}(\theta)}{\partial \theta}$, and Ω 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 Ω. 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 is 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

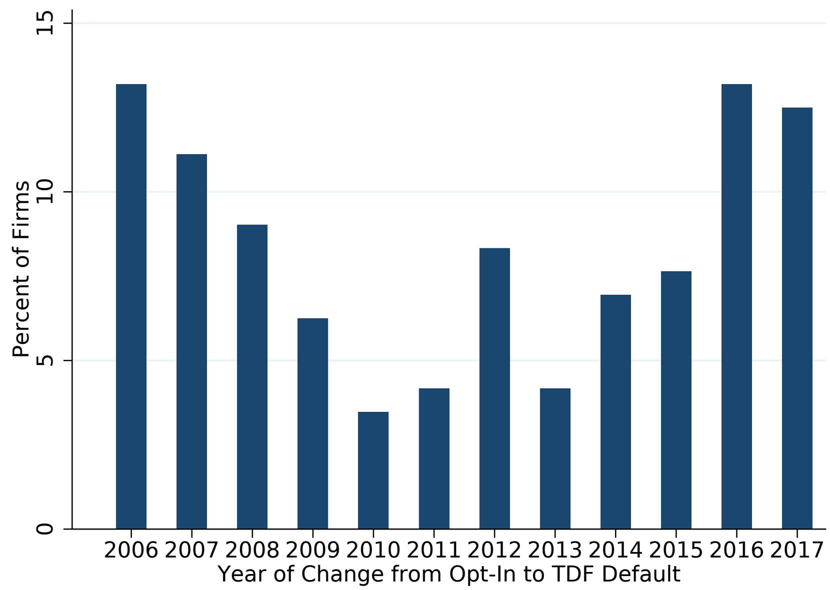


Figure A4. Balance Checks: Money Market to TDF Sample

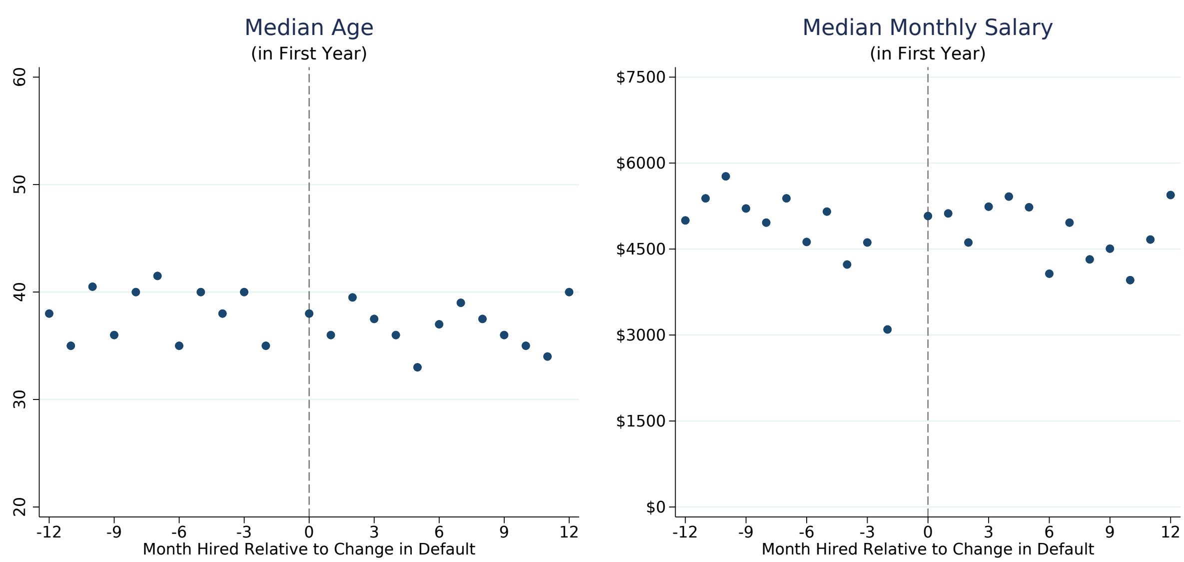
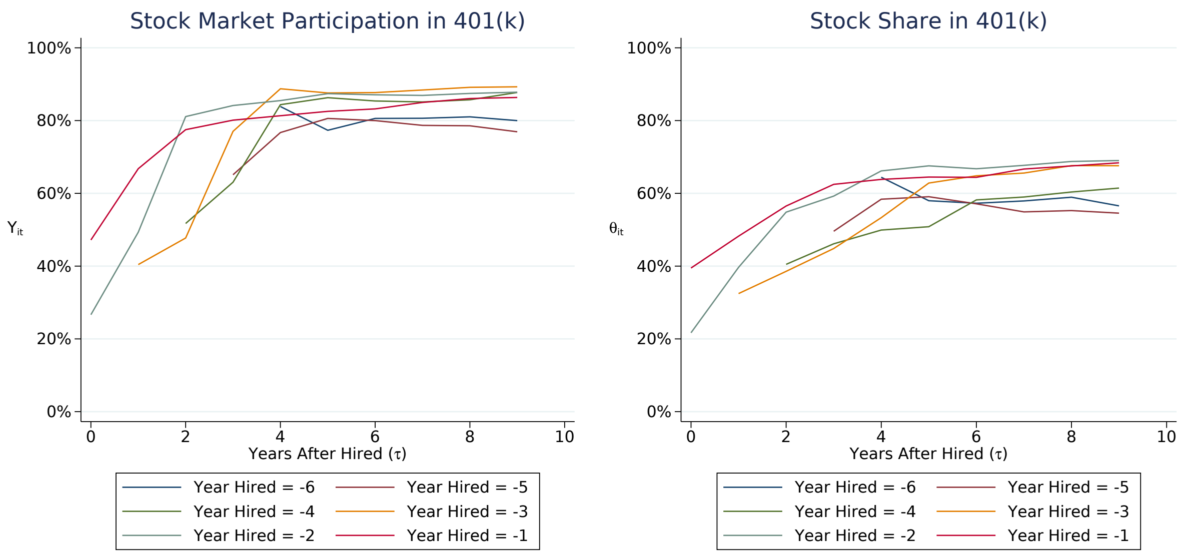


Figure A5. Robustness of Portfolio Choice Response: Money Market to TDF Sample

Panel A: Peer Effects



Panel B: Compositional Change

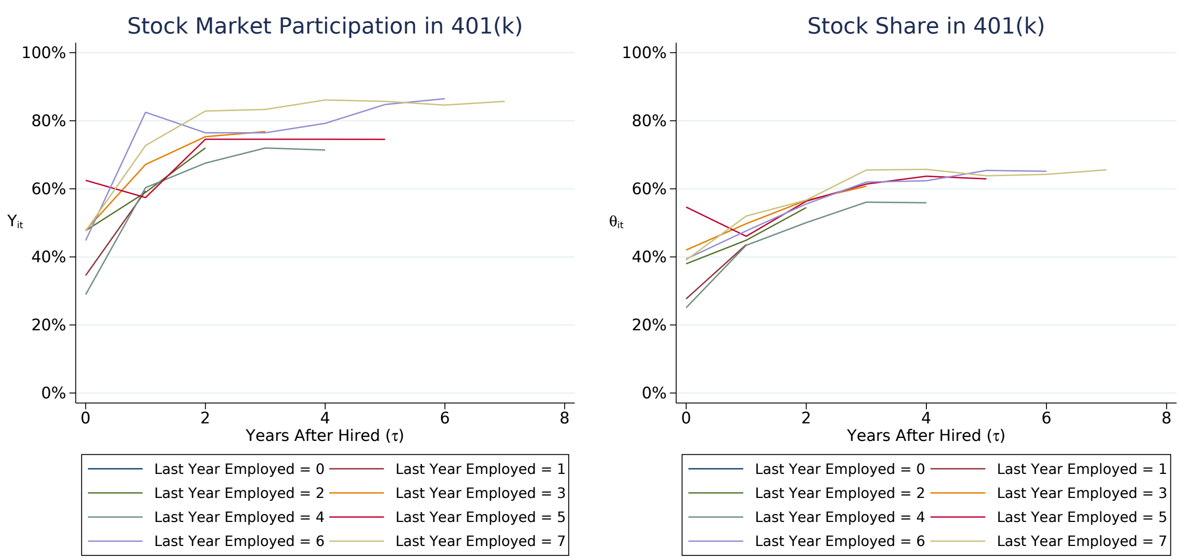
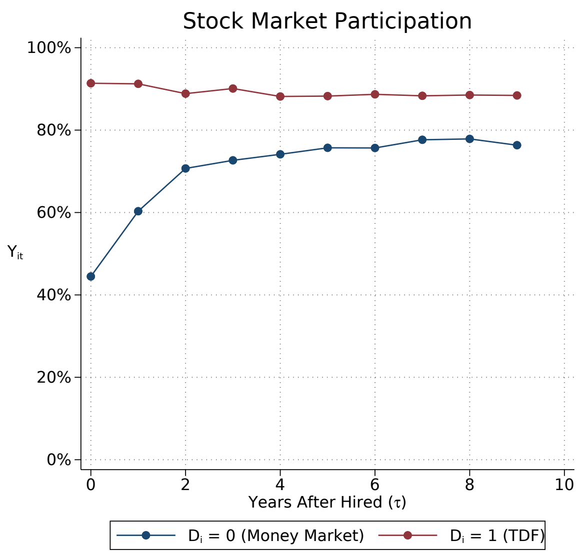
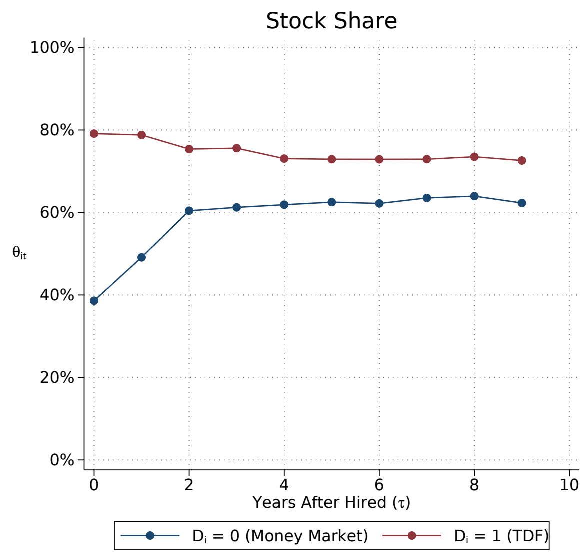


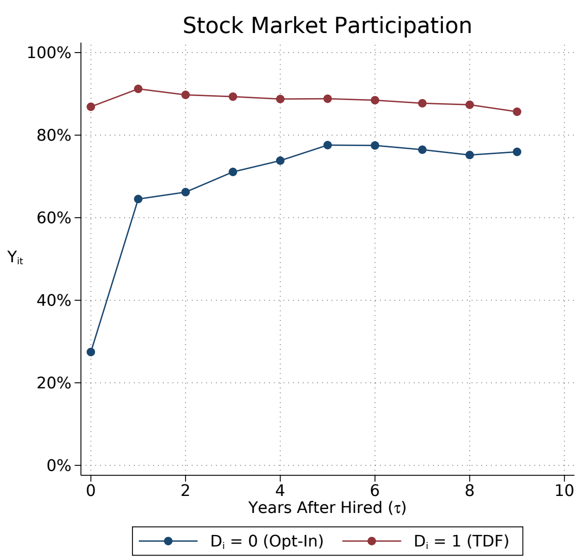
Figure A6. Robustness of Portfolio Choice Response: Portfolio Choices for New Contributions to 401(k)

Panel A: Money Market to TDF Sample





Panel B: Opt-In to TDF Sample



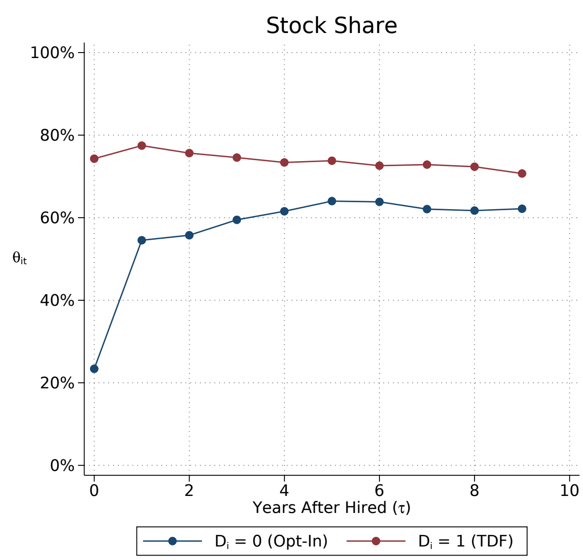
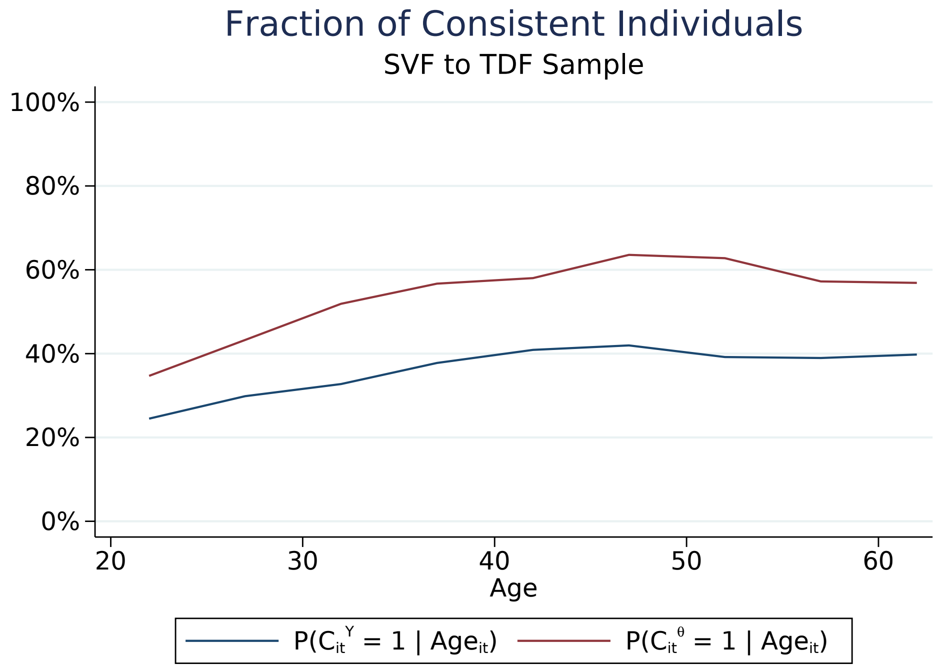


Figure A7. Fraction of Consistent Investors by Age

Panel A: Money Market to TDF Sample



Panel B: Opt-In to TDF Sample

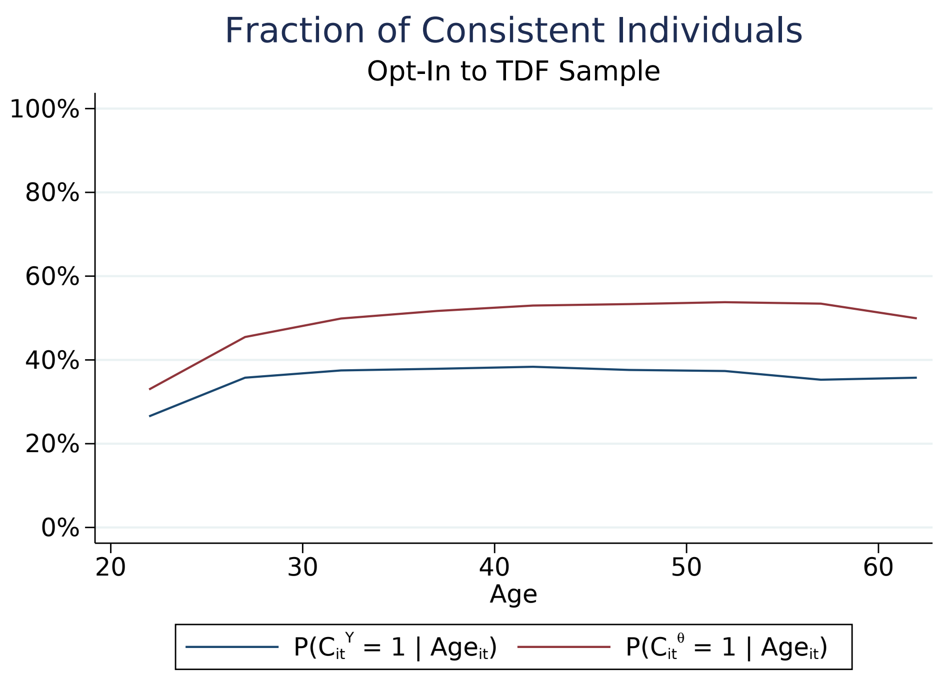
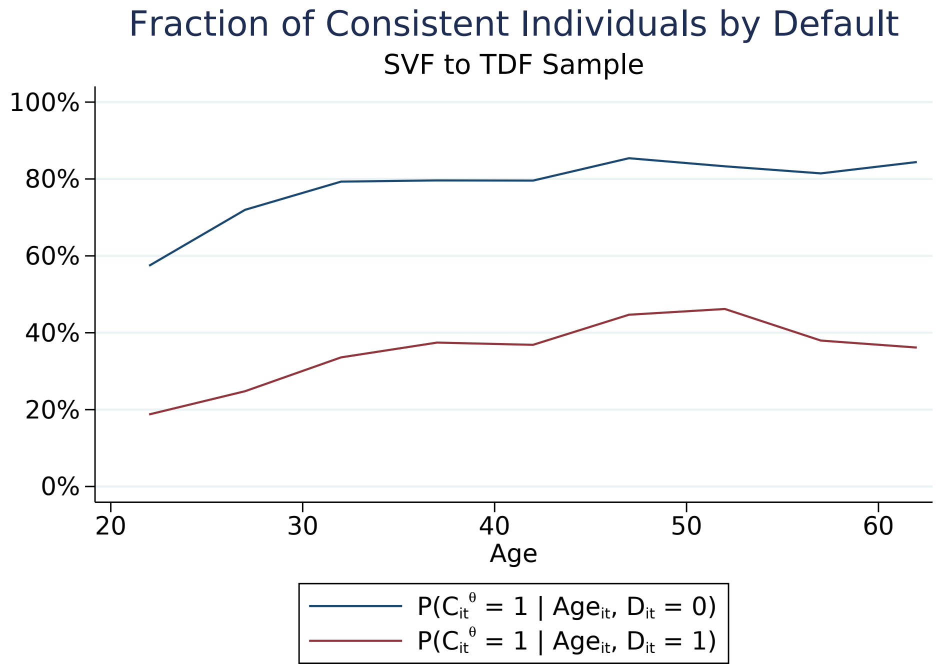


Figure A8. Fraction of Consistent Investors by Age and Default

Panel A: Money Market to TDF Sample



Panel B: Opt-In to TDF Sample

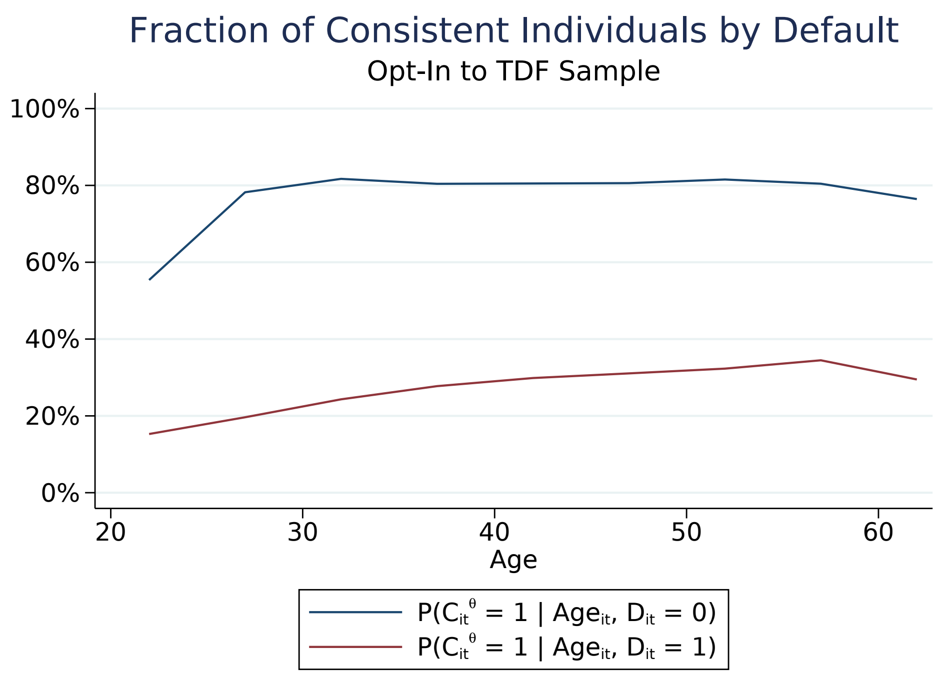
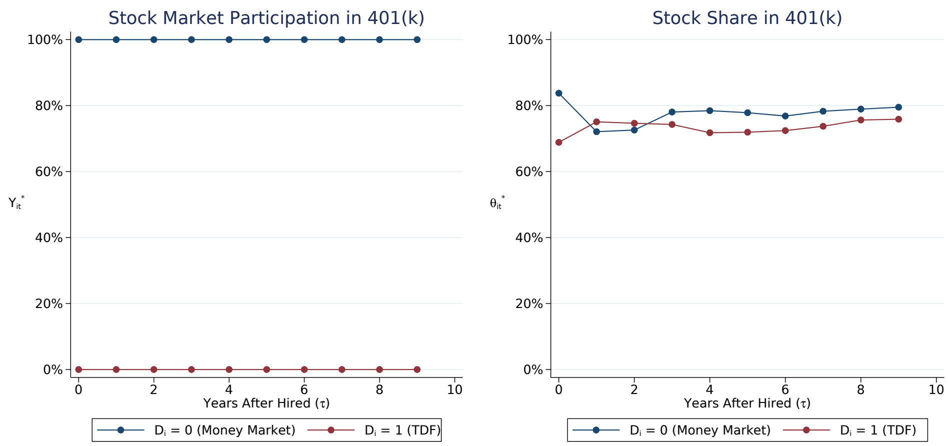


Figure A9. Preferences of Consistent Investors by Default

Panel A: Money Market to TDF Sample



Panel B: Opt-In to TDF Sample

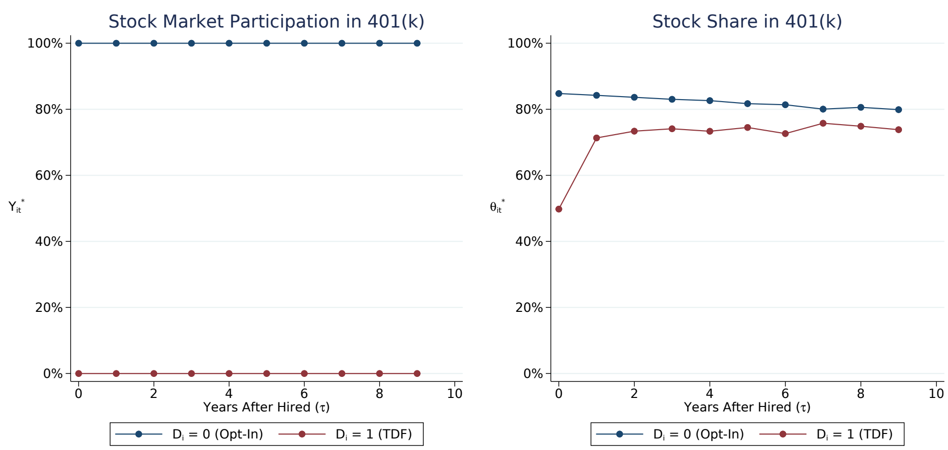


Figure A10. Preferences of Consistent Investors by Tenure of Consistency: Opt-In to TDF Sample

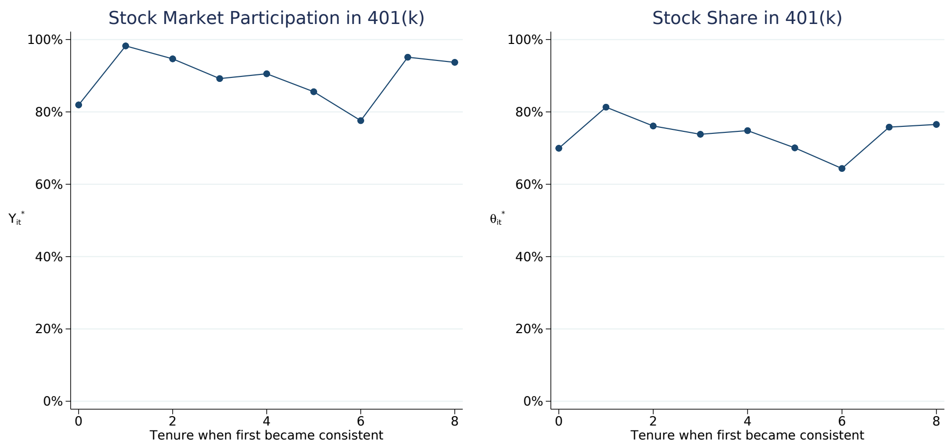
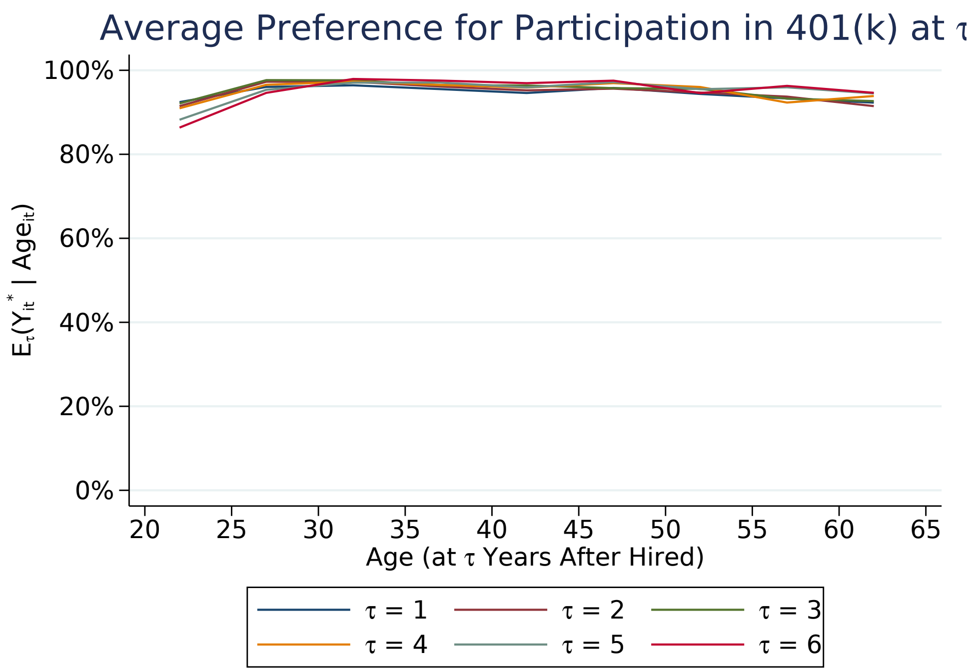


Figure A11. Estimated Preferences by Tenure: Opt-In to TDF Sample

Panel A: Stock Market Participation



Panel B: Stock Share of Retirement Wealth

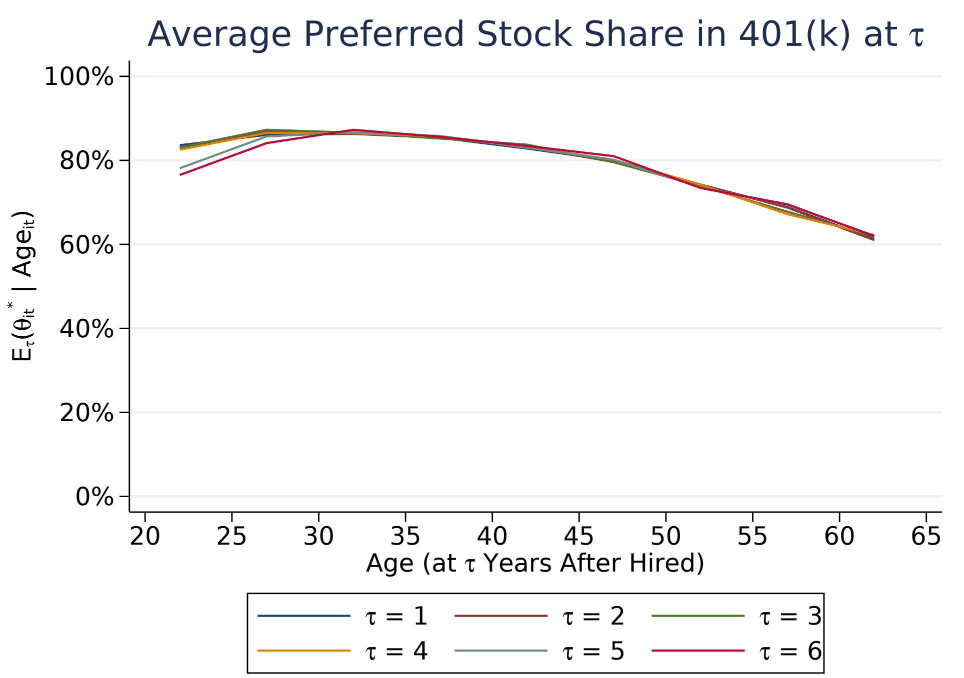
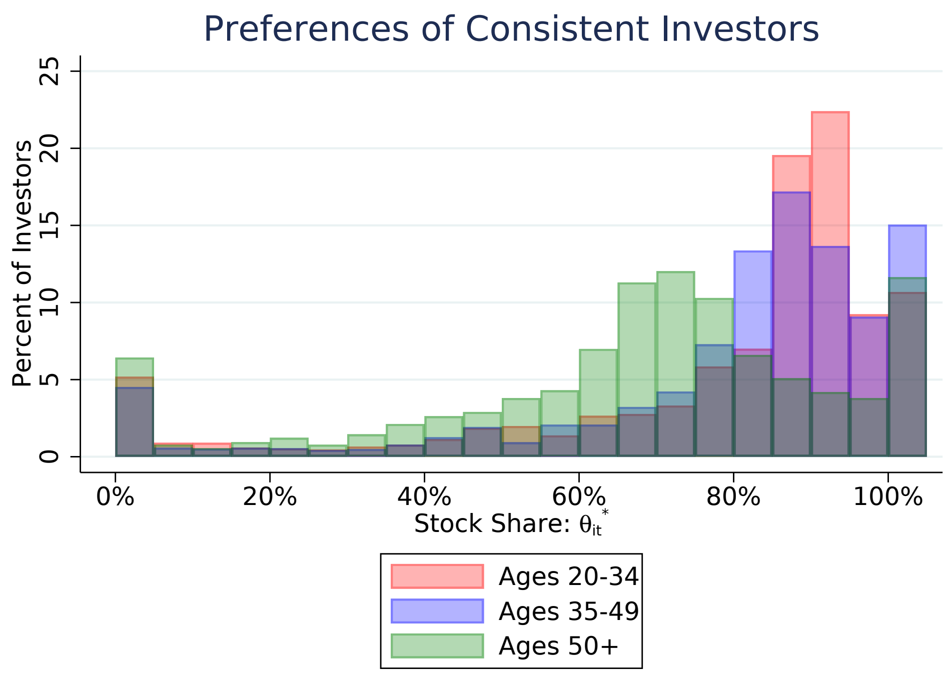


Figure A12. Preference Heterogeneity among Consistent Investors

Panel A: Money Market to TDF Sample



Panel B: Opt-In to TDF Sample

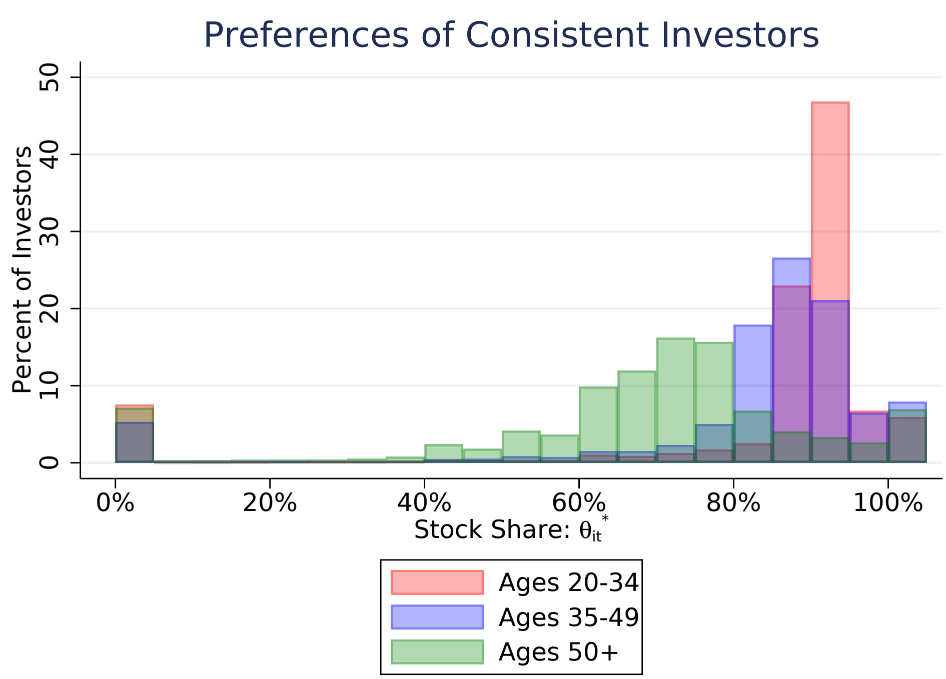
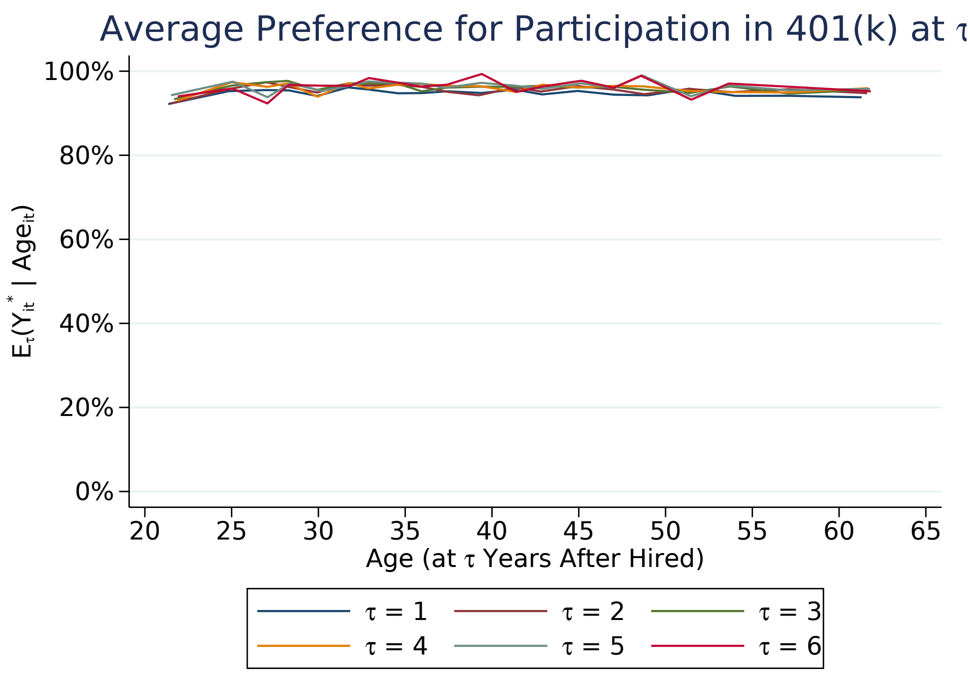


Figure A13. Robustness of Preferences over the Life Cycle: Opt-In to TDF Sample

Panel A: Participation



Panel B: Stock Share of Retirement Wealth

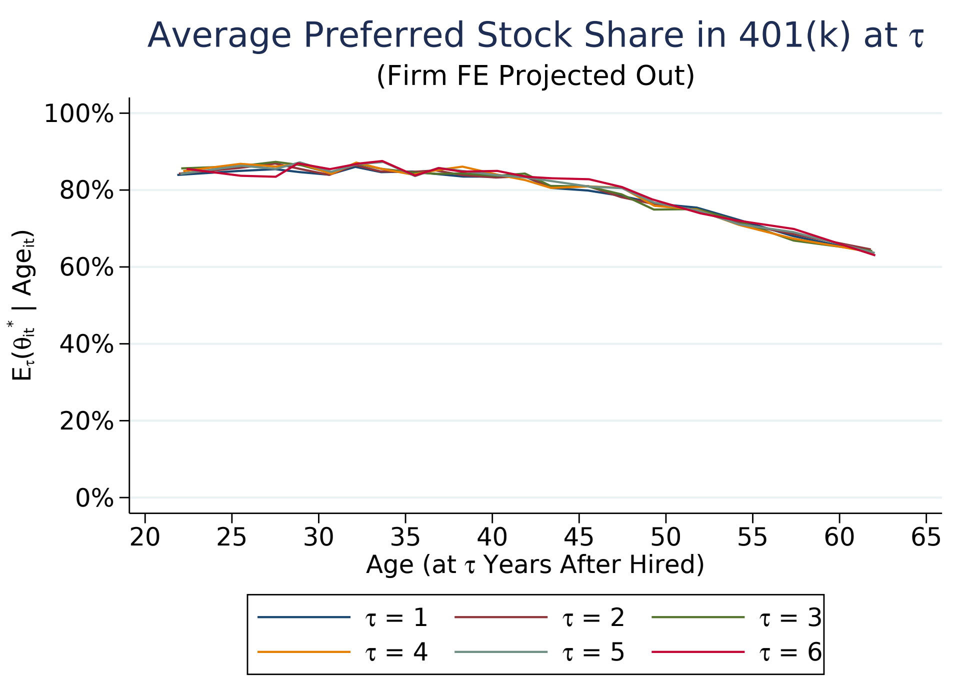
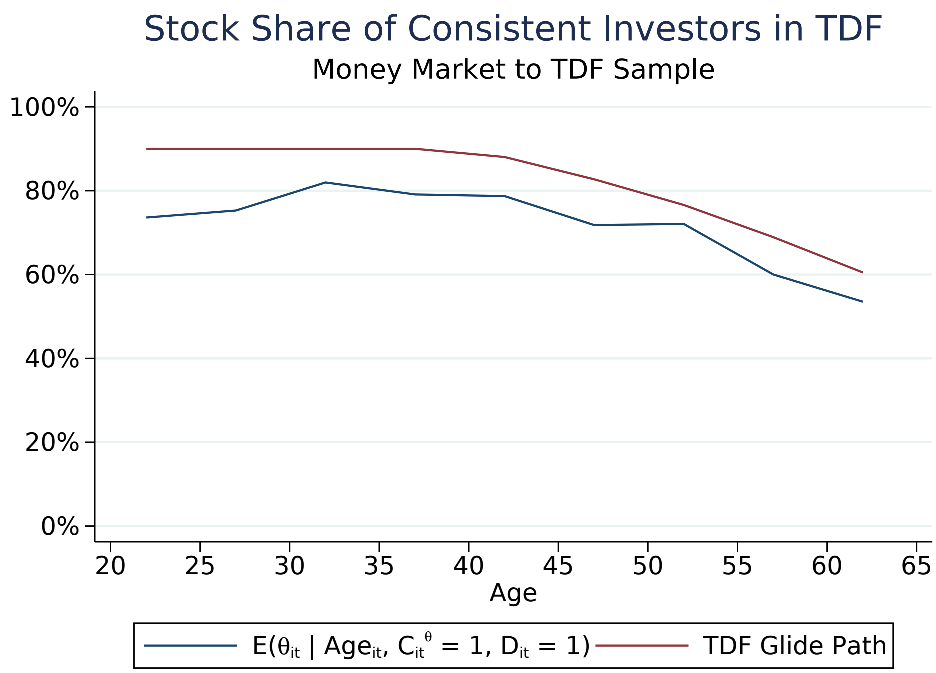


Figure A14. Life Cycle Preferences of Consistent Investors Defaulted into TDF

Panel A: Money Market to TDF Sample



Panel B: Opt-In to TDF Sample

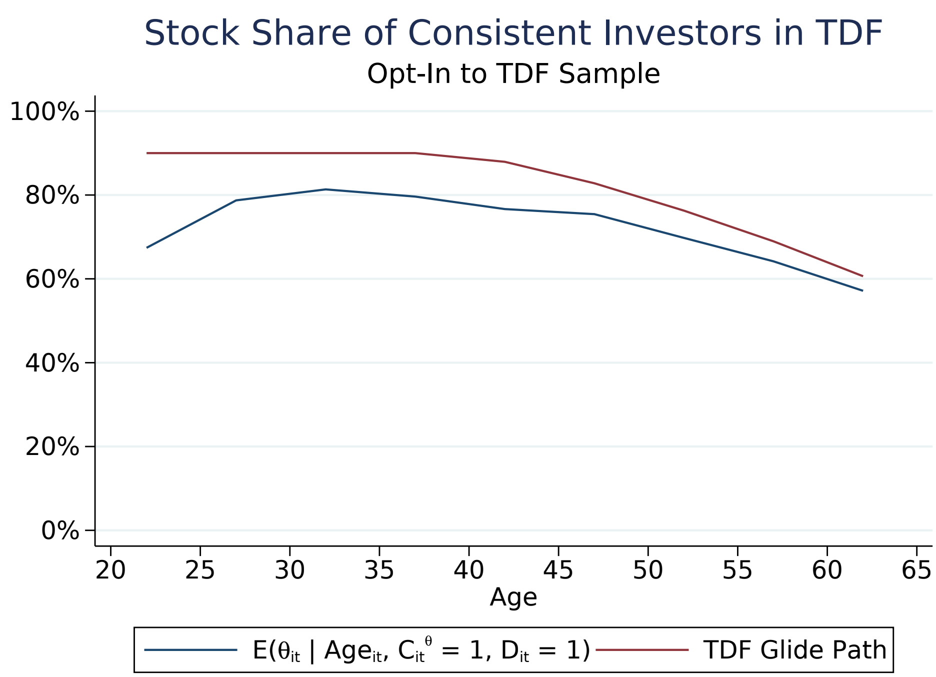
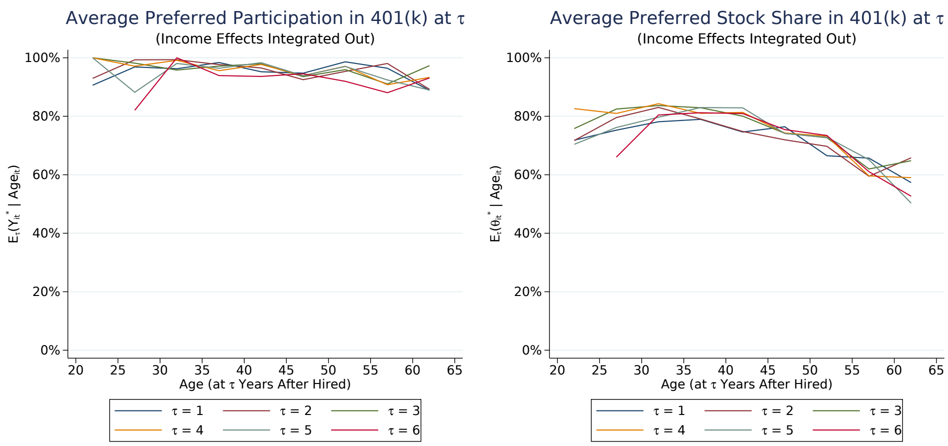


Figure A15. Estimated Preferences Under Weaker Identifying Assumption

Panel A: Money Market to TDF Sample



Panel B: Opt-In to TDF Sample

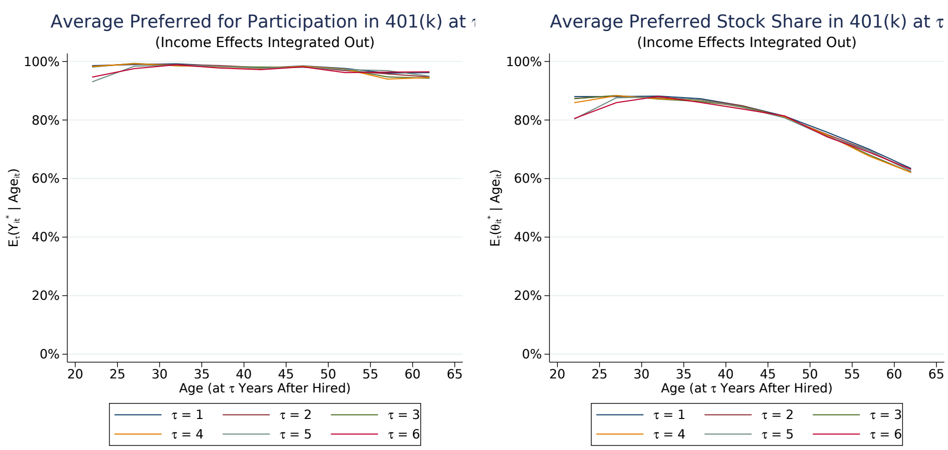
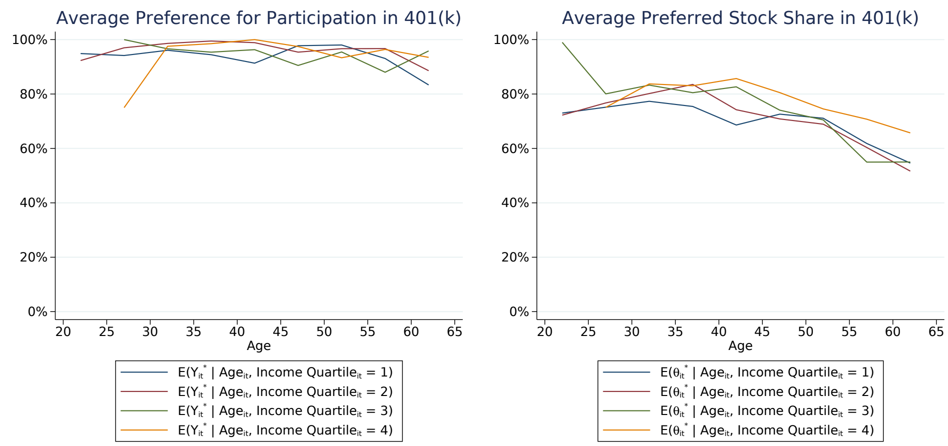


Figure A16. Preferences over the Life Cycle by Income Quartiles

Panel A: Money Market to TDF Sample



Panel B: Opt-In to TDF Sample