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

Taha Choukhmane† Tim de Silva‡

Forthcoming, *Journal of Finance*.

Abstract

We study the role of risk preferences and frictions in portfolio choice using variation in 401(k) default options. Patterns of active choice in response to different default funds imply that, absent participation frictions, 94% of investors prefer holding stocks, with an equity share of retirement wealth declining with age—patterns markedly different from observed allocations. We use this quasi-experiment to estimate a life cycle model and find a relative risk aversion of 2.5, EIS of 0.25, and $160 portfolio adjustment cost. Our results suggest that low levels of stock market participation in retirement accounts are due to participation frictions rather than non-standard preferences such as loss-aversion.

*First draft: November 2021. This version: August 2025. We thank Hunt Allcott, Joesph Briggs (discussant), Sylvain Catherine (discussant), Nuno Clara, Cary Frydman (discussant), Michael Gallmeyer, Francisco Gomes (discussant), Debbie Lucas, Joey Malgesini, Christopher Palmer, Jonathan Parker, Akash Raja, Daniel Reck, Antoinette Schoar, Frank Schilbach, Larry Schmidt, Eric So, David Sraer, David Thesmar, Adrien Verdelhan, Toni Whited, Oliver Xie, Geoff Zhang (discussant), two anonymous referees, and audience members at MIT Economics, MIT Sloan, Duke Fuqua, UIUC Gies, Chicago Fed, Princeton, Wharton, Quantbot Technologies, University of South Carolina, Northwestern Kellogg, Minnesota Carlson, Bocconi, Rutgers, Minnepolis Fed, UCLA Anderson, and participants at the 2022 NBER Behavioral Finance Spring Meeting, 2022 CEPR Conference on Household Finance, 2022 Western Finance Association Annual Meeting, 2022 Society for Economic Dynamics Annual Meeting, 2022 Texas Finance Festival, Inter-Finance PhD Seminar, and the 2023 AFA Annual Meetings for their insightful comments. We also thank the data provider, a large U.S. financial institution, for making available the data used in this paper, helpful discussions, and technical support.

†MIT Sloan, tahac@mit.edu.

‡Stanford GSB and SIEPR, tdesilva@stanford.edu.

Many households, including those with significant financial wealth, do not participate in the stock market. This limited stock market participation is difficult to reconcile with standard economic theory, which predicts that all investors should hold at least a small amount of stocks in the presence of a positive equity premium.[1] On the one hand, investors may prefer holding safer assets because they perceive stocks to be too risky (e.g., due to loss or ambiguity aversion, background risks, or pessimistic beliefs about returns). Alternatively, investors may prefer stocks over safer assets and still 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. Such frictions complicate the identification of investors' preferences because observed allocations may not reveal these preferences. This raises an identification challenge: in the presence of frictions, how do we recover investors' portfolio preferences from observed behavior?

In this paper, we exploit quasi-experimental variation in the auto-enrollment default asset allocation of 401(k) plans to recover the preferences of retirement investors. Some investors are passive and their allocations simply reflect the default investment option chosen by their employer. However, we can make progress on identifying investors' preferences by comparing active choices in response to different default investment options. Investors with no equity exposure in their default investment fund who make an active decision to invest in equity reveal a preference for stock market participation. Conversely, those with positive equity exposure in their default investment fund who make an active decision to opt-out of holding equity reveal a preference for non-participation. Using a non-parametric framework that formalizes this intuition, we estimate that the preferences of retirement investors differ markedly from their observed choices: over 90% of investors in our sample prefer participating in the stock market absent adjustment frictions, and their preferred equity share declines with age. Viewed through the lens of a life cycle portfolio choice model, we find that this evidence is consistent with a coefficient of relative risk aversion of 2.54 and a portfolio adjustment cost of $156. In sum, our results suggest that retirement investors' preferences exhibit moderate risk aversion, and the lack of stock market participation within retirement accounts is, in large part, a response to participation frictions rather than first-order risk aversion, as implied by models of loss, ambiguity, or regret aversion.

An ideal experiment for distinguishing between risk- 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. This would effectively remove one-time adjustment costs associated with participation. If these investors dislike holding risky assets (e.g., due to loss aversion) or if they face large per-period participation costs, they should sell the stocks and move their hold-

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

ings toward safer assets. Alternatively, if non-participation is driven by one-time frictions, such as fixed adjustment costs, investors should 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 U.S. 401(k) plan provider. Such employer-sponsored retirement savings accounts are available to two-thirds of U.S. civilian employees (Myers and Topoleski 2021), and are the main vehicle American households use to invest in financial products.[2] Our identification strategy exploits changes in the default asset allocation of retirement plans at various employers. The 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 and (ii) investors hired under an opt-in regime. Investors in both control groups, by default, have zero equity exposure in their retirement account and must make an active decision to participate.

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

To translate this variation into estimates of preferences, we apply and extend a framework developed by Goldin and Reck (2020). Under a set of assumptions, most importantly that treatment is randomly assigned, we can non-parametrically bound the fraction of investors who would prefer holding stocks within their retirement account absent frictions. In our experiment, 42% of investors defaulted into a money market fund opt-out within one year and move towards stock market participation. Intuitively, these investors reveal their preference for stocks by actively moving away from the money market default, implying at least 42% of investors in our sample prefer stock market participation. Conversely, 5% of investors defaulted into holding stocks make an active decision to opt-out of stock market participation. This minority of investors revealing their preference for

[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 within a retirement account. Only 5% of households participate in the stock market exclusively outside of a retirement account. See Section 1.1 for additional details.

non-participation generates an upper bound of 95% for the fraction of investors that prefer stock market participation. If anything, these results underestimate the level of stock market participation absent frictions for three reasons: (i) we do not observe participation in stocks outside one's retirement account with their current employer; (ii) our quasi-experiment does not remove potential per-period participation costs (e.g., attention costs); and (iii) our experiment might not remove all one-time costs, such costs of learning about stock market investments. We can similarly bound the average preferred stock share of retirement wealth from below at 39%.

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

Finally, we illustrate how the quasi-experimental variation we leverage in our empirical analysis can also be used to identify structural preference parameters in a life cycle model. The model that we consider extends existing portfolio choice models (see Gomes 2020, for a review) to our setting by allowing investors to choose asset allocations for both new and existing contributions into defined-contribution retirement accounts. We estimate the model by targeting the portfolio choices of investors in our quasi-experiment and find it can replicate our empirical evidence with a coefficient of relative risk aversion of 2.54, an (annual) time discount factor of 0.94, an elasticity of intertemporal substitution of 0.25, a portfolio adjustment cost of $156, and a contribution adjustment cost of $488. The difference in the behavior of investors in the treatment and control groups is the crucial moment that allows us to separately identify risk aversion and the portfolio adjustment cost. To illustrate this point, we show that a model without adjustment frictions that is estimated only using the choices of investors in the control group (i.e., hired under an opt-in regime) delivers an estimate of risk aversion of 19, yet around 2 for investors in the treatment group (i.e., automatically enrolled into a TDF). In contrast, by exploiting our quasi-experimental variation to identify the size of the adjustment frictions, our baseline model can simultaneously match the behavior of both groups of investors with the same level of risk aversion.

An important caveat to our analysis is that these conclusions apply to portfolio choices in a sample of moderate-income individuals with access to an employer-sponsored retirement savings account. This is a large and important segment of the population, given that two-thirds of the U.S. civilian workforce has access to such accounts (Myers and Topoleski 2021). While our sample does not represent the full U.S. population, it captures the segment for which limited stock market participation is arguably most important to explain. Stock market participation is already widespread at the top of the income distribution (i.e., 95% of households in the top decile of incomes hold stocks in the 2016 SCF), while households at the bottom of the income distributions have too little investable wealth to meaningfully benefit from participating in the stock market. However, there are other settings where the drivers of portfolio choice might differ. For example, the fact that per-period participation costs are not a first-order driver of non-participation in our setting may reflect that these costs are lower in retirement accounts than brokerage accounts: the latter requires filing tax forms and more frequent monitoring. Additionally, our results and model cannot explain the lack of stock market participation in other segments of the population, for instance, the small minority of high-income households who do not hold stocks or individuals without access to an employer-sponsored retirement account and for whom preference–based explanations (e.g., loss aversion) might be more relevant.

Contribution and related literature. This paper makes several contributions to existing literature. Our main contribution is to provide a new identification strategy for the role of stock market participation frictions. Our results indicate that these frictions are the primary driver of limited stock market participation in retirement accounts. Several papers have shown that reasonably sized frictions or participation costs *can* explain the lack of stock market participation in quantitative life cycle portfolio models. Such participation frictions could be one-time costs, such as adjustment or transaction costs (Alan 2006; Abel, Eberly, and Panageas 2013; Campanale, Fugazza, and Gomes 2015), or per-period costs (Vissing-Jørgensen 2002; Fagereng, Gottlieb, and Guiso 2017; Briggs, Cesarini, Lindqvist, and Östling 2021; Gomes and Smirnova 2022). These costs could be real, such as the cost of opening and maintaining a brokerage account, or psychological, such as the cognitive cost of planning or paying attention to the menu of available choices. However, empirically identifying the effect of these frictions is challenging, as they generally cannot be observed and measured directly in the data.

Our approach to identification has two strengths. The first strength is that it only relies on non-parametric consistency assumptions without fully specifying investors' objective functions, budget constraints, and beliefs. To do so, we build on the framework developed by Goldin and Reck (2020) to infer preferences over binary saving decisions in a single cross-section. We extend this framework to a different domain—portfolio choice—with continuous decisions, and we take advantage of panel data to test key identifying assumptions. The preferences we recover from active decisions have desirable normative properties. For example they could be used to evaluate the welfare impact of target date funds, the focus of a growing literature (e.g., Parker, Schoar, and Sun 2023b; Duarte, Fonseca, Parker, and Goodman 2022; Gomes, Michaelides, and Zhang 2022; Massa, Moussawi, and Simonov 2021; Zhang 2023).[3] Nudging investors toward holding target date funds could be desirable if non-participation reflects inertia and adjustment frictions but potentially harmful if risky assets impose a large disutility on loss-averse investors. The second strength of our approach is that unlike settings studied in prior literature such as inheritances (e.g., Andersen and Nielsen 2011), lottery winnings (e.g., Briggs et al. 2021), and changes in wealth taxation (e.g., Fagereng, Guiso, and Ring 2024), our identifying variation does not create a shock to wealth, which could influence risk preferences directly (as in Meeuwis 2022).

Our second contribution is to evaluate the role of risk preferences in limited stock market participation. This lack of participation has been interpreted as evidence that investors might exhibit first-order risk aversion. 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). Additionally, households may perceive risky assets to have a less attractive return due to background risk (Benzoni, Collin-Dufresne, and Goldstein 2007; Huggett and Kaplan 2016; Catherine 2022), disaster risk (Fagereng et al. 2017), overly pessimistic beliefs (Briggs et al. 2021; Galaasen and Raja 2024), or lack of trust in the financial sector (Guiso, Sapienza, and Zingales 2008). In our setting, these theories would predict that an investor defaulted into stocks will opt-out and move their savings toward safer assets. We reject this prediction for approximately 95% of retirement investors in our sample. Nevertheless, our results leave open the possibility that these explanations, including non-expected utility preferences and first-order risk aversion, matter more in other settings or affect other dimensions of portfolio choice beyond the participation decision—which is outside of the scope of this paper.

Finally, this paper contributes to the literature on quantitative models of life cycle portfolio choice, initiated by Merton (1969) and surveyed by Campbell and Viceira (2001), Gomes (2020), and Gomes, Haliassos, and Ramadorai (2021). We show that a standard life cycle portfolio choice model with moderate risk aversion and adjustment frictions can match the observed impact of automatic enrollment into a default investment fund. Empirically, our results are consistent with the literature documenting the effect of auto-enrollment on asset allocations (e.g., Mitchell and

[3]The general challenge of dealing with failures of revealed preference is a pervasive issue in behavioral welfare economics (e.g., Bernheim and Rangel 2009; Allcott and Taubinsky 2015). As emphasized by Beshears, Choi, Laibson, and Madrian (2008), the preferences estimated using a structural model or revealed from active decisions have better normative properties than those that reflect inertia and passive choice.

Utkus 2022; McDonald, Richardson, and Rietz 2021; Parker, Schoar, Cole, and Simester 2023a). In our structural estimation, we show how bunching of allocations at the 401(k) default investment option can be used to identify the size of portfolio adjustment costs. The participation costs that we estimate should not be interpreted as "deep" preference parameters; their size and form depend on the specifics of the decision environment. In the context of U.S. tax-advantaged retirement accounts, we find support for moderate one-time participation or fixed adjustment costs as the primary driver of non-participation in retirement accounts. In contrast, we do not find support for sizeable per-period costs, which would induce workers automatically enrolled in stocks to opt out of holding equity—a prediction rejected in our data. While these results are specific to our institutional setting, retirement accounts are particularly important, given that they hold 80% on average (100% at the median) of U.S. households' financial investment products (see Table A1).

1 Data and Quasi-Experimental Variation

In this section, we describe the data and quasi-experimental variation that we use to separately identify risk preferences and choice frictions as drivers of limited stock market participation. We then describe our theoretical framework in Section 2.

1.1 Institutional Setting and 401(k) Administrative Data

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 employer-sponsored retirement savings plans, such as a 401(k) or 403(b) (Myers and Topoleski 2021). These accounts are particularly advantageous saving vehicles because the assets accumulate tax-free, contributions can be tax-deferred, and 86% of plans offer an employer matching contribution (Arnoud, Choukhmane, Colmenares, O'Dea, and Parvathaneni 2021).

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

First, our sample of 401(k) plans comes from employees served by one large pension provider, and therefore is not necessarily representative of the broader U.S. workforce. In Table 1, we provide summary statistics on our data. The median income in our sample increases from $27,320 for 2006 to $35,731 for 2017, which is broadly in line with the $24,892 to $31,561 increase in median net compensation per worker in the U.S. population reported by the Social Security Administration (SSA). Additionally, the median age 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. These results suggest that the observable characteristics of our sample align with those of the broader U.S. workforce.

Table 1. Summary Statistics

	Full Sample 2006–2017	
	Mean	Median
Age	42	42
Wage Income		33,157
401(k) Balance	62,436	19,801
Stock Market Participation in 401(k)	0.69	1.00
Stock Share in 401(k)	0.55	0.75

Notes: This table displays summary statistics on the full set of individuals and years within our sample. We do not observe income directly in our data but impute it by dividing the retirement contribution amount (in dollars) by the contribution rate (as a percentage of salary). We can impute the compensation only of employees with a positive contribution rate. To obtain an estimate of the median income in our sample, we assume that all nonparticipating employees have below-median earnings. Note that this implies that 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 identify the portfolio allocations of mixed mutual funds using the CUSIPs. When calculating the mean and median retirement wealth, we condition on the 401(k) balance being positive. Wage income and 401(k) balances are converted to 2006 dollars using the CPI. We restrict to individuals between ages 23 and 64.

A second limitation of our data is that we do not observe employees' saving and investment behavior outside of their current employer 401(k) plans. Individuals in our sample could have accumulated assets in non-retirement accounts or in retirement accounts associated with previous employers that are not observable in our data. This implies that our estimate of stock market participation is a lower bound for stock market participation across all accounts. We address this data limitation in the life cycle portfolio choice model introduced in Section 3 by modeling separately the assets held in the retirement account with the current employer (which are observable in our data and targeted in the estimation), as well as both retirement assets accumulated with previous employers and non-retirement liquid savings (which are not observable). Additionally, we believe that behavior in retirement accounts offers a good indication of individual attitudes toward risky assets. Due to their advantageous tax properties and widespread availability, defined contribution accounts are the main instrument used by American workers to invest in financial products: for individuals eligible to contribute to a retirement savings account in the SCF 2007–2016 waves, on average 85% (99.5% at the median) of their financial investment products (defined as stocks, bonds, money and non–money market mutual funds, trusts, and CDs) are held in a retirement account (see Table A1). Only 5% of households in the SCF participate in the stock market exclusively outside of a retirement account.

1.2 The Ideal Experiment

The ideal experiment for identifying preferences in the presence of frictions would be to randomly give some individuals who are not participating in the stock market an investment account with stocks. By assigning these accounts, we would exogenously eliminate the effects of any one-time participation (or adjustment) costs.[4] Ideally, we would also eliminate any per-period participation costs, such as the cost of maintaining a brokerage account.

In this experiment, if investors prefer safe assets over risky ones (for example, because they are loss-averse) and face no adjustment costs, they will sell the stocks they were randomly given. Alternatively, if they were not participating due to one-time participation or adjustment costs, they should keep the stocks they were randomly given because these costs have been eliminated. Therefore, the participation choices of investors assigned to accounts with and without stock market exposure would reveal the relative strength of preferences and frictions in driving non-participation. In reality, it is possible that investors prefer safe assets *and* face adjustment costs: our formal framework in Section 2 that we use to estimate investors' preferences allows for this.

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

We study two quasi-experiments motivated by the ideal experiment described above. In both experiments, we compare the portfolio choices of employees hired within 12 months before to those hired within 12 months after their employers changed the 401(k) default asset allocation to include stocks. Those hired before the change need to actively decide to participate in the stock market, while those hired after the change are automatically enrolled in a 401(k) plan invested in a target date fund (TDF) with positive stock market exposure. The investors in the latter group thus need to make an active decision to move away from stocks.

An advantage of this 401(k) setting is that, in contrast to a brokerage account, there are no

[4] There might be some one-time participation costs that our experiment doesn't remove, such as the costs of learning about investments.

explicit per-period costs associated with maintaining or managing the account. However, our quasi-experiments do not remove the effect of any per-period psychological costs, such as the ongoing cost of paying attention to the stock market. As a result, our estimates isolate the effect of one-time fixed or adjustment costs and provide a lower bound on the importance of frictions.

The two quasi-experiments we consider differ in terms of the control group. In the first quasi-experiment, we compare the portfolio choices of employees hired around the time 6 firms changed their automatic enrollment default asset allocation from a money market fund (i.e., with no stock market exposure) to a target date fund (i.e., with stock market exposure). The control group consists of 1,086 employees hired in the 12 months prior to the change, who are defaulted into a money market fund, while the treatment group consists of 1,321 investors hired *at the same firms* after the change, who are defaulted into a TDF. We refer to this as the money market-to-TDF sample.[5] Under the assumption that the investors hired before and after the changes are similar (and other assumptions formalized in Section 2), this quasi-experiment provides a close approximation of the ideal experiment: some employees are quasi-randomly assigned a retirement account with positive stock exposure (i.e., the TDF default), while others are quasi-randomly assigned a retirement account with safe assets (i.e., a money market fund).

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 in a TDF as the default asset allocation. The control group consists of 40,337 investors hired before the change under the opt-in regime, while the treatment group consists of 52,400 investors hired after the change and automatically enrolled into a TDF. Figure A1 shows the percentage of the total number of firms that change their default in each year is relatively evenly distributed between 2006 and 2017. We refer to this as the opt-in-to-TDF sample.[6] Compared to the money market-to-TDF sample, the opt-in-to-TDF sample has the advantage of being a much larger sample of firms and investors. However, an important difference is that in the opt-in-to-TDF sample, the treatment and control groups differ in terms of both the frictions they face in adjusting their retirement asset allocation *and* the frictions that they face in contributing to the 401(k) plan.

In Panels A and B of Figure 1, we plot the variation that we use in the two quasi-experiments. For the money market-to-TDF sample, Panel A plots 401(k) participation, money market participation, and stock market participation within the 401(k) for investors in their first year of tenure based on the month in which they were hired relative to the policy change. The investors in the left

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

[6] We verified the menu of funds available is broadly similar before vs. after the adoption of a new default fund. Results are available upon request.

half of each graph are in the control group (hired before the change), while the investors in the right half are in the treatment group (hired after the change). Consistent with a large literature on default effects (e.g., Madrian and Shea 2001), we find that participation in the money market fund decreases discontinuously while stock market participation within the 401(k) plan increases discontinuously for workers in the treatment group (i.e., hired right after the change in the default). In contrast, 401(k) participation remains unchanged. Panel B shows the analogous plot for the opt-in-to-TDF sample, in which we observe a discontinuous increase in 401(k) participation and stock market participation within the 401(k) plan for investors in the treatment group.[7]

1.4 Results from Quasi-Experiments

1.4.1 Investors Defaulted into Non-Participation Rebalance into Equity, while Investors Defaulted into TDFs Maintain a High Stock Share

Figure 2 plots the results from the first quasi-experiment (money market-to-TDF).[8] We plot the fraction of investors participating in the stock market and their average stock share of retirement wealth τ years after being hired, where $\tau = 0$ corresponds to their choice immediately upon being hired. In both samples, we find that almost all 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 within their retirement account. Note that this difference in opt-out rates between the two groups suggests that the frictions impacting investors' behavior are not pure time-dependent frictions à la Calvo, which would predict that the propensity to make an active decision should be similar in both groups. Results for the second quasi-experiment (Opt-in-to-TDF) are similar and presented in Figure A3.

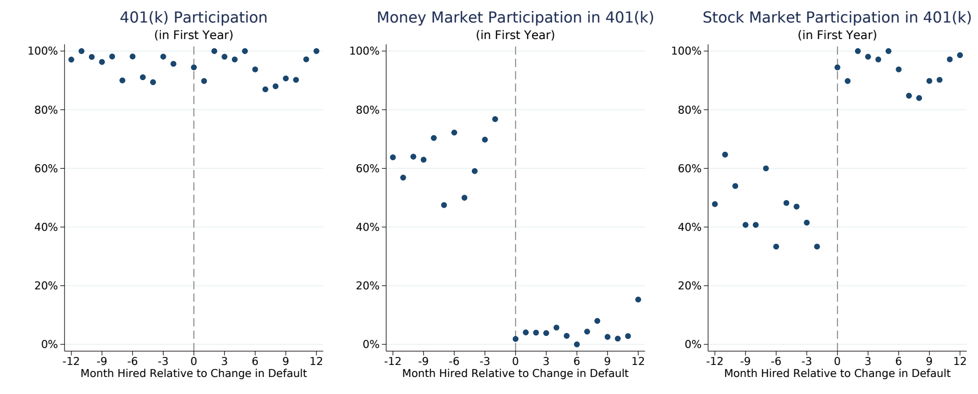
In both samples, we also observe that the investors in the treatment group maintain a relatively high stock share of retirement wealth of approximately 80%. In contrast, investors in the control groups start with a lower stock share of retirement wealth and converge toward the level in the treatment group. Table A2 shows that the treatment group has a stock market participation rate within the 401(k) plan that is 19–25 percentage points higher than that in the control group on average, with a stock share of retirement wealth that is between 20 and 23 percentage points higher.

[7] In Figure A2, 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.

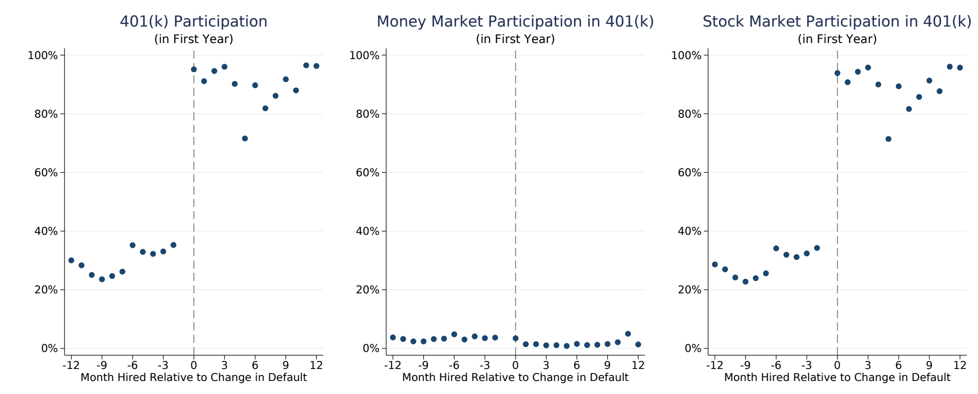
[8] For the rest of the analysis, we focus only on portfolio choices made within 10 years of being hired. We drop choices made after 10 years since few investors remain that long at the firm.

Figure 1. Identifying Variation in Quasi-Experiments

Panel A: Money Market-to-TDF Sample

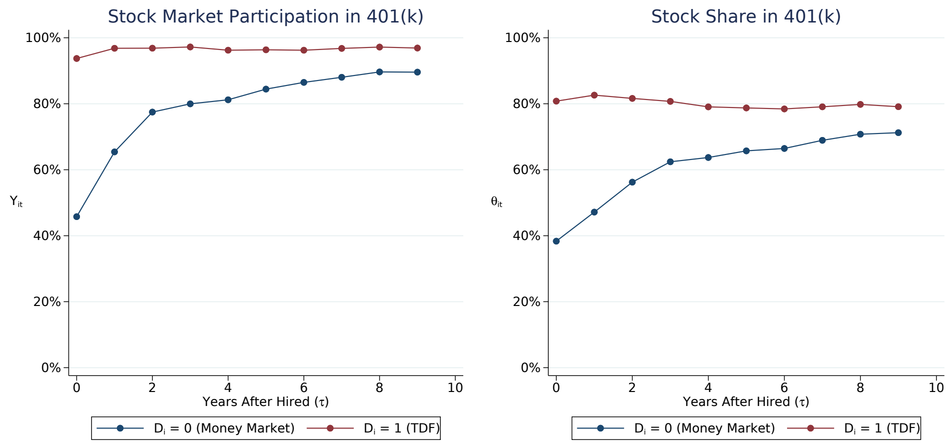


Panel B: Opt-In-to-TDF Sample



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., have no stock market exposure), and the treatment group is 1,321 investors hired *at the same firms* after the change, who are defaulted into a TDF (i.e., have 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 in 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.

Figure 2. Observed Portfolio Choice Response: Money Market-to-TDF Sample



Notes: This figure plots the observed portfolio responses for employees hired within 12 months of their employer changing the default asset allocation τ years after they were hired. The left panel shows the stock market participation rate and the right panel shows average unconditional stock shares of current employer retirement wealth. The blue lines are employees automatically enrolled in a money market fund; the red lines are employees automatically enrolled in a TDF.

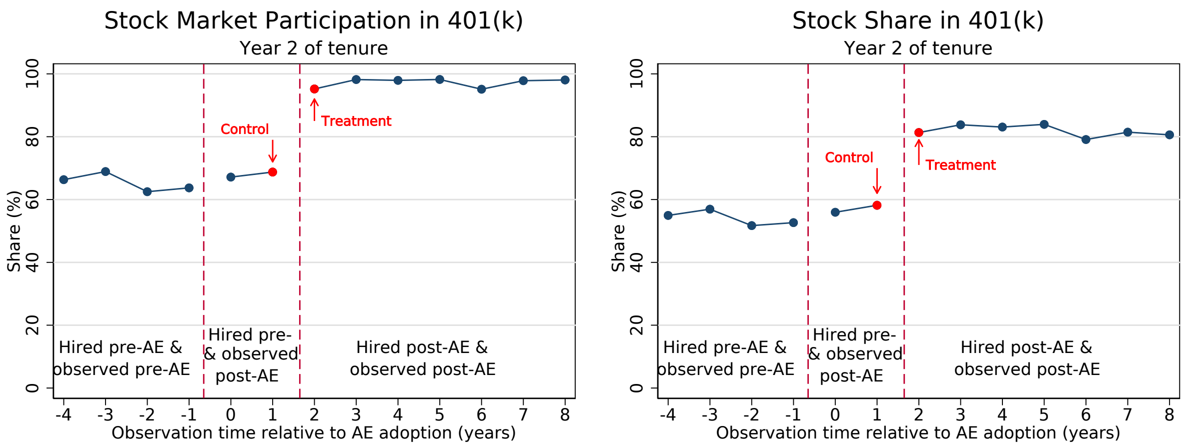
1.4.2 Limited Evidence of Peer Effects

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.[9] For instance, peer effects from colleagues automatically enrolled into a TDF may lead employees in our control groups to increase the equity share in their retirement account. Similarly, their employers may start advertising and encouraging higher equity allocation after the policy change.

To address this concern, Figure 3 compares the behavior of three cohorts of employees: (i) those hired and observed before the default change; (ii) those hired before but observed after the default change; (iii) those hired and observed after the default change. Comparing the first two cohorts isolates the possibility of a peer effect since both cohorts are not directly affected by the default change, but the latter observes their employer endorsing a new default option. As shown in Figure 3, there is no noticeable difference in the choices of these two groups after two years of tenure; Panel A of Figure A4 confirms this is also true after four years of tenure. In contrast, the difference appears only among those hired after the default change, who have higher participation and equity shares.

[9]This would violate the stable unit treatment value assumption that we implicitly make by writing an investor's choices as a function of potential outcomes.

Figure 3. Test of Peer Effects: Money Market-to-TDF Sample



Notes: This figure plots stock market participation rates in the left panel and average stock shares of retirement wealth in the right panel for different groups of individuals in the Money Market-to-TDF Sample. The first group on the left are those hired and observed before the default change. The second group in the middle are those hired before but observed after the default change. The final group on the right are those hired and observed after the default change.

1.4.3 Robustness

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

Survivorship bias. We do not observe investors after they separate from their employer. This implies selection into our sample by different tenure levels. A potential concern is that the convergence between the treatment and control groups over tenure may be driven by survivorship bias: those who remain with the firm over a long tenure horizon may be more likely to make similar allocation decisions. In Panel B of Figure A4, we show that the responses of investors in the control group are similar regardless of when the investor separates from her employer, which indicates that the increased stock share of the control group over time is not driven by a change in the composition of employees remaining at the firm.

Passive rebalancing. A third concern is that the evolution (and convergence) of equity shares in the retirement account is driven by passive rebalancing. In Figure A5, 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 2. The equity share of new contributions reflects only allocation decisions and is not subject to portfolio drift. These results suggest that the dynamic responses of portfolio shares in Figure 2 are primarily driven by investors' active portfolio decisions rather than passive changes in portfolio allocations as returns are realized.

2 Identifying Risk Preferences Using 401(k) Default Switches

In this section, we apply a theoretical framework developed by Goldin and Reck (2020) that allows us to map the results in Figure 2 to estimate investors' preferences, taking into account the fact that some individuals do take actions that reveal their preferences. We follow the assumptions and results in Goldin and Reck (2020), who study preferences for savings in a 401(k) plan, but adapt and extend the framework to study a different domain: asset allocation decisions. All derivations are presented in Appendix B.

2.1 Intuition for Identification Approach

To build intuition for our identification approach, consider a simple example illustrated in Table 2. Assume there are two possible 401(k) defaults, a safe asset (e.g., money market fund) and a stock fund (e.g., target date fund), and that we observe the choices of investors under both possible defaults. In this example, there are three types of investors illustrated in the three columns in Table 2. The first type of investor sticks with the default asset allocation in both cases. We define this investor as *inconsistent* (or passive) because her allocation reflects the default chosen by the employer rather than a stable personal preference.[10] The second investor type is one who, when defaulted into holding safe assets, keeps the safe assets, but when defaulted into stocks, makes an active decision to move away from stocks and toward safe assets, thus revealing her preference for stock market non-participation. The final type of investor is one who, when defaulted into a stock fund, keeps the stocks, but when defaulted into safe assets, makes an active decision to buy stocks, thus revealing her preference for stock market participation. In contrast to the first type, these two types of investors are *consistent* because their choices do *not* depend on the default.

The key insight from the framework below is that we can infer the preferences of consistent investors from their observed choices. Since consistent investors' choices are independent of the default, their active choices reveal their preferences. The key challenge is how to identify the preferences of the first type of (passive) investors, which requires additional assumptions.

[10] The use of the term *inconsistent* does not mean that the investor's choice is suboptimal; it is simply the terminology we use to refer to an investor whose choices depend on the default.

Table 2. Simplified Example of Identification Approach

	Investor Participates in Stock Market?		
401(k) Default	Type 1	Type 2	Type 3
Safe Asset (e.g., Money Market Fund)	No	No	Yes
Stock Fund (e.g., Target Date Fund)	Yes	No	Yes
Consistent	✗	✓	✓
Prefers Stocks	?	✗	✓

2.2 Revealed Preference Framework

2.2.1 Setup

Consider individual i hired at time $t = 0$ that makes asset allocation choices at different tenure levels $t = 0, \ldots, T$. An individual's unobserved preference for stock market participation and preferred equity share at each tenure are denoted by $Y^*_{it} \in \{0, 1\}$ and $\theta^*_{it} \in [0, 1]$, where $Y^*_{it} = 1$ corresponds to preferring participating in the stock market. The preferred allocations can be different from the observed allocations, denoted by Y_{it} and θ_{it}, if individuals are subject to inertia or adjustment frictions. The plan contains a default option (or frame) denoted by $D_i \in \{0, 1\}$, where $D_i = 1$ corresponds to auto-enrollment into a TDF as the default asset allocation (i.e., the treatment groups in the two quasi-experiments) and $D_i = 0$ otherwise (i.e., the control groups). We denote $\theta^d_i(D_i)$ the default asset allocation faced by investor i who remains fully invested in the default TDF.

Our goal is to identify investors' average preferences, Y^*_{it} and θ^*_{it}, from their observed allocations under different defaults. Individuals are characterized by a set of potential outcomes, $\{Y_{it}(d), \theta_{it}(d)\}_{d \in \{0,1\}}$, which correspond to their observed allocations under the alternative default options. 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^Y_{it} and C^θ_{it}, where

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

As in the example in Section 2.1, there are two possible types of investors for each decision: (i) consistent (i.e., active) investors, whose choices are unaffected by the default, and (ii) *in*consistent (i.e., passive) investors, whose choices *are* affected by the default.

2.2.2 Identifying Assumptions

In order to use variation in the default asset allocation for identification, we follow Goldin and Reck (2020) and impose the following four identifying assumptions.

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

Intuitively, frame separability requires that the default option changes investors' observed allocations but not their underlying preferences. For instance, this assumption rules out the possibility that investors view the default as providing information and start valuing stocks more highly when defaulted by their employer into a stock fund and valuing safe assets more when defaulted into the money market fund. While this is a strong assumption, we provide supporting evidence in Figure A7. If Assumption 1 was violated, we would expect that, once they make an active decision and deviate from the default asset allocation, investors initially defaulted into the Money Market Fund would choose a lower equity share than those initially defaulted into the TDF. In contrast, Figure A7 shows that stock shares chosen by investors who deviate from both default allocations are very similar, consistent with Assumption 1.

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

Frame exogeneity requires the default option chosen by the employer to be independent of investors' preferences or, equivalently, that investors in the treatment and control groups have similar preferences. This assumption rules out the possibility that the employer changed the default asset allocation in expectation of a change in the type of employees they plan to hire. We believe this is a reasonable assumption in our setting given: (i) the observable characteristics of employees hired before and after the policy change are balanced (Figure A2) and (ii) changes in the investment default option are mainly driven by changes in regulation following the Pension Protection Act of 2006 rather than in the preferences of new hires (e.g., Parker et al. 2023a).

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

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

Frame monotonicity rules out the presence of contrarian investors whose choices are pushed in the opposite direction of the default. This assumption is analogous to the monotonicity or no-defiers assumption in the LATE theorem (Angrist and Pischke 2008). It is also consistent with many models of default effects, such as fixed or convex adjustment costs, limited attention (Gabaix 2019), and cognitive uncertainty (Enke and Graeber 2023).

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

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

The consistency principle requires that consistent investors reveal their preferences. For example, if an investor chooses to invest in stocks regardless of the default, we assume the investor has revealed a preference for stock market participation. This is the key identifying assumption that allows us to recover the preferences of consistent investors from observed choices.

2.3 Results

2.3.1 Bounding the Average Preference for Stock Market Participation

Under the previous four assumptions, we can use variation in the default asset allocation to bound the average preference for retirement account stock market participation in our sample.

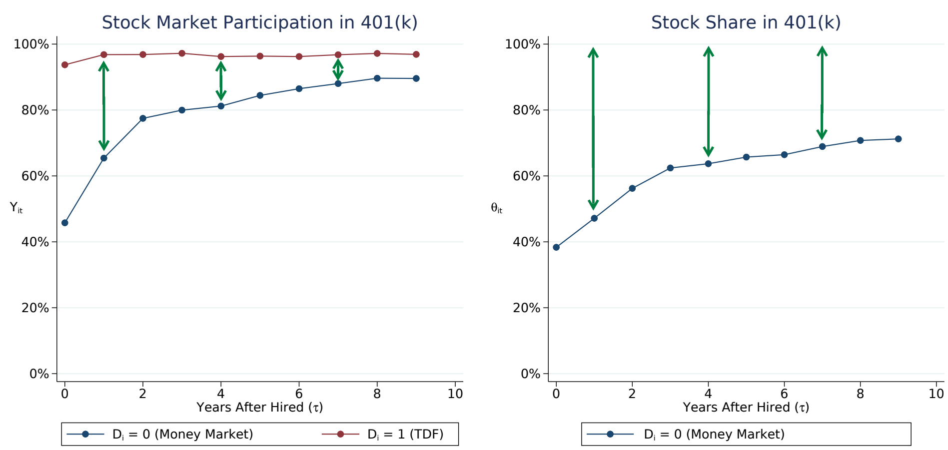
Proposition 1. *Under Assumptions 1–4, the average population preference for stock market participation within retirement accounts among investors with tenure $t = \tau$ is partially identified:*

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

The intuition for this result is straightforward. The average preference for participation is the weighted average of the preferences of consistent and inconsistent investors. The preferences of consistent investors are identified from their choices. The bounds correspond to the two extreme cases where all inconsistent (i.e., passive) investors either prefer participation or do not prefer participation.

According to Proposition 1, the results in the left panel of Figure 2 provide the required information to bound the average preferences for stock market participation within retirement accounts. By (1), the average preferences for participation among all investors in our population lie somewhere between the choices of the treatment and control groups, which is illustrated in the left panel of Figure 4 for the money market-to-TDF sample.[11] For example, we can bound the fraction of employees with 2 years of tenure who prefer holding stocks in their 401(k) plan between 78% and 95%. As tenure increases, more investors in the control group become consistent and reveal their preferences, resulting in a tighter bound.

Figure 4. Bounding Population Preferences: Money Market-to-TDF Sample



Notes: This figure plots the same data as in Figure 2 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.

2.3.2 Bounding the Average Preferred Stock Share

We now turn to identification of investors' average preferred stock share of retirement wealth. Unlike in the previous section, Assumptions 1–4 are not sufficient to place meaningful bounds on the average preferences because stock shares are continuous variables.[12] Instead, we introduce a new assumption relative to the Goldin and Reck (2020) framework and replace Assumption 4 with the following stronger assumption.

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

Assumption 5 requires that an investor who makes an active decision (and deviates from the default asset allocation) chooses her preferred asset allocation. This assumption is consistent with

[11] As is evident from Figure 2, we find similar results across both samples.

[12] To see why, consider an investor with $0 < \theta_{i\tau}(0) < \theta_{i\tau}(1) < 1$, for some $\tau \geq 0$. This investor is inconsistent at τ. If this investor has $\theta_{i\tau}^* \in (0, \theta_{i\tau}(0))$, which is not ruled out by any of our assumptions, a bound similar to Proposition 1 would be invalid because we would have $E_\tau(\theta_{it}^*) < E_\tau(\theta_{it} \mid D_i = 0)$.

a large class of models of default effects in which investors' preferences can be represented as if deviating from a default requires incurring a fixed cost (see Masatlioglu and Ok 2005, for an axiomatization). The fact that many investors make large and infrequent portfolio adjustments is consistent with this assumption.[13] However, this assumption is violated in some models, such as those with a convex adjustment cost.

With Assumption 5, we can place a lower bound on population preferences for stock shares of retirement wealth analogously to the lower bound on participation 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:*

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

We display this bound in the right panel of Figure 4. For employees in their third year of tenure, we can bound the average preferred stock share of retirement wealth from below at 62% in the money market-to-TDF sample. In a life cycle portfolio choice model with CRRA preferences, no labor income risk, and a constant investment opportunity set (e.g. Merton 1969), this lower bound implies an upper bound on the coefficient of relative risk aversion of 2.1.[14]

2.3.3 Estimating Average Preferences

We now discuss how we point-estimate the average preference for stock market participation and preferred stock share. Without any additional assumptions, we can characterize them as follows.

Proposition 3. *Under Assumptions 1–5, average preferences are:*

$$E_\tau(Y_{it}^*) = E_\tau\left(Y_{it}^* \mid C_{it}^Y = 1\right) - \frac{1}{E_\tau(C_{it}^Y)} \underbrace{cov_\tau\left(Y_{it}^*, C_{it}^Y\right)}_{\text{selection bias}}, \tag{2}$$

$$E_\tau(\theta_{it}^*) = E_\tau\left(\theta_{it}^* \mid C_{it}^\theta = 1\right) - \frac{1}{E_\tau(C_{it}^\theta)} \underbrace{cov_\tau\left(\theta_{it}^*, C_{it}^\theta\right)}_{\text{selection bias}}, \tag{3}$$

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

[14] In this calculation we assume annual risk premium of 5.5% and an annualized standard deviation of 16%.

where the preferences of consistent investors are identified as:

$$E_\tau\left(Y_{it}^* \mid C_{it}^Y = 1\right) = E_\tau(Y_{it} \mid Y_{it} \neq D_i), \quad E_\tau\left(\theta_{it}^* \mid C_{it}^\theta = 1\right) = E_\tau(\theta_{it} \mid \theta_{it} \neq \theta_i^d(D_i)). \tag{4}$$

Proposition 3 shows that average population preferences consist of two terms. The first term in (2) and (3) reflects the preferences of consistent investors. This term is simply equal to the average choices of active investors, as shown in (4). The second term represents a form of selection bias that arises if consistent investors have preferences different from those of inconsistent investors. In general, this selection bias is unbounded without placing further restrictions on investor decision-making.

To derive point estimates of 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, at a given tenure, consistent (active) and inconsistent (passive) investors have similar preferences over risky assets in their retirement accounts. Thus, under Assumption 6, population preferences at each tenure are given by the observed preferences of consistent investors. We plot these estimates in Figure A9: at tenure $\tau = 3$, the average preference for stock market participation within retirement accounts is 94%, and the average preferred stock share of retirement wealth is 76%.

Assumption 6 is a strong assumption that 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 portfolio choices of investors who are quick to make active decisions (more consistent) with those of investors who are more passive and wait several years before making any change to their asset allocation (less consistent).[15] In Figure A8, we show the choices of investors who make an active decision in their first year of tenure are similar to those who wait up to eight years to make an active decision. While this is suggestive evidence in support of Assumption 6, we cannot rule out that this assumption may fail. In that event, we can either: (i) rely on the bounds for average preferences from Section 2.3, (ii) model explicitly the endogenous

[15] Formally, this test is justified under the following *decision-quality exclusion restriction* introduced by Goldin and Reck (2020): preferences, Y_{it}^* and θ_{it}^*, are independent of tenure, τ.

selection into making an active decision (as we do in our structural model in Section 3), or (iii) consider a weaker version of Assumption 6 as we do in the following subsection.

2.3.4 Estimating Preferences over the Life Cycle

Assumption 6 rules out the possibility that consistency and preferences might both vary with age (conditional on tenure). This is restrictive given that the stock of human capital—the central driver of portfolio choice in standard life cycle models—decreases with age, and there are reasons to believe that consistency also varies with age. For example, older investors may have more wealth as well as a lower option value from delaying adjusting their portfolio.[16]

We thus relax Assumption 6 by making the following assumption.

Assumption 7. *For all i, τ, and all ages 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 (2) and (3) to obtain the following life cycles of preferences for investors of tenure $t = \tau$:

$$E_{\tau}(Y_{it}^{*} \mid age_{it} = A) = E_{\tau}(Y_{it} \mid Y_{it} \neq D_i, age_{it} = A), \tag{5}$$

$$E_{\tau}(\theta_{it}^{*} \mid age_{it} = A) = E_{\tau}\left(\theta_{it} \mid \theta_{it} \neq \theta_i^{d}(D_i), age_{it} = A\right). \tag{6}$$

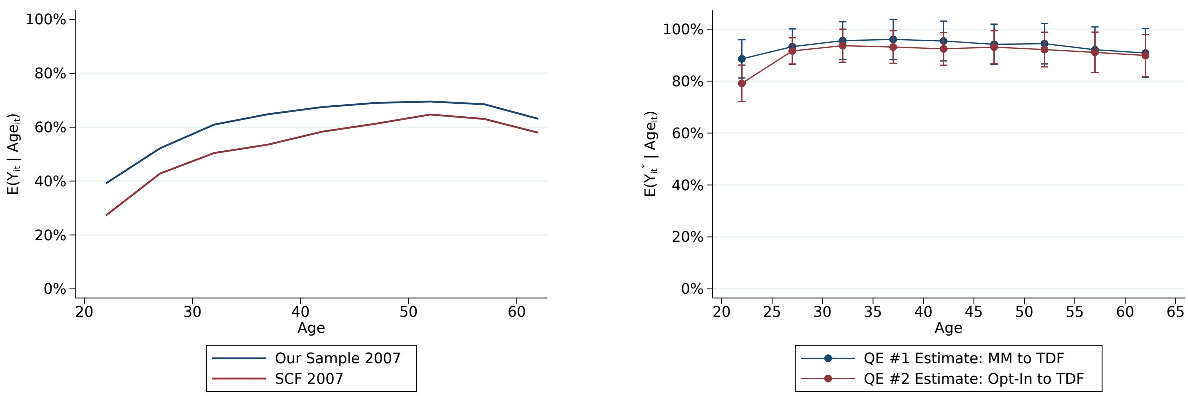
Using Assumption 7, we uncover two main results in both quasi-experiments. First, the average preference for stock market participation in retirement accounts, shown in the right panel of Figure 5, is high–over 90%–and flat over the life cycle. Second, the average preferred equity share of retirement wealth, shown in the right panel of Figure 5, is also high–above 60% at all ages–and mostly decreasing over the life cycle.[17] These estimated preferences are broadly consistent with the predictions of standard life cycle portfolio choice models with risky labor income that is uncorrelated with stock returns (Campbell and Viceira 2001; Cocco et al. 2005). Interestingly,

[16] Consistent with this hypothesis, we show in Figure A6 that the fraction of consistent investors is indeed slightly increasing with age.

[17] Our estimates are statistically indistinguishable across our two quasi-experiments, which provides support for our identifying assumptions.

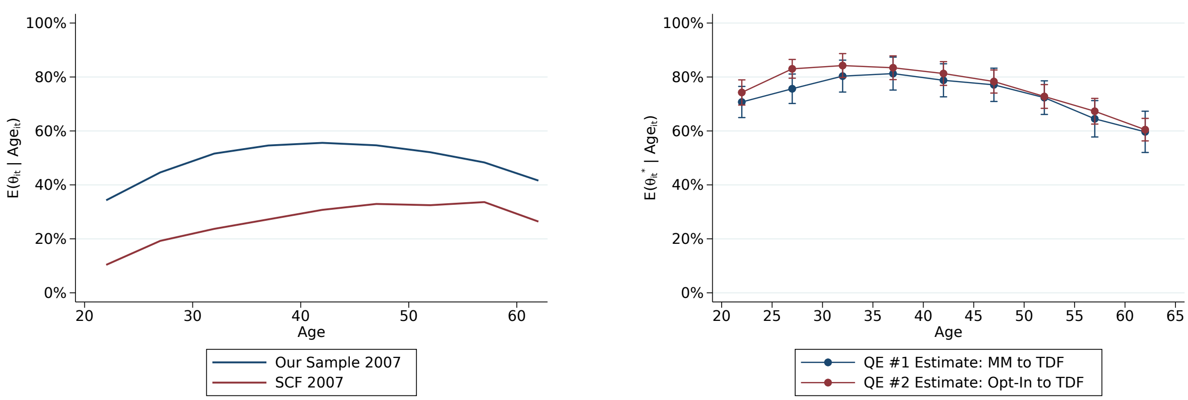
[Figure A13](#) shows this age profile is lower than the glide path of the TDF in our sample, especially for younger individuals.

Figure 5. Stock Market Participation in 401(k) Plans over the Life Cycle: Choices vs. Preferences



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

Figure 6. Stock Share in 401(k) Plans over the Life Cycle: Choices vs. Preferences

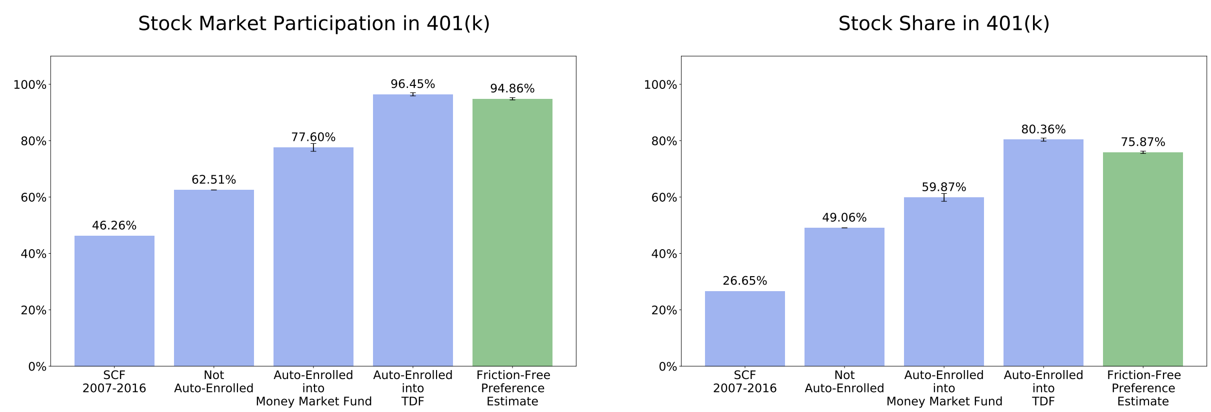


Notes: This figure plots our estimate of investors' preferences for stock shares of retirement wealth in the right panel in comparison to their observed choices in the left panel. In the left panel, we plot the average stock share of retirement wealth among all investors in our data in 2007 across different 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 the 90% confidence intervals based on standard errors clustered by investor for our first quasi-experiment and by firm for our second quasi-experiment.

In contrast, the observed age profiles of stock market participation and equity shares in the cross-section are quite different and do not align with the predictions of standard models. In the left panel of Figure 5 we show that, consistent with typical findings in the literature, the life cycle profile of stock market participation is relatively low and increasing in age, both in our sample of retirement investors in 2007 and for total financial wealth in the SCF 2007 wave. Similarly, observed stock shares of retirement wealth are relatively hump-shaped over the life cycle (as in Ameriks and Zeldes 2004) and are strictly below our estimates of preferred stock shares.

Figure 7 summarizes our results by comparing our estimate of investors' preferences in green to the observed choices of different groups of investors in blue. First, our sample has higher stock market participation than the general population covered by the Survey of Consumer Finances because it is selected based on having access to an employer-sponsored retirement plan. Still, the majority of investors in our sample are not auto-enrolled and exhibit relatively low stock market participation and stock shares, with only 62% having positive equity exposure inside their 401(k) plan. In contrast, investors auto-enrolled into a TDF have much higher stock market participation rates and stock shares. The difference between the choices of these two groups highlights the importance of one-time fixed or adjustment costs. The contribution of our non-parametric approach to identifying preferences is to show that investors' preferences are close to the choices made by the latter group.

Figure 7. Preference Estimates vs. Observed Choices

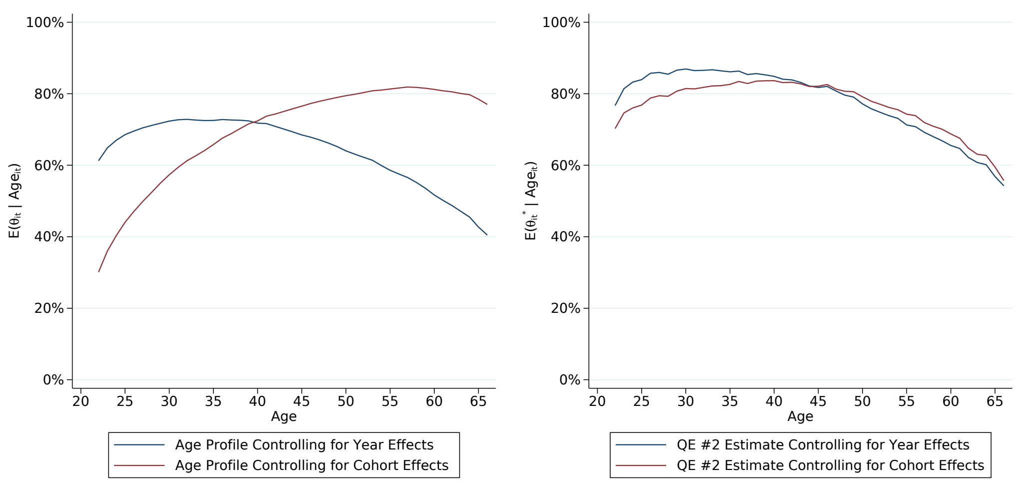


Notes: This figure compares our estimates of preferences to observed choices for retirement wealth stock market participation in the left plot and unconditional stock shares of retirement wealth in the right plot. The first bar, SCF 2007-2016, plots the averages in the SCF 2007, 2010, 2013, and 2016 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 2.3.4, where the values plotted come from taking weighted averages of the results in Figures 5 and 6 across ages.

2.4 Additional Results and Robustness

Year, cohort, and firm effects. Because age, time, and cohort effects are collinear, it is impossible to separately identify them in a linear model (Deaton and Paxson 1994). Using SCF and retirement account data similar to ours, Ameriks and Zeldes (2004) and Parker et al. (2023a) show that the life cycle profile of equity shares is sensitive to the inclusion of either year or cohort effects: it is increasing with age in the presence of cohort dummies and flat or decreasing with age when year dummies are included. In the left panel of Figure 8, we replicate this finding in our data: the life cycle profile of the equity share is more upward-sloping when we include cohort instead of year dummies. In contrast, the right panel of Figure 8 shows that our preference estimates are very similar under our baseline specification (with no cohort or time effects) and under the specifications including either year or cohort effects.[18] These results suggest a substantial fraction of the year and cohort variation in equity shares within retirement accounts could come from frictions changing over time, for example, due to changes in retirement plans technology and default options. Additionally, in Figure A12, we show that our estimates of preferences are robust to including firm fixed effects.

Figure 8. 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 6 with and without controls for cohort and year effects, respectively. For both panels, we obtain the predicted values by adding the median cohort or year coefficient to each age coefficient.

[18]In the right panel of Figure 8, we show the evidence using our second quasi-experiment (with the opt-in control group). The results are similar to those of our first quasi-experiment and are available upon request.

Heterogeneity. In Figure A11, we explore heterogeneity over the life cycle by plotting the distribution of preferred stock shares among consistent investors for three different age groups: 20–34, 35–49, and over 50. These three groups are approximately evenly spaced terciles. We find that heterogeneity increases over the life cycle: most investors in the lowest age group prefer a stock share of over 80%, while there is much more dispersion in the preferred stock shares among the highest age group. This is qualitatively consistent with the formulation of standard life cycle models, in which heterogeneity increases with age due to greater cross-sectional variance in the model's state variables.

Conditioning on income. In our data, we can impute the salary of employees who contribute positive amounts to their 401(k) plans.[19] 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 A14, we plot the estimates of preferences over the life cycle at different tenures based on this weaker assumption. The results show that our estimates of preferences are unaffected. In Figure A15, we plot our estimates of preferences over the life cycle by income quartile, after integrating over tenure. The results show that our preference estimates are mostly similar across income quartiles, consistent with the results in Figure A14.

3 Life Cycle Portfolio Choice Model

In this section, we build and estimate a rich life cycle portfolio choice model using the variation from our quasi-experiments. This model builds on the consumption-saving model of Choukhmane (2024) and extends it to include multiple assets and portfolio choice decisions. Agents choose their level of consumption, retirement wealth, and liquid wealth, as well as their portfolio allocations.

To accurately capture the patterns observed in our quasi-experiments, the model includes three key elements. First, investors can choose different asset allocations for their stock of accumulated retirement wealth and for the flow of new contributions to their retirement account. This is important because the change in the default asset allocation only affects the allocation of new contributions, not the stock of existing assets. Second, investors must pay separate adjustment costs to deviate from the default contribution rate in their retirement account and the default portfolio allocation. When agents are hired, these default options are specified by their employer; in later periods, the previous period choices become the default. Finally, investors face uncertainty about

[19] Among automatically enrolled employees, we can impute salary for over 95% of employees since almost all make at least one positive contribution at some point after being hired.

their future earnings and employment status. Employment uncertainty, including the possibility of unemployment and job-to-job transitions, is essential for obtaining reasonable estimates of adjustment costs. For example, an investor who expects to remain in the same job for their entire career would require much larger adjustment costs to justify inaction. Appendix A provides a summary of the model parameters.

3.1 Model Description

3.1.1 Demographics and Preferences

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

Investors have recursive Epstein–Zin–Weil preferences (Epstein and Zin 1989; Weil 1990) over consumption streams. We denote investors' annualized time discount factor as β, elasticity of intertemporal substitution as σ^{-1}, and relative risk aversion as γ. Per-period consumption at t is adjusted for an equivalence scale that captures the evolution of household size over the life cycle, which we denote by n_t.

3.1.2 Labor Market

Employers are indexed by e. At any point in time, investors can be in one of four employment statuses, denoted emp_t: E = employed by the same employer as in the previous period, JJ = employed by a different employer than in the previous period, U = unemployed in the current period, and Ret = retired.

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

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

$$\ln w_t = \delta_0 + \delta_1 a_t + \delta_2 a_t^2 + \delta_3 a_t^3 + \eta_t, \quad \eta_t = \rho \eta_{t-1} + \xi_t^E, \tag{7}$$
$$\xi_0^E \sim N(0, \sigma_{\xi_0}^2), \quad \xi_t^E \sim N(0, \sigma_\xi^2)\ \forall t > 0.$$

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

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

$$\ln w_t = \delta_0 + \delta_1 a_t + \delta_2 a_t^2 + \delta_3 a_t^3 + \eta_t, \quad \eta_t = \rho \eta_{t-1} + \xi_t^{JJ}, \quad \xi_t^{JJ} \sim N(\mu^{JJ}, \sigma_\xi^2). \tag{8}$$

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

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

$$\ln w_{t+1} = \delta_0 + \delta_1 a_{t+1} + \delta_2 a_{t+1}^2 + \delta_3 a_{t+1}^3 + \eta_{t+1}, \quad \eta_{t+1} = \rho \eta_t + \xi_{t+1}^U, \quad \xi_{t+1}^U \sim N(\mu^{UE}, \sigma_\xi^2). \tag{9}$$

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

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

3.1.3 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 that corresponds to a diversified stock market index and pays a stochastic i.i.d. gross return of $R_t^S = R_t$ per year, where

$$\ln R_t^S = \ln R_f + \mu_s + \varepsilon_t, \quad \varepsilon_t \sim \mathcal{N}(0, \sigma_s^2). \tag{10}$$

Finally, investors have access to a liquid risk-free asset that has a constant gross return of $1+r$ per year. Stock returns are uncorrelated with shocks to labor income in our model. If they were correlated (as in, e.g., Benzoni et al. 2007; Huggett and Kaplan 2016; Catherine 2022), this would make stocks less attractive and thus push down our estimate of relative risk aversion.

3.1.4 Savings Accounts

Investors start with zero assets at $t = 0$ and cannot borrow. They can accumulate assets inside three savings accounts, which we now describe in turn.

Liquid savings account. Investors can invest in the liquid risk-free asset inside a liquid taxable account. The balance of this account, denoted by L_t, evolves according to:

$$L_{t+1} = \left(L_t + s_t^l\right)\left[1 + r(1 - \tau_c)\right], \quad L_0 = 0, \tag{11}$$

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

Retirement wealth. Retirement wealth consists of a combination of bonds and stocks, subject to the restriction of no margin trading (i.e., no leveraged purchases or short sales). Total retirement wealth, A_t, consists of assets held in the current employer retirement account, A_t^e, as well as assets accumulated in previous employer retirement accounts, A_t^p, where $A_t = A_t^e + A_t^p$. We keep track of both accounts separately because we only observe the *current* employer retirement account in our data. Returns earned in these accounts are tax-free, unlike those earned in the liquid savings account. The asset allocation of retirement wealth depends on *two* portfolio choice decisions: (i) the portfolio shares for the stock of previously accumulated assets in stocks and bonds, denoted by $\left\{\Theta_t^B, \Theta_t^S\right\}$, and (ii) the portfolio shares for new contributions to the current employer retirement account, denoted by $\left\{\theta_t^B, \theta_t^S\right\}$. This distinction, which matches the institutional features of 401(k) asset allocation decisions, is important in our model because investors are subject to default effects (described in Section 3.1.5). For tractability, we assume that when an individual changes the asset allocation of existing assets, it simultaneously affects savings in both the current and previous employer retirement plans. In contrast, a change in the allocation of new contributions affects only the asset allocation within the current employer retirement saving plan.

Retirement account #1: current employer retirement account. Each time an investor is matched with a new employer, she is given access to a new employer-sponsored retirement savings account. This is the model counterpart to the 401(k) accounts we observe in our data. She can contribute a fraction $s_t^{dc} \geq 0$ of her salary to this account, which is tax-deferred and matched by an employer contribution $\mathcal{M}_e(\cdot)$. Contributions are matched at a rate $match_e$ up a threshold cap_e of salary. Additionally, we adjust these employer matches by a factor $\Upsilon_e(\cdot) \leq 1$ to capture the possible loss of match if investors separate from the employer before vesting is complete. Employer matching contributions are thus given by:

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

Denote as t_J the period in which an individual was hired by her current employer: $t_J = sup\{s : s \leq t, emp_s = JJ\}$. We denote as $\tilde{\Theta}_t^j$ the portfolio share of asset j in wealth accumulated at the current employer, which evolves according to:

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

The balance of the current employer retirement account then evolves according to:

$$A_{t+1}^e = A_t^e \times \sum_{j \in \{B,S\}} \tilde{\Theta}_t^j R_{t+1}^j + w_t \times \mathcal{M}_e(s_{t+1}^{dc}, t, ten_t, emp_t) \times \sum_{j \in \{B,S\}} \theta_t^j R_{t+1}^j, \tag{12}$$

(13)

with the initial conditions $A_{t_J}^e = \Theta_{t_J}^j = 0$.

Retirement account #2: accumulated assets from previous employers. When an investor separates from an employer, her current retirement assets are rolled over into the legacy account with balance A_t^p. The investor cannot otherwise contribute to this account but can make (possibly tax-penalized) withdrawals $d_t^{dc} \geq 0$ when unemployed or retired. The balance of the legacy account starts at $A_0^p = 0$ and evolves according to:

$$A_t^p = \begin{cases} (A_{t-1}^p - d_{t-1}^{dc}) \times \sum_{j\in\{B,S\}} \Theta_t^j R_{t-1}^j + A_{t-1}^e \times \sum_{j\in\{B,S\}} \tilde{\Theta}_t^j R_{t-1}^j & \text{if } emp_t \neq E \text{ and } emp_{t-1} = E, \\ (A_{t-1}^p - d_{t-1}^{dc}) \times \sum_{j\in\{B,S\}} \Theta_t^j R_{t-1}^j & \text{else.} \end{cases}$$

Defined contribution account during employment transitions. When investors become unemployed or retired, we assume they can only withdraw and cannot make new contributions to their DC account. After a job transition, the employer matching function, denoted by $\mathcal{M}_e(\cdot)$ in (12), and the default asset allocation for new contributions, described in Section 3.1.5, change to those specified by the new employer.

3.1.5 Default Options and Adjustment Costs

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

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

$$\theta_{d,t}^j = \begin{cases} \overline{\theta}_e^j & \text{if } emp_t = JJ, \\ \theta_{t-1}^j & \text{else.} \end{cases} \tag{14}$$

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

$$\Theta_{d,t}^j = \begin{cases} \frac{A_{t-1}\Theta_{t-1}^j R_t^j + \mathcal{M}_e(s_{t-1}^{dc})\theta_{t-1}^j R_t^j}{A_{t-1}\sum_j \Theta_{t-1}^j R_t^j + \mathcal{M}_e(s_{t-1}^{dc})\sum_j \theta_{t-1}^j R_t^j} & \text{if } s_{t-1}^{dc} > 0, \\ \frac{A_{t-1}\Theta_{t-1}^j R_t^j}{A_{t-1}\sum_j \Theta_{t-1}^j R_t^j} & \text{else.} \end{cases} \tag{15}$$

Note that the specification embeds the assumption that when investors dis-save out of their DC account, they sell assets in proportion to their current portfolio allocations. The initial condition is $\Theta^j_{d,0} = 0$, since investors are born with no assets.

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

$$s_{d,t} = \begin{cases} \overline{s}^{dc}_e & \text{if } emp_t = JJ, \\ s^{dc}_{t-1} & \text{else.} \end{cases} \tag{16}$$

Adjustment costs. Investors in our model face adjustment costs in changing their asset allocations and savings contribution rates from the default option. Denote $\Xi_t = \left(\Theta^B_t, \Theta^S_t, \theta^B_t, \theta^S_t\right)$ as the vector of the portfolio allocations in the defined contribution account. If an investor chooses $\Xi_t \neq \Xi_{d,t}$, where

$$\Xi_{d,t} = \left(\Theta^B_{d,t}, \Theta^S_{d,t}, \theta^B_{d,t}, \theta^S_{d,t}\right),$$

she incurs a utility cost k_θ. This cost is designed to capture any (real or cognitive) costs associated with making portfolio choice decisions, such as the costs associated with reassessing investment options to deviate from the default allocation. Similarly, choosing $s^{dc}_t \neq s_{d,t}$ requires incurring a utility cost of k_s.

We choose to model these costs as adjustment costs rather than one-time fixed participation costs for two reasons. First, in each year, only 16% of the investors in our sample make an active decision to change the asset allocation of their retirement contributions, which suggests the presence of adjustment rather than one-time costs.[20] Second, adjustment costs are likely more relevant in the context of a retirement account. When investors change their portfolio allocation in a 401(k), the actions required are relatively similar regardless of whether they are doing this for the first time. In contrast, in a brokerage account, adjusting the portfolio for the first time likely requires incurring additional costs not present in subsequent periods, such as the costs of setting up the account.

3.1.6 Government

Unemployment benefits. Investors receive an unemployment benefit of $ui(\eta_t)$ when their employment ends. This benefit depends on the labor productivity, η_t, from the last period in which

[20]This estimate is close to Meeuwis, Parker, Schoar, and Simester (2022), who, in a similar setting, finds that only "20% of people in the sample have an investor-initiated trade over the year." We find that this adjustment probability increases with tenure, consistent with a state- rather than time-dependent models of portfolio adjustment.

the agent was employed.

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

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

Investors also pay Medicare premiums that are directly deducted from these social security benefits.

Taxation. Investors face a nonlinear income tax schedule $tax_i(\cdot)$, which depends on their taxable income y_t^{tax}:

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

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.[21] Capital gains in the liquid savings account are taxed at rate τ_c.

3.1.7 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, and $s_{d,t}$ = default contribution to the DC account. Using the fact that the portfolio shares sum to one, we can reduce this to a problem with 10 state variables by dropping the portfolio shares in the bond. Denote the vector of these state variables as X_t.

In this optimization problem, investors have 8 controls: c_t = consumption, $\Xi_t \in \mathbb{R}^4$ = portfolio shares, s_t^{dc} = defined contribution savings rate, d_t^{dc} = defined contribution withdrawal rate, and s_t^l = liquid savings. As above, this can be reduced to 5 controls given that the portfolio shares sum to one and that consumption is pinned down by the budget constraint. In choosing these controls, we restrict investors from borrowing and engaging in any margin trading (i.e., short-selling or taking

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

leveraged positions):

$$A_t \geq 0, \quad L_t \geq 0, \quad \Theta_t^j \in [0,1], \quad \theta_t^j \in [0,1], \quad \sum_j \Theta_t^j = \sum_j \theta_t^j = 1. \tag{17}$$

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

Retirement: $emp_t = Ret$**.** There are two sources of uncertainty when decisions are made at time t: mortality occurring with probability $= m_t$ and asset return shocks, ε_{t+1}. An investor's value function is thus characterized by the following recursive equation[22]:

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

subject to: (10), (11), (12), (14), (15), (17), and

$$s_t^l = ss_t - d_t^{dc} - c_t - tax_i(y_t^{tax}),$$
$$V(a_T, \cdot)^{1-\gamma} = 0,$$
$$s_t^{dc} = 0, \quad d_t^{dc} \geq 0.$$

Working life: $emp_t \in \{E, JJ\}$**.** There are five sources of uncertainty when decisions are made at time t: mortality occurring with probability $= m_t$; 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}; and the type of future employer after a job change, e. An investor's value function is thus characterized by the following recursive equation:

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

subject to: (7), (8), (10), (11), (12), (14), (15), (17), and

$$s_t^{dc} * w_t + s_t^l = w_t - c_t - tax_i(y_t^{tax}),$$
$$0 \leq s_t^{dc} \leq limit_{e,t}, \quad d_t^{dc} = 0.$$

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

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

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

subject to: (9), (10), (11), (14), (15), (16), (17), and

$$s_t^l = ui_t - c_t - d_t^{dc} * (1 - pen_{e,t}) - tax_i(y_t^{tax}),$$

$$s_t^{dc} = 0, \quad d_t^{dc} \geq 0.$$

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

3.2 Estimation

We estimate the model parameters in two stages. 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 D. The second stage consists of using the simulated method of moments to estimate the model's five preference parameters: the intertemporal discount factor (β), relative risk aversion (γ), elasticity of intertemporal substitution (σ^{-1}), and the two adjustment costs (k_θ and k_s).

3.2.1 First-Stage Parameter Estimation

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

Labor income process. We use data from the Survey of Income Programs and Participation (SIPP) to estimate parameters of the labor income process and transition probabilities at the annual frequency. This income process has several components. First, we estimate an earnings process for workers staying in the same job, corresponding to (7), which contains a deterministic and stochastic component. We allow for measurement error and use a standard two-step minimum distance approach (as in, e.g., Guvenen 2009). Our estimates (provided in Table A3) are consistent with those in prior literature. In particular, we estimate a relatively high persistence of permanent income shocks. Second, we use data on employment transitions from SIPP to estimate the median salary increase following a job-to-job transition, μ^{JJ}, and the median salary decrease when workers transition back to employment after an unemployment spell, $-\mu^{EU}$. Thirdly, we use SIPP microdata to estimate the three transition probabilities between the three labor market states. Finally, we set the initial unemployment rate equal to 22%, which is the share in SIPP of unemployed individuals at age 22, and calibrate average annual earnings to be $37,000, which matches the average net compensation per worker in the 2006 SSA National Average Wage Index.[23]

Assets returns. We set the net risk-free rate to be constant at 2% to match the annualized average return of the money market provided by our data provider after subtraction of the expense ratio.[24] We set the equity premium to be 6.4%, which is equal to the average inflation-adjusted return on the CRSP Value-Weighted Index between 1925 and 2006 minus our 2% risk-free rate.[25] We set the volatility of log stock returns to 20%, which matches that of the CRSP Value-Weighted Index. We assume that asset returns are uncorrelated with shocks to labor income and employment transition probabilities. We set the net return on the liquid asset, r, to be the same as the net risk-free rate.

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

Vesting schedule. If an investor separates from her employer before the end of the vesting period, she may lose part (or all) of the employer-matching contribution. To account for this, we adjust the level of the employer matching contribution to equal the certainty equivalent given 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.

Tax and benefit system. Investors' tax liability, $tax_i(\cdot)$, is calculated according to the 2006 U.S.

[23] We use 2006 as the reference year for the calibration because it is the first available year in our 401(k) dataset.

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

[25] We adjust for inflation using the CPI.

federal income tax schedule. We calculate Social Security benefits according to the 2006 formula with a Supplemental Security Income program floor. Unemployment benefits are computed with a replacement rate of 40%, which was the average across U.S. states as of 2018. During retirement, investors pay Medicare Part B and Part D premiums based on the 2006 Supplementary Medical Insurance formula. These Medicare payments are directly deducted from investors' Social Security benefits. We set the capital gains tax rate, τ_c, to 21%.

3.2.2 Identification of Second-Stage Preference Parameters

The five preference parameters in our model are jointly estimated using the Simulated Method of Moments (SMM). In what follows, we provide some intuition for which variation in the data helps identify the different parameters. While all parameters are jointly identified, certain moments are particularly sensitive to a given parameter.

Portfolio and contribution adjustment costs. We identify the size of the portfolio and contribution adjustment costs, k_θ and k_s, by targeting the level of bunching at the default options (at various tenure levels). If the portfolio adjustment cost is equal to zero, there would be no difference between the asset allocation of employees defaulted into the TDF and those defaulted into the money market fund (which is clearly rejected by Figure 2). Similarly, if the contribution adjustment cost is zero, there would be no bunching at the employer default contribution rate. On the other hand, if these adjustment costs are infinitely large, all individuals should remain at the default options assigned by their employers. Thus, the extent to which investors bunch at the allocation and contribution default options helps identify the size of these adjustment costs.

Risk preferences. Risk preferences in the model are governed by the coefficient of relative risk aversion, γ. Relative risk aversion is primarily identified from the asset allocation decisions of consistent investors who deviate from the default asset allocation. At the limit of extremely high risk aversion, we would expect investors in the treatment (i.e., TDF default) group to reduce their equity exposure despite the adjustment cost. Similarly, with low risk aversion, we would expect investors in the control group (i.e., money market) to increase their equity exposure.

Time preferences. Time preferences are governed by two parameters: β and σ. Separately identifying the intertemporal discount factor β and the EIS, σ^{-1}, is generally challenging because both parameters affect the level of saving. To identify the EIS, we exploit the discontinuity in the return to saving generated by the fact that employers match contributions up to a threshold (i.e., a 50% match up to 6% of salary in our sample). Because the EIS governs the sensitivity of savings to the interest rate, it is identified by the amount of bunching at the employer match threshold—the point at which the discontinuity in the return to savings occurs. This identification strategy is similar to Best, Cloyne, Ilzetzki, and Kleven (2020) and Choukhmane (2024). The overall level of retirement contributions identifies the level of intertemporal discounting β.

While our setting offers useful variation for identifying key preference parameters, an important limitation is that we don't observe wealth and equity held outside of retirement accounts. As a result, we view our results as applicable for the large share of households who keep most of their financial wealth inside retirement accounts and less applicable for other households (in particular, the wealthiest ones) that hold sizeable non-retirement financial wealth.[26]

3.2.3 Second-Stage Parameter Estimation

Empirical moments. We use 38 empirical moments in total. First, we use the stock market participation rates in the retirement account between tenures of 0 and 6 years for the control and treatment groups in our first quasi-experiment. This gives moments similar to those in Panel A of Figure 2, with the only difference being in this estimation that we restrict the sample to investors between ages 24 and 62. Second, we use two life cycle profiles of average unconditional stock shares: one for those defaulted into the money market fund and another for those defaulted into the target date fund. Both of these life cycle profiles are calculated at the end of workers' first years of tenure, conditional on workers having a positive balance in the account. We construct these profiles from ages 24 to 62 in bins of 5, giving 8 bins per profile for a total of 8×2=16 moments. The final set of moments that we use is the distribution of contribution rates among investors in our sample during their first year of tenure. Specifically, we use the 34 401(k) plans in our sample for which the exact date of auto-enrollment is available that have a 3% initial auto-enrollment default contribution rate with no auto-escalation feature and a 50% employer match contribution of up to 6% of income, which matches the structure of the 401(k) plans in our model exactly. We then calculate the fraction of workers who, during their first year of tenure, contribute one of the following four fractions of their income: 0%, 3%, 6%, or 10% and above. We do this for two samples of investors: investors hired under the opt-in regime within 12 months prior to the change to auto-enrollment and investors hired within 12 months after the change. This gives us a total of 4×2=8 moments, which help identify time preferences and the contribution adjustment cost.

Model simulation experiments. To estimate our five preference parameters using SMM, we

[26] Among those eligible to contribute to a retirement account in the SCF 2007 to 2016 waves, these accounts represent on average 85% (99.5% at the median) of households' holdings of financial investment products (see Table A1).

construct moments from our model that are analogous to the 38 empirical moments that we discussed above. We do this by running the following simulation exercises designed to match our empirical variation as closely as possible. First, we simulate income processes for 7,500 investors (approximately 5 times our sample size). Next, for each investor i, we randomly select a period $t = \tau_i$ in which the investor transitions into a new job, either out of unemployment or following a job-to-job transition. Prior to τ_i, all employers are subject to the same opt-in enrollment regime with a zero default contribution rate $\bar{s}_e^{dc} = 0\%$ and zero-equity default asset allocation $\overline{\theta}_e^S = 0$. We simulate this investor's choices up to τ_i under this regime. Finally, starting from period τ_i, we simulate investor i under three (unexpected) scenarios about her new job retirement plan:

1. *Opt-in Regime:* no change in the default options $\bar{s}_e^{dc} = 0\%$ and $\overline{\theta}_e^S = 0$
2. *Money Market Default:* auto-enrollment with $\bar{s}_e^{dc} = 3\%$ and $\overline{\theta}_e^S = 0$
3. *TDF-like Default:* auto-enrollment with $\bar{s}_e^{dc} = 3\%$ and an age-dependent default allocation $\overline{\theta}_e^S = G^\theta(t)$, where $G^\theta(t)$ is set to match the glide-path of the TDF in our data

The model was solved under each of these three regimes first, and the change in regime at τ_i is unexpected. We do not model the fact a TDF automatically reduces the equity exposure as the investor ages.[27]

Model moments. Using simulated data for the *current* employer retirement account across the "Money Market Default" and "TDF-like Default" scenarios, we calculate the share with a positive equity share by tenure (14 moments) and the average unconditional stock share by age at the end of the first year of tenure (16 moments). Similarly, we compute the distribution of contribution rates in the first at $t = \tau_i$ in the "Opt-in Regime" and the "TDF-like Default" simulations (8 moments).

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

[27] Modeling this feature of TDFs requires introducing two additional choice and state variables (one for new and one for existing assets), which we avoid doing for computational reasons. However, for the length of a typical employment spell—which only lasts a few years on average—the TDF glide path is either flat (for younger employees) or declines modestly. Furthermore, in the estimation, we only target portfolio choices for six years following the change in the default asset allocation, over which the glide path's change in equity exposure is small.

3.3 Estimation Results

Column (1) of Table 3 presents the results from our baseline estimation. Our estimate of the (annualized) discount factor is $\beta = 0.94$. This estimate is slightly lower than existing estimates that target life cycle consumption–savings profiles (e.g., Gourinchas and Parker 2002). However, our estimate is higher than estimates from the literature on life cycle portfolio choice, which typically needs a lower value to slow down the decline in the human-to-financial wealth ratio with age to match the relatively low average equity shares. Column (1) also shows that our estimate of relative risk aversion is 2.54, which is lower than typical estimates in existing literature. We estimate a value of the EIS of approximately 0.25, which is consistent with typical estimates in other settings (see Havránek 2015, for a meta-analysis).

Consistent with the presence of frictions impacting portfolio decisions, we estimate a positive portfolio adjustment cost of $156, which is necessary to explain investors' tendency to stick with the default asset allocation. This estimate is relatively modest in comparison to typical values of participation costs in life cycle portfolio choice models (e.g., Gomes 2020; Catherine 2022). Finally, we estimate a contribution adjustment cost of $488. This contribution cost is larger than the portfolio adjustment cost, which suggests that investors' non-participation in stocks may also be influenced by frictions associated with opting-in and opening a defined contribution savings account.[28].

Figure 9 shows how our model fits the first quasi-experiment in Panel A of Figure 2, which was targeted in the estimation. The model fits the targeted variation in investors' portfolio choices on the extensive margin relatively well across both default options. The portfolio adjustment cost allows us to match investors' tendency to slowly rebalance into stocks when the default has no stock market exposure, which most investors prefer, given our relatively low estimate of risk aversion. Additionally, the portfolio adjustment cost coupled with our estimate of risk aversion means that relatively few investors rebalance out of stocks when the default asset has stock market exposure.

In Figure 10, we show that our model also fits investors' portfolio choices on the *intensive* margin well. Our model replicates the tendency for investors in the control group to increase their equity exposure while most investors in the treatment group stick with their TDF default. In our model, the latter result is driven by the fact that investors' preferred stock shares are relatively close to the share in a TDF, so it is not worth the adjustment cost to only slightly improve the portfolio allocation. In contrast, for the control group, the default allocation with 0% equity is far enough

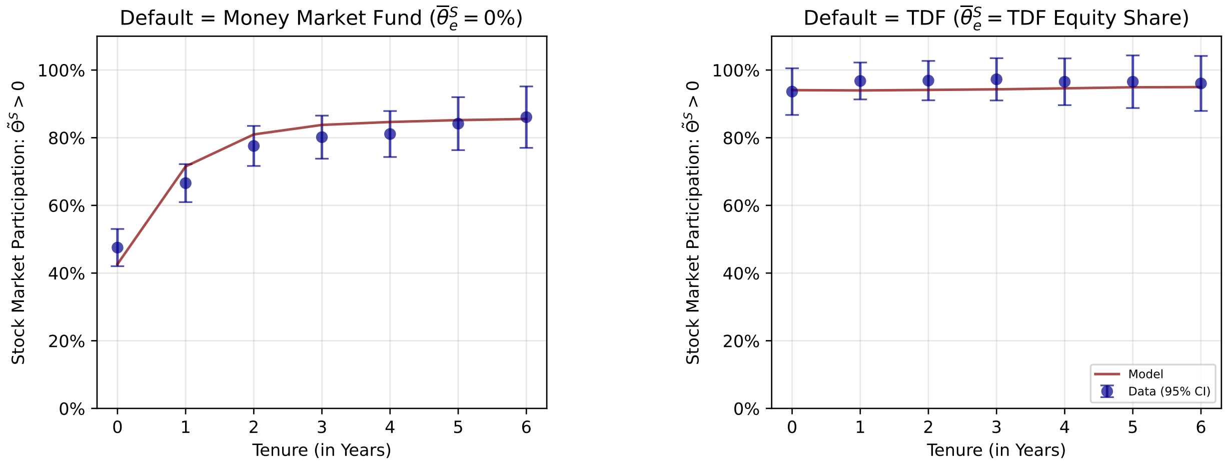
[28]Our estimate is larger than Choukhmane (2024) possibly because the value of participating in a retirement account is larger in our model due to the equity premium.

Table 3. Second-Stage SMM Preference Parameter Estimates

		Estimation			
Preference Parameter		(1)	(2)	(3)	(4)
Discount Factor	β	0.940	0.934	0.791	0.960
		(0.001)	(0.001)	(0.004)	(0.001)
Relative Risk Aversion	γ	2.54	2.81	18.94	2.25
		(0.09)	(0.017)	(0.246)	(0.123)
Elasticity of Intertemporal Substitution	σ^{-1}	0.253	·	0.481	0.513
		(0.018)	·	(0.012)	(0.040)
Portfolio Adjustment Cost	k_θ	\$156	\$194		
		(\$6.01)	(\$3.90)	·	·
Contribution Adjustment Cost	k_s	\$488	\$522		
		(\$16.60)	(\$26.00)	·	·
Model Specification					
Preference Specification		EZW	CRRA	EZW	EZW
No Adjustment Costs				✓	✓
Moments Targeted					
Participation (MM Default)		✓	✓	✓	
Participation (TDF Default)		✓	✓		✓
Equity Share by Age (MM Default)		✓	✓	✓	
Equity Share by Age (TDF Default)		✓	✓		✓
Contribution Rates (Opt-In)		✓	✓	✓	
Contribution Rates (AE at 3%)		✓	✓		✓
Total Number of Moments		38	38	19	19

Notes: This table shows the results from different second-stage simulated method of moments estimations, each in separate columns. The upper half of the table shows our preference parameter estimates along with standard errors. Missing values in different columns indicate that the parameter values were restricted in estimation. The bottom half shows the different preference specifications that we employ, where Epstein–Zin–Weil is denoted by EZW and the special case of $\gamma = \sigma^{-1}$ is denoted by CRRA, in addition to the different moments that we target. In columns (3) and (4), we restrict the adjustment costs to be equal to zero. All estimations are performed with the optimal weighting matrix. For additional details on this second-stage estimation, see Appendix E.

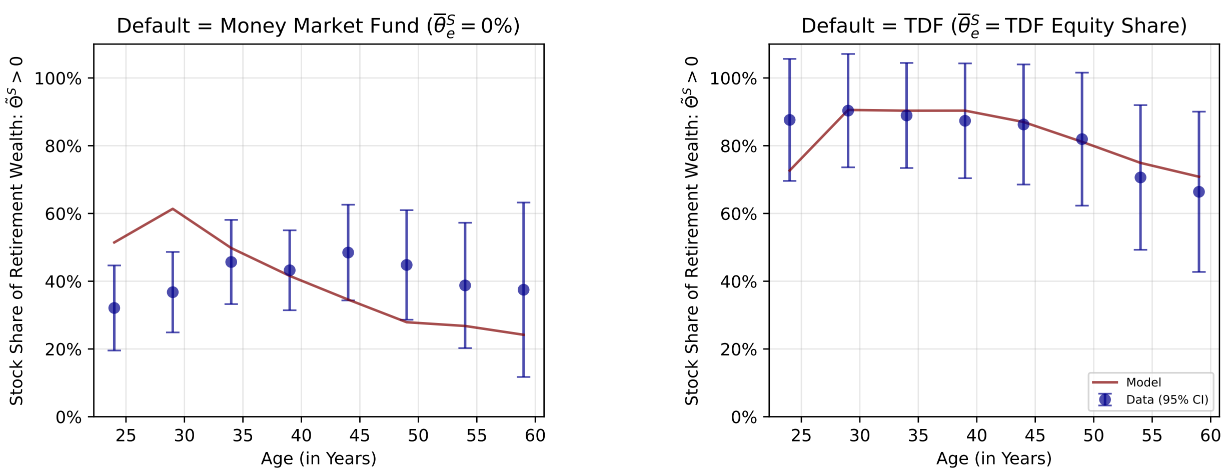
Figure 9. Model Fit: Stock Market Participation in 401(k) from Quasi-Experiment #1



Notes: This figure presents the fit of our model on the response of stock market participation within the current employer retirement account for our first quasi-experiment. The data moments in this figure correspond to the moments from our first quasi-experiment in the left half of Figure 2 Panel A for the first six years of tenure, along with the 95% confidence intervals. The model moments are from a simulation of this experiment within the model described in the main text at our SMM estimates of preference parameters reported in column (1) of Table 3.

from their preferred allocation that many choose to incur the adjustment cost and increase their equity share.

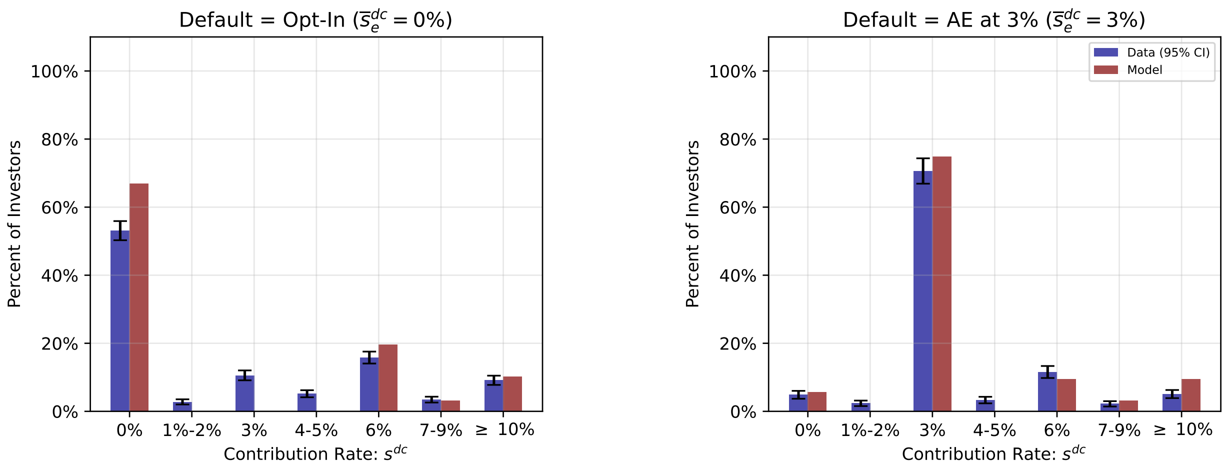
Figure 10. Model Fit: Stock Shares by Age in First Year of Tenure



Notes: This figure presents the fit of our model on the age profile of equity shares within the current employer retirement account separately for the treatment and control groups in our first quasi-experiment. The data moments are calculated on the same sample that is used in Figure 2 and are shown with their 95% confidence intervals. The model moments are from a simulation of this experiment within the model described in the main text at our SMM estimates of the preference parameters reported in column (1) of Table 3.

In Figure 11, we show the model also provides a reasonable fit to the distribution of contribution rates. These moments help identify investors' time preferences and the contribution adjustment

Figure 11. Model Fit: Contribution Rates in First Year of Tenure



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

cost. First, our model reproduces the bunching at the 3% default contribution rate, which is key for the identification of the contribution adjustment cost. Second, the model replicates the tendency of investors to bunch at the 6% cap on employer matching—which is key for the identification of the EIS. Finally, the model matches the average level of contributions—an important target for the intertemporal discount factor— but tends to fail at generating investors deviating from the default savings rate by a small amount.[29]

Comparison with the Survey of Consumer Finances (SCF). We compare nontargeted moments from our baseline model to those in the SCF among respondents eligible for an employer-sponsored retirement savings account. Figure A18 shows that financial wealth accumulation by age in the baseline model is similar to that observed in the SCF at the 25th, 50th, and 75th percentiles. Figure A19 shows that, as in the SCF, the baseline model generates stock market participation rates that increase with age and income. However, the level of stock market participation is higher in the model than in the SCF, which is consistent with the fact that stock market participation in our administrative 401(k) data is higher than in the SCF (Figure 7). The conditional equity share of total wealth is also significantly higher in the model than in the SCF, especially at older ages.[30]

[29] With homogeneous preferences and a fixed adjustment cost, the s-S inaction region is too large for individuals to choose small deviations from the default.

[30] There are several potential explanations for this discrepancy. First, our estimation sample captures a different population from the SCF. Second, the SCF, which relies on survey responses, might underestimate equity shares relative to administrative 401(k) data as discussed by Parker et al. (2023a). Consistent with the view that surveys might

3.4 Separating Risk Aversion and the EIS

A unique feature of our setting is our ability to separately identify both risk aversion (γ) and intertemporal substitution (σ^{-1}) in the presence of choice frictions: (i) we use the asset allocation decisions to identify risk aversion, (ii) bunching at employer matching threshold to identify intertemporal substitution, and (iii) bunching at the default options to identify the size of the frictions. In column (2) of Table 3, we perform the same estimation as in the previous section but restrict to time-separable preferences by imposing $\sigma = 1/\gamma$. In this case, our estimate of risk aversion, which is now also the inverse elasticity of substitution, is 2.81—slightly higher than the estimate in column (1). Nevertheless, Figures A20 to A22 shows that the fit of this model is almost as good. We thus conclude that, in our setting, imposing $\sigma = 1/\gamma$ (as with CRRA utility) provides a good description of investors' risk preferences.

3.5 The Role of Choice Frictions

The key contribution of our identification strategy is to use the behavior of investors in the treatment and control groups to identify structural preference parameters in the presence of choice frictions. We conclude by showing how our inferences about investors' preferences change if we abstract from choice frictions.

In particular, we estimate our model with zero adjustment costs using two subsets of the data. First, column (3) uses the stock market participation rates by tenure and life cycle profile of equity shares among individuals in the money market default and contribution rates under an opt-in regime. This corresponds to the retirement savings environment that most retirement investors faced prior to the 2006 Pension Protection Act and that many still face. As shown in column (3), we estimate a much higher risk aversion of 18.94 relative to our baseline estimate of 2.54 in column (1). This is because, without frictions, a higher value of risk aversion is needed to match the relatively low stock market participation rates and stock shares under the opt-in regime. These results suggest that other features of the model or calibration do not drive the moderate level of risk aversion in our baseline estimation.

Our second estimation is shown in column (4), which uses the choices of investors with a TDF

underestimate stock-market participation through DC plans, Dushi and Iams (2010) found that 24% of private-sector and 36% of public-sector respondents to the 2006 Survey of Income and Program Participation (SIPP) misreported making a tax-deferred DC contribution relative to their W2 records (with false negatives being most common). Finally, the model may be missing features of the savings and investing environment outside of retirement accounts that could explain why the simulated conditional equity shares differ from those observed in the SCF.

default and auto-enrollment at 3%, corresponding to the retirement savings environment that an increasing number of employees are facing today. In contrast to the results in column (3), we estimate a much lower level of risk aversion of approximately 2.25. This difference from column (3) is striking because these two subsets of the data are drawn from a very similar population (employees in the same firms, hired within 12 months a change in the 401(k) default options).

The results in columns (3) and (4) highlight the importance of considering both portfolio and contribution adjustment costs when estimating investors' preferences. Omitting these choice frictions leads to very different estimates of risk preferences depending on the data used to estimate the model: extremely high levels of risk aversion for employees hired under a money market default and much lower levels of risk aversion for those hired after the switch to a TDF default. As the retirement savings environment shifts towards widespread adoption of auto-enrollment with a TDF default investment fund, these findings suggest retirement investors will appear less risk-averse through the lens of frictionless models even if their underlying risk attitudes have not changed.

4 Conclusion

Much of the life cycle portfolio choice literature has been interested in explaining two empirical patterns: the low level of stock market participation and the age profile of equity shares. A variety of explanations, both rational and behavioral, have been presented to reconcile these empirical patterns with models of portfolio choice. Often these explanations consist of augmenting the canonical model with features that generate a preference for holding safe assets, such as first-order risk aversion, background risk, or pessimistic beliefs. Implicit in these explanations is the assumption that investors' observed choices accurately reflect their underlying preferences and beliefs.

This paper shows that, in the context of retirement accounts, these empirical patterns are primarily explained by frictions, such as fixed adjustment and participation costs. These frictions drive a large wedge between investors' observed choices and their underlying portfolio preferences. Absent such frictions, we estimate that the preferred asset allocation of retirement investors broadly aligns with canonical models of portfolio choice: stock market participation is high throughout the life cycle (over 90%) and the preferred equity share declines with age.

References

Abel, Andrew B., Janice Eberly, and Stavros Panageas (2013), "Optimal Inattention to the Stock Market With Information Costs and Transactions Costs." *Econometrica*, 81, 1455–1481.

Alan, Sule (2006), "Entry costs and stock market participation over the life cycle." *Review of Economic Dynamics*, 9, 588–611.

Allcott, Hunt and Dmitry Taubinsky (2015), "Evaluating behaviorally motivated policy: Experimental evidence from the lightbulb market." *American Economic Review*, 105, 2501–2538.

Ameriks, John and Stephen P Zeldes (2004), "How Do Household Portfolio Shares Vary With Age?" *Working Paper*.

Andersen, Steffen and Kasper Meisner Nielsen (2011), "Participation constraints in the stock market: Evidence from unexpected inheritance due to sudden death." *Review of Financial Studies*, 24, 1667–1697.

Angrist, Joshua D. and J. Pischke (2008), *Mostly Harmless Econometrics*. Princeton University Press, Princeton, NJ.

Arnoud, Antoine, Taha Choukhmane, Jorge Colmenares, Cormac O'Dea, and Aneesha Parvathaneni (2021), "The Evolution of US Firms' Retirement Plan Offerings: Evidence from a New Panel Data Set." *Working Paper*.

Barberis, Nicholas, Ming Huang, and Richard H. Thaler (2006), "Individual preferences, monetary gambles, and stock market participation: A case for narrow framing." *American Economic Review*, 96, 1069–1090.

Benzoni, Luca, Pierre Collin-Dufresne, and Robert S. Goldstein (2007), "Portfolio choice over the life-cycle when the stock and labor markets are cointegrated." *Journal of Finance*, 62, 2123–2167.

Bernheim, B. Douglas and Antonio Rangel (2009), "Beyond revealed preference: choice-theoretic foundations for behavioral welfare economics." *Quarterly Journal of Economics*, 124, 51–104.

Beshears, John, James J. Choi, David Laibson, and Brigitte C. Madrian (2008), "How are preferences revealed?" *Journal of Public Economics*, 92, 1787–1794.

Best, Michael Carlos, James S Cloyne, Ethan Ilzetzki, and Henrik J Kleven (2020), "Estimating the Elasticity of Intertemporal Substitution Using Mortgage Notches." *The Review of Economic Studies*, 87(2), 656–690.

Bommier, Antoine, Asen Kochov, and François Le Grand (2017), "On Monotone Recursive Preferences." *Econometrica*, 85, 1433–1466.

Briggs, Joseph, David Cesarini, Erik Lindqvist, and Robert Östling (2021), "Windfall gains and stock market participation." *Journal of Financial Economics*, 139, 57–83.

Campanale, Claudio, Carolina Fugazza, and Francisco J. Gomes (2015), "Life-cycle portfolio choice with liquid and illiquid financial assets." *Journal of Monetary Economics*, 71, 67–83.

Campbell, John Y. and Luis M. Viceira (2001), *Strategic Asset Allocation: Portfolio Choice for Long-Term Investors*.

Carroll, Christopher D (2024), "Solution methods for microeconomic dynamic stochastic optimization problems." *Working Paper*.

Catherine, Sylvain (2022), "Countercyclical Income Risk and Portfolio Choices over the Life-Cycle." *Review of Financial Studies*, 35, 4016–4054.

Chapman, David A. and Valery Polkovnichenko (2009), "First-Order risk aversion, heterogeneity, and asset market outcomes." *Journal of Finance*, 64, 1863–1887.

Choukhmane, Taha (2024), "Default Options and Retirement Saving Dynamics." *Working Paper*, 1–78.

Cocco, João F., Francisco J. Gomes, and Pascal J. Maenhout (2005), "Consumption and portfolio choice over the life cycle." *Review of Financial Studies*, 18, 491–533.

Deaton, Angus S and Christina H Paxson (1994), "Saving, Growth, and Aging in Taiwan." *Working Paper*.

Duarte, Victor, Julia Fonseca, Jonathan A. Parker, and Aaron Goodman (2022), "Simple Allocation Rules and Optimal Portfolio Choice Over the Lifecycle." *Working Paper*.

Duffie, Darrell and Kenneth J. Singleton (1993), "Simulated Moments Estimation of Markov Models of Asset Prices." *Econometrica*, 61(4).

Dushi, Irena and Howard M Iams (2010), "The impact of response error on participation rates and contributions to defined contribution pension plans." *Soc. Sec. Bull.*, 70, 45.

Enke, Benjamin and Thomas Graeber (2023), "Cognitive Uncertainty." *The Quarterly Journal of Economics*, 138, 2021–2067.

Epstein, Larry and Tan Wang (1994), "Intertemporal Asset Pricing under Knightian Uncertainty." *Econometrica*, 62, 283–322.

Epstein, Larry G. and Stanley E. Zin (1989), "Substitution, Risk Aversion, and the Temporal Behavior of Consumption and Asset Returns: A Theoretical Framework." *Econometrica*, 57, 937–963.

Erickson, Timothy and Toni M. Whited (2002), "Two-Step GMM Estimation of the Error-in-Variables Model Using High-Order Moments." *Econometric Theory*, 18, 776–799.

Fagereng, Andreas, Charles Gottlieb, and Luigi Guiso (2017), "Asset Market Participation and Portfolio Choice over the Life-Cycle." *Journal of Finance*, 72, 705–750.

Fagereng, Andreas, Luigi Guiso, and Marius Ring (2024), "How much and how fast do investors respond to equity premium changes? evidence from wealth taxation." *Working Paper*.

Gabaix, Xavier (2019), "Behavioral inattention." *Handbook of Behavioral Economics*, 2, 261–343.

Galaasen, Sigurd Molster and Akash Raja (2024), "The Dynamics of Stock Market Participation." *Working Paper*.

Goldin, Jacob and Daniel Reck (2020), "Revealed-preference analysis with framing effects." *Journal of Political Economy*, 128, 2759–2795.

Gomes, Francisco J. (2005), "Portfolio choice and trading volume with loss-averse investors." *Journal of Business*, 78, 675–706.

Gomes, Francisco J. (2020), "Portfolio Choice over the Life Cycle: A Survey." *Annual Review of Financial Economics*, 12, 277–304.

Gomes, Francisco J., Michael Haliassos, and Tarun Ramadorai (2021), "Household Finance." *Journal of Economic Literature*, 59, 919–1000.

Gomes, Francisco J., Alexander Michaelides, and Yuxin Zhang (2022), "Tactical Target Date Funds." *Management Science*, 68, 2377–3174.

Gomes, Francisco J. and Oksana Smirnova (2022), "Stock Market Participation and Portfolio Shares Over the Life-Cycle." *SSRN Electronic Journal*, 1–84.

Gourinchas, Pierre Olivier and Jonathan A. Parker (2002), "Consumption over the life cycle." *Econometrica*, 70, 47–89.

Guiso, Luigi, Paola Sapienza, and Luigi Zingales (2008), "Trusting the stock market." *Journal of Finance*, 63, 2557–2600.

Guvenen, Fatih (2009), "An empirical investigation of labor income processes." *Review of Economic dynamics*, 12, 58–79.

Guvenen, Fatih, Fatih Karahan, Serdar Ozkan, and Jae Song (2021), "What Do Data on Millions of U.S. Workers Reveal About Lifecycle Earnings Dynamics?" *Econometrica*, 89, 2303–2339.

Havránek, Tomáš (2015), "Measuring intertemporal substitution: The importance of method choices and selective reporting." *Journal of the European Economic Association*, 13, 1180–1204.

Horowitz, Joel L. (2001), "The Bootstrap." *Handbook of Econometrics*, 5, 3159–3228.

Huggett, Mark and Greg Kaplan (2016), "How large is the stock component of human capital?" *Review of Economic Dynamics*, 22, 21–51.

Judd, Kenneth L. (1998), *Numerical Methods in Economics*. MIT Press.

Low, Hamish, Costas Meghir, and Luigi Pistaferri (2010), "Wage risk and employment risk over the life cycle." *American Economic Review*, 100, 1432–67.

Lusardi, Annamaria, Pierre Carl Michaud, and Olivia S. Mitchell (2017), "Optimal financial knowledge and wealth inequality." *Journal of Political Economy*, 125, 431–477.

Madrian, Brigitte C. and Dennis F. Shea (2001), "The Power of Suggestion: Inertia in 401(k) Participation and Savings Behavior." *The Quarterly Journal of Economics*, 116, 1149–1187.

Masatlioglu, Yusufcan and Efe A Ok (2005), "Rational choice with status quo bias." *Journal of Economic Theory*, 121, 1–29.

Massa, Massimo, Rabih Moussawi, and Andrei Simonov (2021), "The Unintended Consequences of Investing for the Long Run: Evidence from Target Date Funds." *Working Paper*.

McDonald, Robert, David Richardson, and Thomas Rietz (2021), "Investment defaults and retirement savings allocations." *Working Paper*.

McFadden, Daniel (1989), "A Method of Simulated Moments for Estimation of Discrete Response Models Without Numerical Integration." *Econometrica*, 57, 995–1026.

Meeuwis, Maarten (2022), "Wealth Fluctuations and Risk Preferences: Evidence from U.S. Investor Portfolios." *Working Paper*.

Meeuwis, Maarten, Jonathan A. Parker, Antoinette Schoar, and Duncan Simester (2022), "Belief Disagreement and Portfolio Choice." *Journal of Finance*, 77, 3191–3247.

Merton, Robert C. (1969), "Lifetime Portfolio Selection under Uncertainty: The Continuous-Time Case." *Review of Economics and Statistics*, 51, 247–257.

Mitchell, Olivia S. and Stephen P. Utkus (2022), "Target Date Funds and Portfolio Choice in 401(k) Plans." *Journal of Pension Economics and Finance*, 21, 519–536.

Myers, Elizabeth A. and John J. Topoleski (2021), "Worker participation in employer-sponsored pensions: Data in brief." Technical report, Congressional Research Services.

Newey, Whitney K. and Daniel McFadden (1994), "Large Sample Estimation and Hypothesis Testing." *Handbook of Econometrics*, 4, 2111–2245.

Pagel, Michaela (2018), "A News-Utility Theory for Inattention and Delegation in Portfolio Choice." *Econometrica*, 86, 491–522.

Parker, Jonathan A., Antoinette Schoar, Allison T. Cole, and Duncan Simester (2023a), "Household Portfolios and Retirement Saving over the Life Cycle." *Working Paper*.

Parker, Jonathan A., Antoinette Schoar, and Yang Sun (2023b), "Retail Financial Innovation and Stock Market Dynamics : The Case of Target Date Funds." *Journal of Finance*, 78, 2673–2723.

Rabin, Matthew (2000), "Risk Aversion and Expected Utility Theory: A Calibration Theorem." *Econometrica*, 68, 1281–1292.

Tauchen, George (1986), "Finite state markov-chain approximations to univariate and vector autoregressions." *Economics letters*, 20, 177–181.

Vissing-Jørgensen, Annette (2002), "Limited asset market participation and the elasticity of intertemporal substitution." *Journal of Political Economy*, 110, 825–853.

Weil, P. (1990), "Nonexpected Utility in Macroeconomics." *Quarterly Journal of Economics*, 105, 29–42.

Zhang, Adam (2023), "Before and After Target Date Investing: The General Equilibrium Implications of Retirement Savings Dynamics." *Working Paper*.

INTERNET APPENDIX

This internet appendix contains the following additional materials.

- Appendix A: Table of parameters for the life cycle model presented in Section 3.
- Appendix B: Additional details, proofs, and derivations of results in Section 2.
- Appendix C: Details on solution algorithm for the model presented in Section 3.
- Appendix D: Details on first stage estimation of the model presented in Section 3.
- Appendix E: Details on second stage estimation procedure for the model in Section 3.
- Appendix F: Additional figures and tables referenced in the main text and this appendix.

Appendix A. Life Cycle Model Parameters

	Preferences
β	Discount factor
σ^{-1}, γ	EIS and RRA
k_s	Contribution adjustment cost
k_θ	Portfolio adjustment cost
$V(\cdot)$	Value function
	State Variables
X	Vector of all state variables
a	Age
emp	Employment status
ten	Tenure
L	Liquid assets
A	DC wealth stock
A^e	Current employer DC wealth
A^p	Legacy DC wealth
ae	Average lifetime earnings
η	Labor productivity
e	Employer DC plan type
s_d	Default contribution rate
Θ_d	Default allocation existing funds
θ_d	Default allocation new contributions
	Choices
c	Consumption
s^{dc}, d^c	DC contribution and withdrawal rates
s^l	Savings in liquid assets
Θ	Asset allocation for existing funds
θ	Asset allocation for new contributions
	Defined Contribution Account
$\overline{\theta}_e^j$	Employer-specified default asset allocation
$\overline{s}_e^{dc}$	Employer-specified default contribution rate
$\mathcal{M}_e(\,)$	Employer DC matching function
$match_e$	Employer matching rate
cap_e	Threshold on employer matching
$\Upsilon_e(\cdot)$	Vesting risk-adjustment
t_J	Period of last job transition
$\tilde{\Theta}$	Asset allocation for wealth with current employer
	Assets
$1+r$	Rate of return on liquid assets
R_f	Risk-free rate
$R^S(\cdot)$	Return on risky assets
μ_s	Log-risk premium
σ_s^2	Variance of log risky asset returns
	Labor Market
$\pi^{JJ}(\cdot)$	Job-to-job transition probability
$\pi^{EU}(\cdot)$	Unemployment transition probability
$\pi^{UE}(\cdot)$	Out-of-unemployment transition probability
$\{\delta_i\}_{i=0}^3$	Deterministic component of earnings
w	Labor earnings
ρ	Autocorrelation in earnings shocks
ξ	Earnings innovation if continuously employed
$\sigma_{\xi_0}^2$	Variance of the first earnings innovation
σ_ξ^2	Variance of subsequent innovations
ξ^{JJ}	Earnings innovation after job-to-job transition
μ^{JJ}	Avg. wage gain after a job-to-job transition
ξ^U	Earnings innovation out of unemployment
μ^{UE}	Avg. wage loss out of unemployment
ι	Measurement error in earnings
σ_ι^2	Variance of measurement error
ϕ	Earnings innovation plus measurement error
	Demographics
T	Maximum years of life
T_w	Number of working years
m_t	Mortality risk
n_t	Equivalence scale
	Tax and Benefit System
$tax_i(\cdot)$	Tax on income
$limit_a$	Tax limit on DC contributions
pen_a	Tax penalty of early DC withdrawals
$ui(\cdot)$	Unemployment insurance benefit
$ss(\cdot)$	Public pension income
τ_c	Capital gains tax in liquid account

Appendix B. Proofs of Non-Parametric Identification Results

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 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. □

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 (4). An identical argument follows for stock shares. Finally, (2) and (3) follow from applying the following identity that holds for any pair of random variables V and W such that W is binary:

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

$\square$

Appendix C. Model Solution Details

Discretization of state variables. We have eight continuous state variables that need to be placed onto grids: labor productivity, tenure, average lifetime income, DC retirement wealth, liquid wealth, two default portfolio shares, and the default contribution rate. We discretize labor productivity following Tauchen (1986) using 5 grid points. We place tenure on a grid with 3 components (i.e., 1 year of tenure, 2 years of tenure, and 3+ years of tenure). We place average lifetime income on a grid with 5 points. We then place liquid assets and retirement assets on grids with 15 points during working life and 30 points during retirement. These wealth grids are spaced according to a power function, where the gaps increase as the values of the variables increase. We place the default portfolio shares and contribution rates on the grids that we choose below for the corresponding choices of each variable. Our grids for these continuous state variables and the choice variables described below are relatively coarse. We have experimented with grids that are 2 times larger in each dimension and found that our moments used for estimation changed by no more than an average of 0.95%.[31]

Discretization of choice variables. We have 4 continuous choice variables. Contribution rates to the retirement accounts are (round) percentages of wage income, between 0% and 15%. When agents are unemployed, they can withdraw a percentage $-s_t^{dc}$ of their retirement balance from a grid with 10 elements ranging from 0% to 100% of their retirement balance. When agents are retired, we choose an evenly spaced grid with 30 grid points between zero and negative one. Stock shares are bounded between 0% and 100% and the grid points are multiples of 10%. We choose to place these choice variables on a grid because the portfolio and savings choices of investors in our sample generally correspond to a round number that is included in these grids. Consumption (or equivalently liquid savings) is not placed on a grid and we use a standard golden-section search to find its policy function.

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

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

the Epstein-Zin-Weil value function is linear in wealth (Merton 1969). In our quantitative model, this value function is approximately linear above low values of liquid wealth, where borrowing constraints don't bind. We thus choose to interpolate using linear interpolation, which provides very good accuracy despite coarse grids due to the approximate linearity of the value function.[32] To integrate over the distribution of stock returns, we use a Gauss-Hermite quadrature with 6 nodes.

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

[32] See Carroll (2024) for additional details, which shows quasi-linear interpolation substantially reduces approximation error with CRRA preferences. The quasi-linear transformation suggested by Carroll (2024) is equivalently the transformation between an Epstein-Zin and CRRA value function in the case when $\gamma = \sigma$.

Appendix D. First-Stage Estimation Details

D.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.

D.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 (18). It depends on both the cumulative job-separation probability and the vesting schedule. It is smaller than one and increasing in tenure before the end of the vesting period, and equal to one afterward. Importantly, this specification captures the fact that vesting matters more for investors who—based on their age and tenure—are more likely to separate from their employer.

$$\Upsilon_e(t,ten) = 1 - \sum_{j=0}^{T^R-t}\left(\prod_{k=1}^{j-1}\left(1-\pi^{EU}_{t+k,ten+k}-\pi^{JJ}_{t+k,ten+k}\right)\right)\left(\pi^{EU}_{t+j,ten+j}+\pi^{JJ}_{t+j,ten+j}\right)\left(1-vst_e(ten+j)\right) \tag{18}$$

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 (2024). 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.

D.3 Taxes and Benefit System

Income taxation. 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 $\left\{\tilde{\kappa}^\tau_i\right\}_{i=1}^5 = \{\$5,150;\$7,550;\$30,650;\$74,200;\$154,800\}$.[33] Quarterly tax brackets are defined as: $\kappa^\tau_i = \frac{1}{4}\tilde{\kappa}^\tau_i$. The quarterly income tax liability is given in the following equation, which we aggregate to an annual frequency by multiplying by four.

$$tax^i_t = \begin{cases} 0 & if\, y^{tax} \le \kappa^\tau_1 \\ 0.10\,(y^{tax}-\kappa^\tau_1) & if\, \kappa^\tau_2 \ge y^{tax} > \kappa^\tau_1 \\ 0.10\,(\kappa^\tau_2-\kappa^\tau_1)+0.15\,(y^{tax}-\kappa^\tau_2) & if\, \kappa^\tau_3 \ge y^{tax} > \kappa^\tau_2 \\ 0.10\,(\kappa^\tau_2-\kappa^\tau_1)+0.15\left(\kappa^\tau_3-\kappa^\tau_2\right)+0.25\left(y^{tax}-\kappa^\tau_3\right) & if\, \kappa^\tau_4 \ge y^{tax} > \kappa^\tau_3 \\ 0.10\,(\kappa^\tau_2-\kappa^\tau_1)+0.15\left(\kappa^\tau_3-\kappa^\tau_2\right)+0.25\left(\kappa^\tau_4-\kappa^\tau_3\right)+0.28\,(y^{tax}-\kappa^\tau_4) & if\, \kappa^\tau_5 \ge y^{tax} > \kappa^\tau_4 \\ 0.10\,(\kappa^\tau_2-\kappa^\tau_1)+0.15\left(\kappa^\tau_3-\kappa^\tau_2\right)+0.25\left(\kappa^\tau_4-\kappa^\tau_3\right)+0.28\left(\kappa^\tau_5-\kappa^\tau_4\right)+0.33\left(y^{tax}-\kappa^\tau_5\right) & if\, y^{tax} > \kappa^\tau_5 \end{cases}$$

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 Sup-

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

plemental Security Income program (with a monthly benefit $si = \$603$). Annual public pension benefits are equal to:

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

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

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

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[34]

D.4 Labor Market Parameters

We estimate our labor market parameters using the same data and estimation procedure as in Choukhmane (2024), 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 (19), which is the empirical counterpart of the model earning process in equation (7) with one additional term: serially uncorrelated measurement error $\iota_{i,t} \sim N\left(0, \sigma_\iota^2\right)$.

$$\ln w_{i,t} = \delta_0 + \delta_1 a_{i,t} + \delta_2 a_{i,t}^2 + \delta_3 a_{i,t}^3 + \underbrace{\phi_{i,t}}_{\eta_{i,t}+\iota_{i,t}} \tag{19}$$

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 (19) 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-

[34] 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.

covariance matrix of earnings residuals and its theoretical counterpart implied by the statistical model. The resulting estimates are provided in Table A3.

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 (20)) or moves to non-employment (given in equation (21)) 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):

$$\pi^{JJ}(a, ten) = \sum_{k=1}^{6} \alpha_k^{JJ} a^k + \sum_{j=1}^{3} \iota_k^{JJ} 1\{(ten = j)\} \tag{20}$$

$$\pi^{EU}(a, ten) = \sum_{k=1}^{6} \alpha_k^{EU} a^k + \sum_{j=1}^{3} \iota_k^{UE} 1\{(ten = j)\} \tag{21}$$

The probability that an unemployed investor finds a job, given in equation (22), is defined as a sixth-order polynomial in age.

$$\pi^{UE}(a) = \sum_{k=1}^{6} \alpha_k^{EU} a^k \tag{22}$$

We estimate equations (20), (21), and (22) using a linear probability regression. Estimates for the age component of labor market transitions are reported in Figure A16. Estimates for the tenure component are reported in Figure A17.

Appendix E. Second-Stage Estimation Details

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

E.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.

E.2 Weighting Matrices

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

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

such that

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

Given a moment condition $Eg(X_i,\theta)=0$, standard arguments (a mean value expansion of first-order condition to the GMM objective) imply the influence function for an GMM estimator with an optimal weighting matrix of 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.

E.3 Optimization Algorithm

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

E.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 F. Additional Figures and Tables

Table A1. Summary Statistics: SCF 2007, 2010, 2013, and 2016

	All Households		Retirement Account Eligible	
	Mean	Median	Mean	Median
Age	44	45	44	45
Wage Income	47,236	34,006	59,547	43,723
Retirement Wealth	53,206	1,815	76,689	16,513
Investable Wealth	106,348	3,878	132,161	20,106
Ratio of Retirement to Investable Wealth	0.80	1.00	0.85	1.00
Stock Share of Retirement Wealth	0.29	0.00	0.42	0.40
Ratio of Equity Holdings in Retirement to Total	0.42	0.00	0.63	0.97
Stock Market Participation in Retirement Wealth	0.49	0.00	0.73	1.00
Stock Market Participation Outside Retirement	0.13	0.00	0.15	0.00
Stock Market Participation Only Outside Retirement	0.04	0.00	0.02	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. (2023a) 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 and converted in 2006 US dollars using the CPI. The sample is restricted to individuals between ages 23 and 64.

Figure A1. Distribution of Treatment and Control Groups by Year: Opt-In to TDF Sample

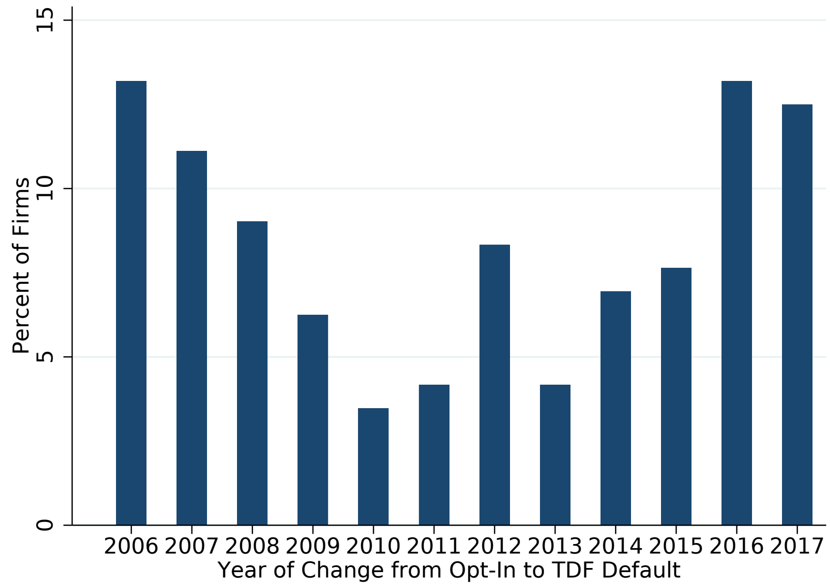


Figure A2. Balance Checks: Money Market to TDF Sample

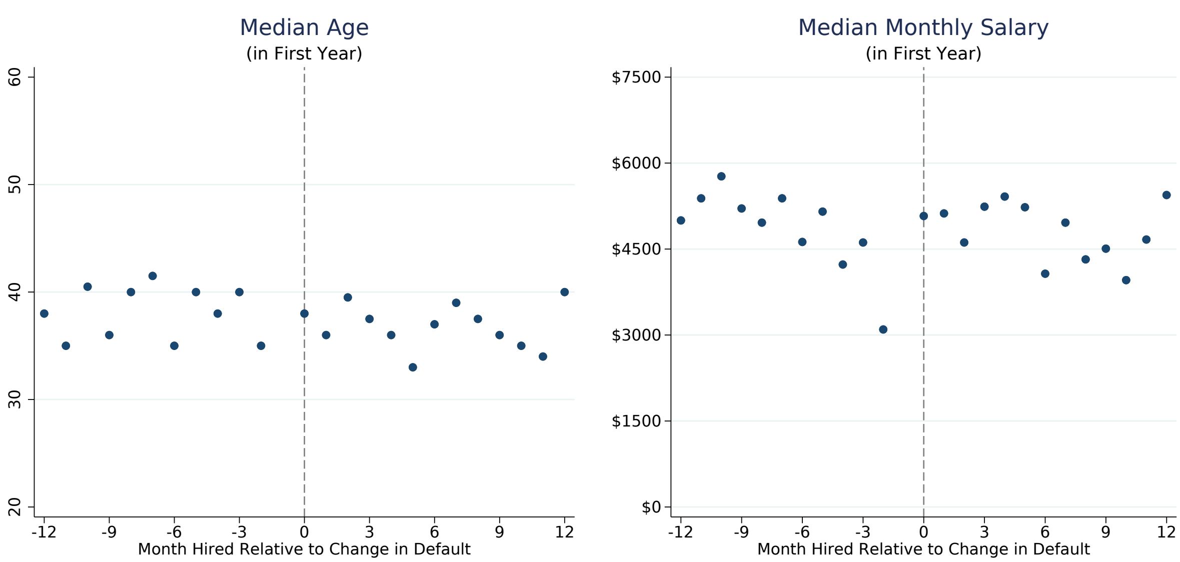
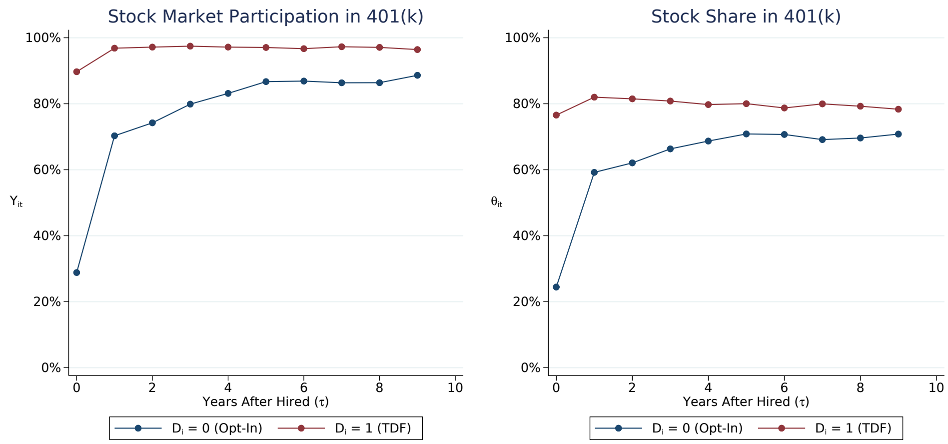


Figure A3. Observed Portfolio Choice Response: Opt-In-to-TDF Sample



Notes: This figure plots the observed portfolio responses for employees hired under an opt-in regime and those automatically enrolled in a target date fund.

Table A2. 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	76.50	76.42	76.94	76.63	58.90	58.83	59.43	59.21
	(5.971)	(5.095)	(3.673)	(2.797)	(4.912)	(4.280)	(3.404)	(2.824)
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)	(5.806)	(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

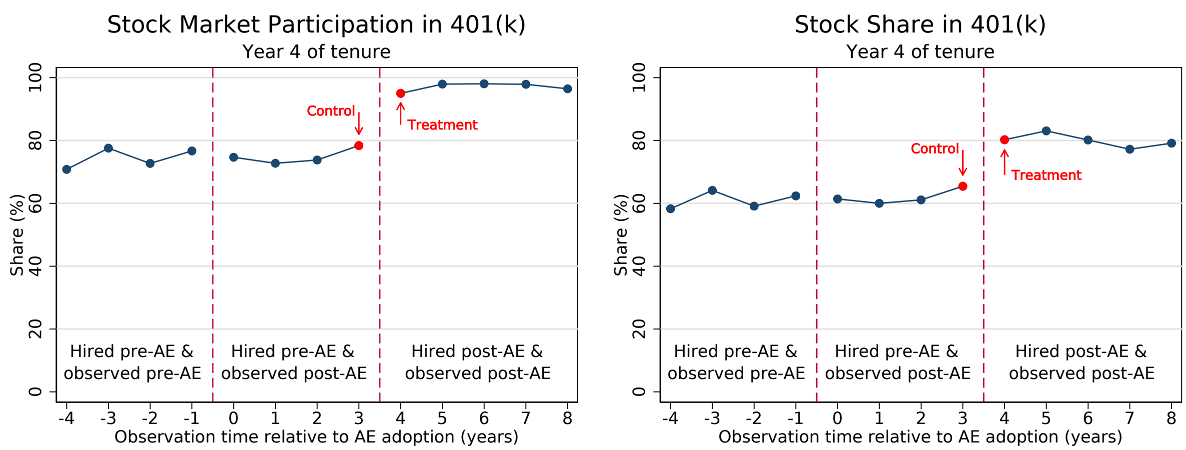
Panel B: Opt-In-to-TDF Sample

	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 2, 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 assigned 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 assigned by default into an opt-in 401(k) plan with those assigned into an automatic enrollment 401(k) plan with a TDF as the default asset. In both panels, two-way clustered standard errors by firm and year are shown in parentheses.

Figure A4. Robustness of Portfolio Choice Response: Money Market-to-TDF Sample

Panel A: Peer Effects



Panel B: Compositional Change

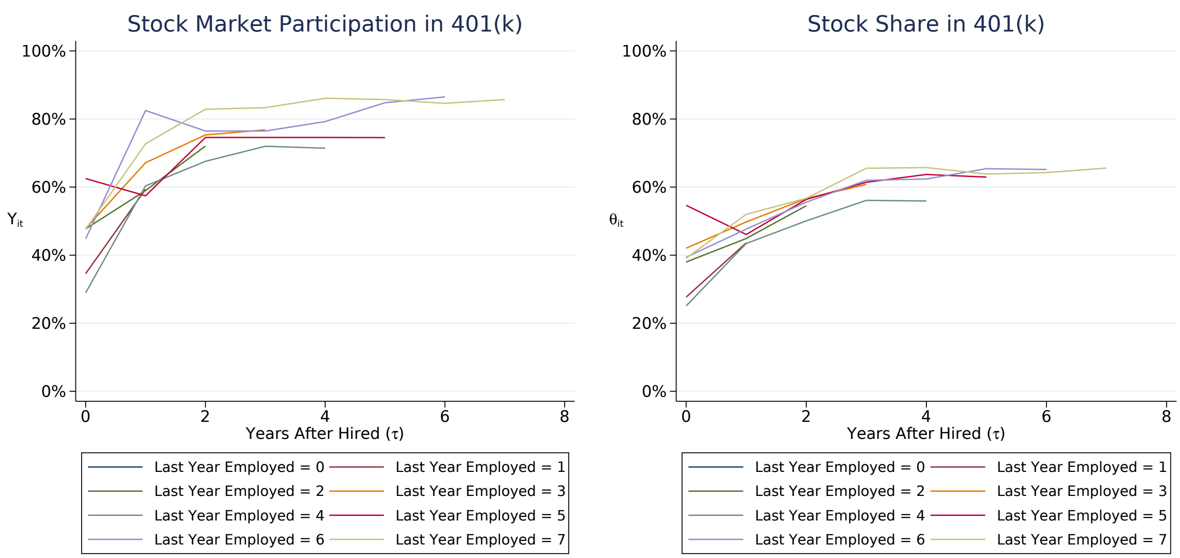
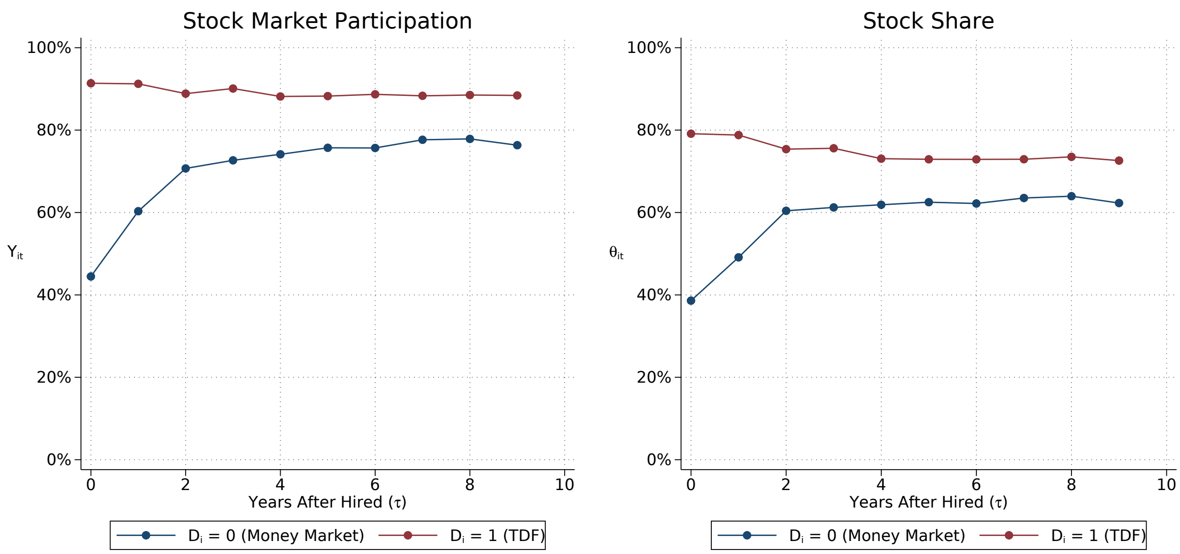


Figure A5. Robustness of Portfolio Choice Response: Portfolio Choices for New Contributions to 401(k)

Panel A: Money Market to TDF Sample



Panel B: Opt-In to TDF Sample

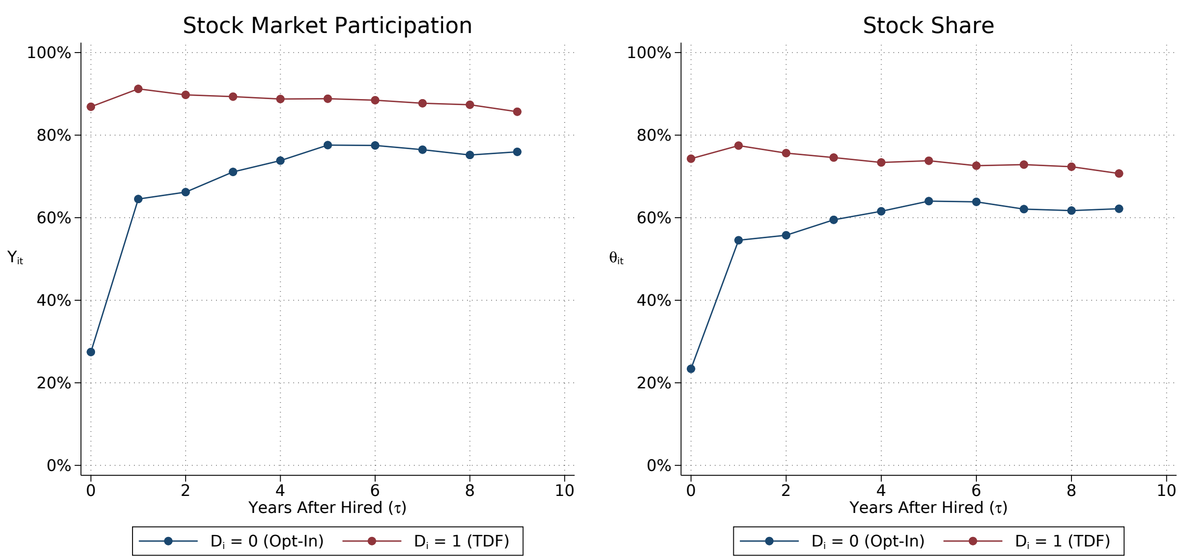
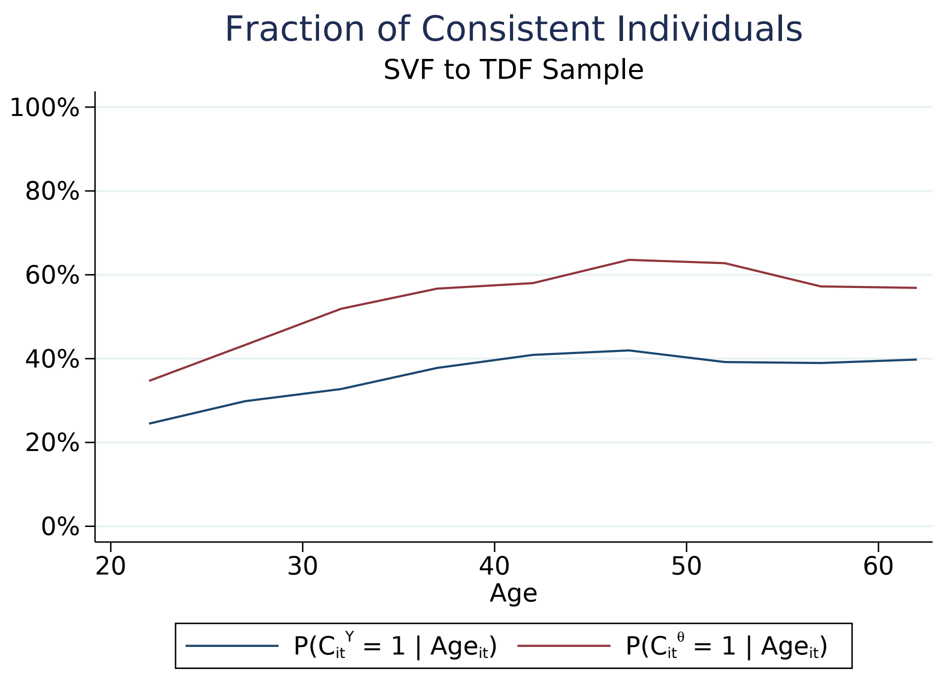


Figure A6. Fraction of Consistent Investors by Age

Panel A: Money Market to TDF Sample



Panel B: Opt-In to TDF Sample

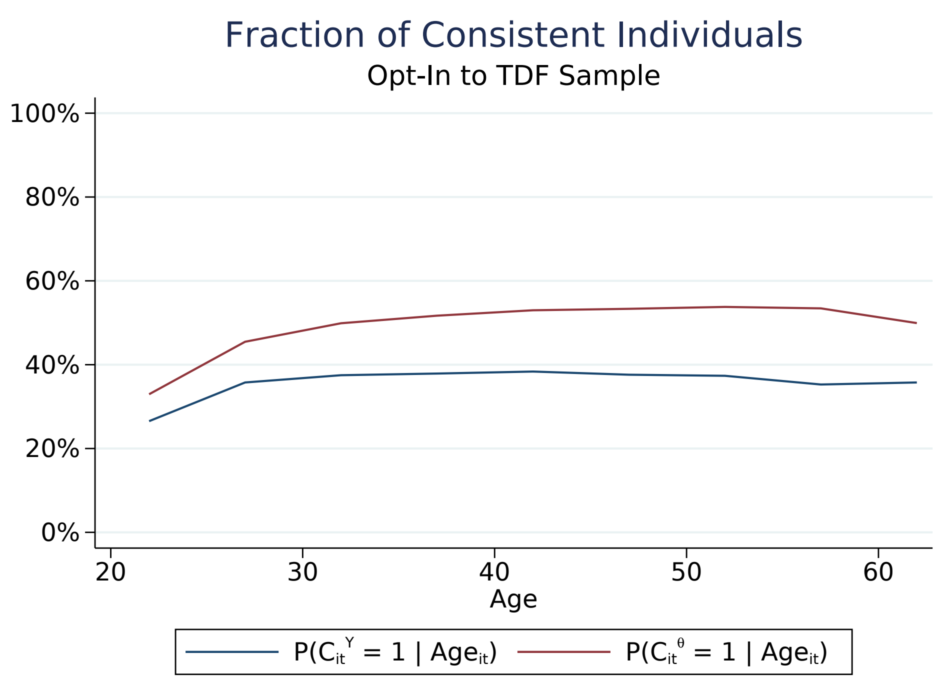


Figure A7. Preferences of Consistent Investors by Default: Money Market to TDF Sample

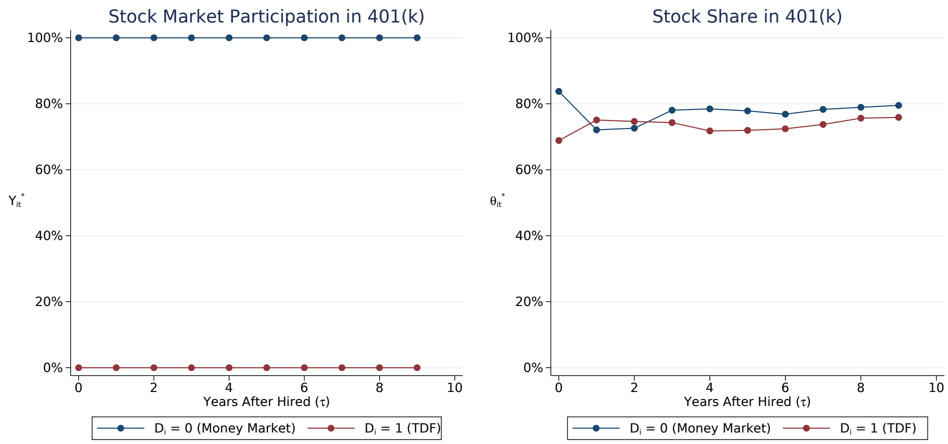


Figure A8. Preferences of Consistent Investors by Tenure of Consistency: Opt-In to TDF Sample

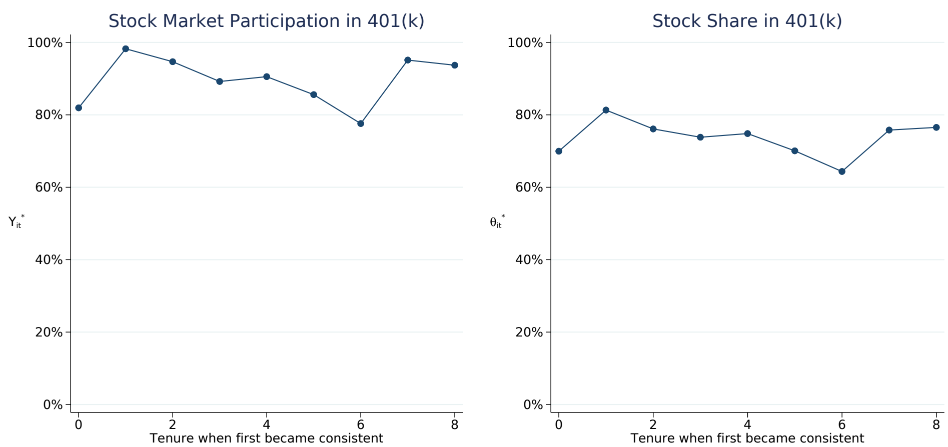
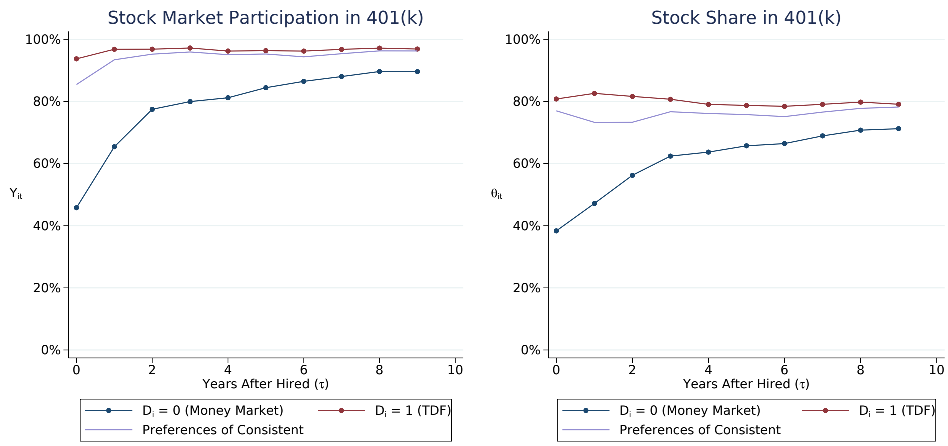
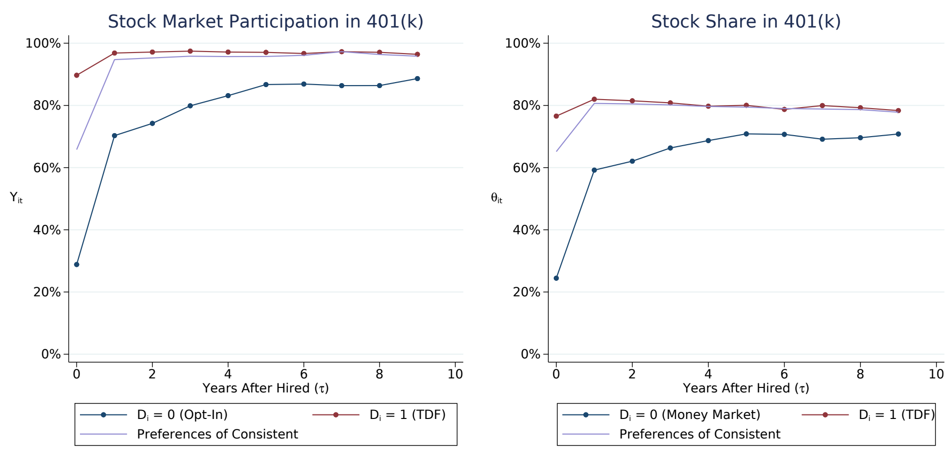


Figure A9. Preferences of Consistent Investors

Panel A: Money Market to TDF Sample



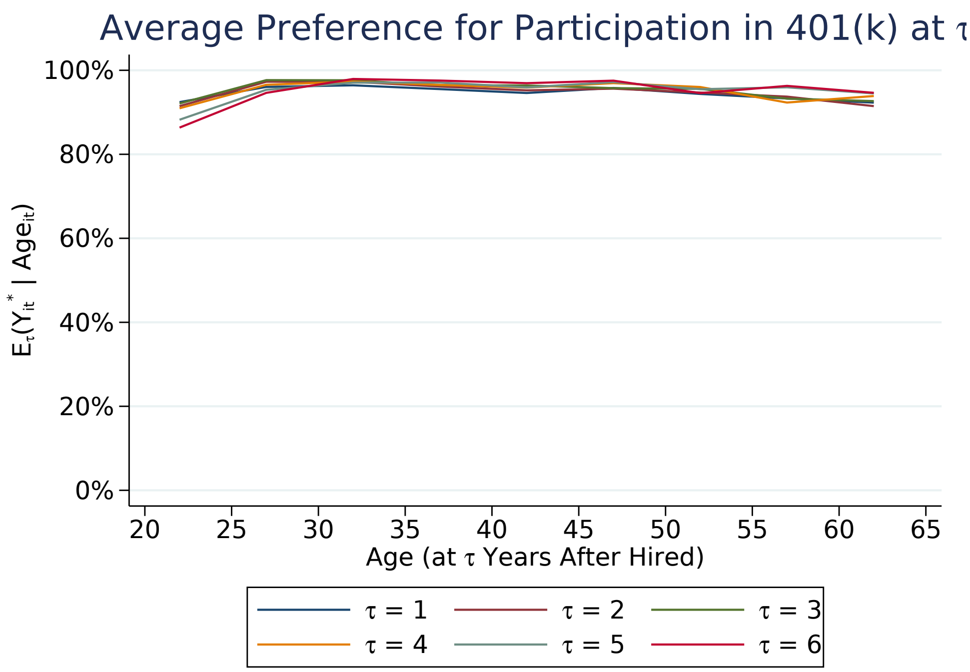
Panel B: Opt In to TDF Sample



Notes: This figure plots the same data as in Figure 2 but includes our point estimates for the consistent investors under Assumptions 1–4 for stock market participation within 401(k) plans and Assumptions 1–3 and 5 for the stock share of retirement wealth. Under Assumption 6, these estimates provide an estimate of the preferences of the entire population.

Figure A10. Estimated Preferences by Tenure: Opt-In to TDF Sample

Panel A: Stock Market Participation



Panel B: Stock Share of Retirement Wealth

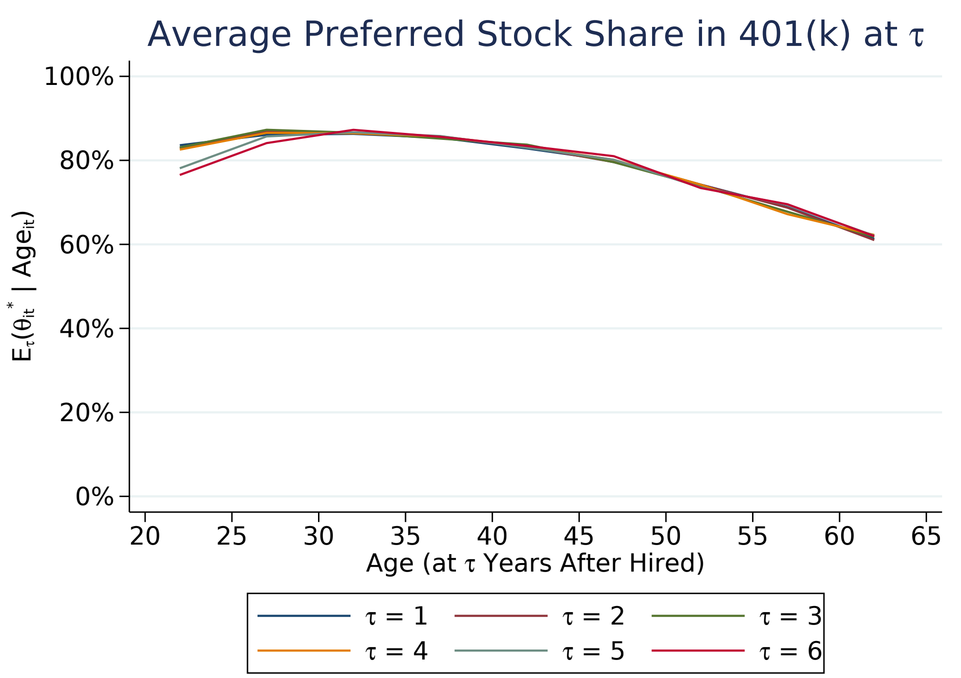
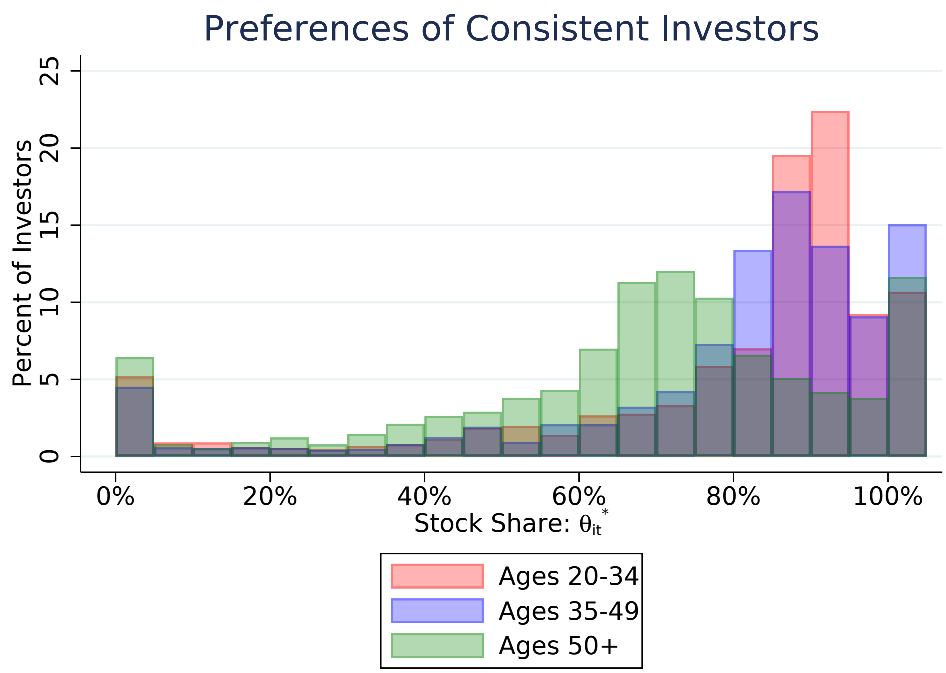


Figure A11. Preference Heterogeneity among Consistent Investors

Panel A: Money Market to TDF Sample



Panel B: Opt-In to TDF Sample

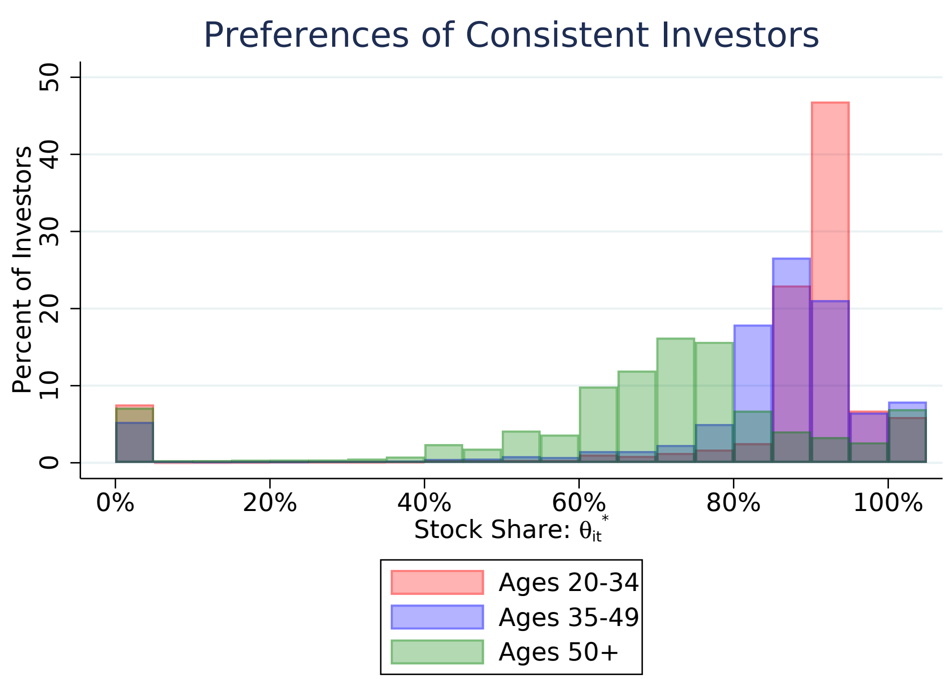
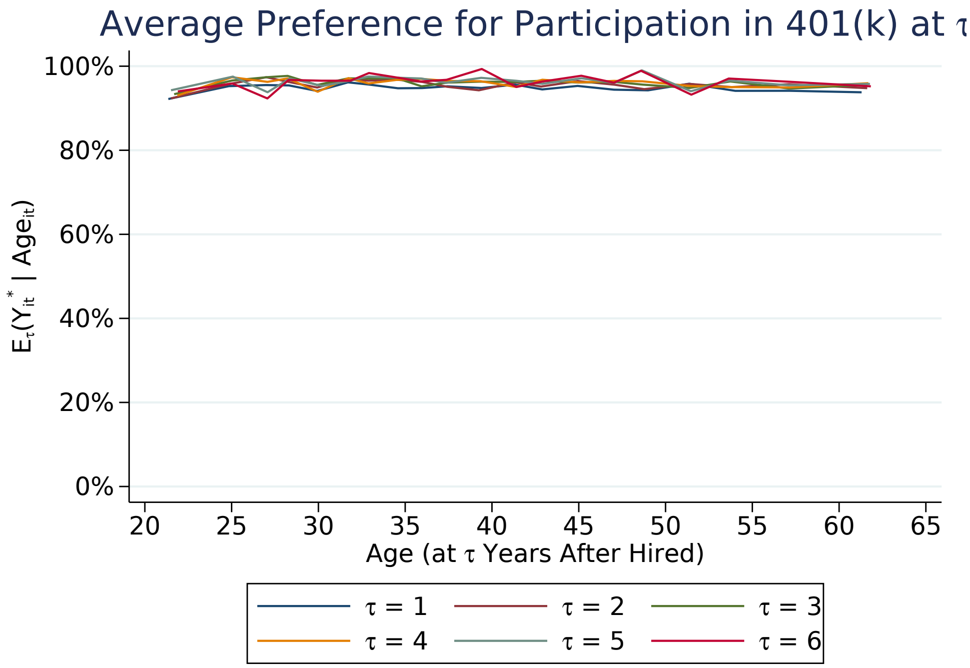


Figure A12. Robustness of Preferences over the Life Cycle: Opt-In to TDF Sample

Panel A: Participation



Panel B: Stock Share of Retirement Wealth

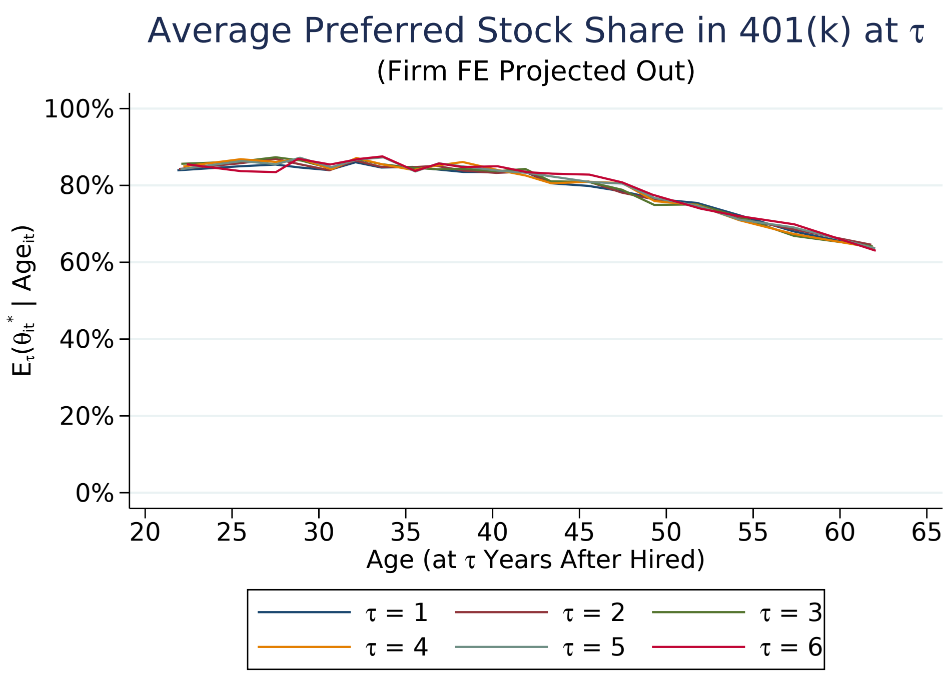
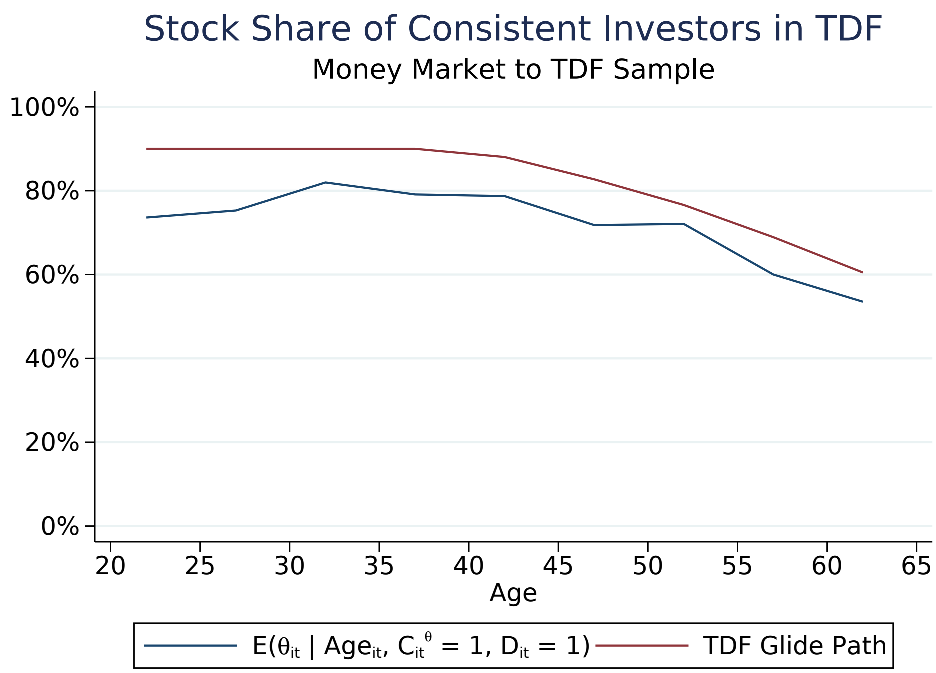


Figure A13. Life Cycle Preferences of Consistent Investors Defaulted into TDF

Panel A: Money Market to TDF Sample



Panel B: Opt-In to TDF Sample

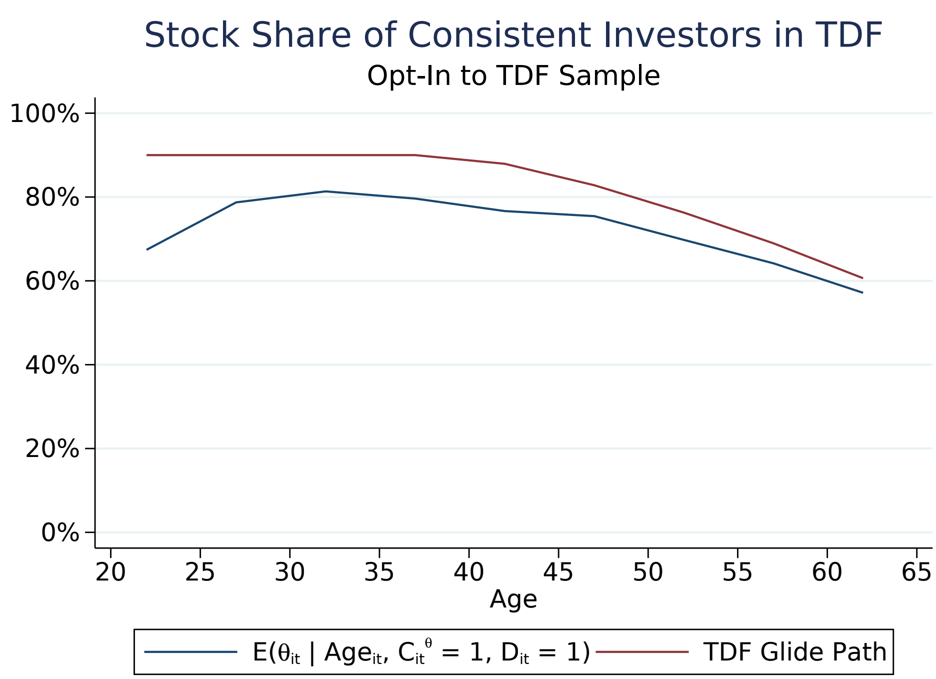
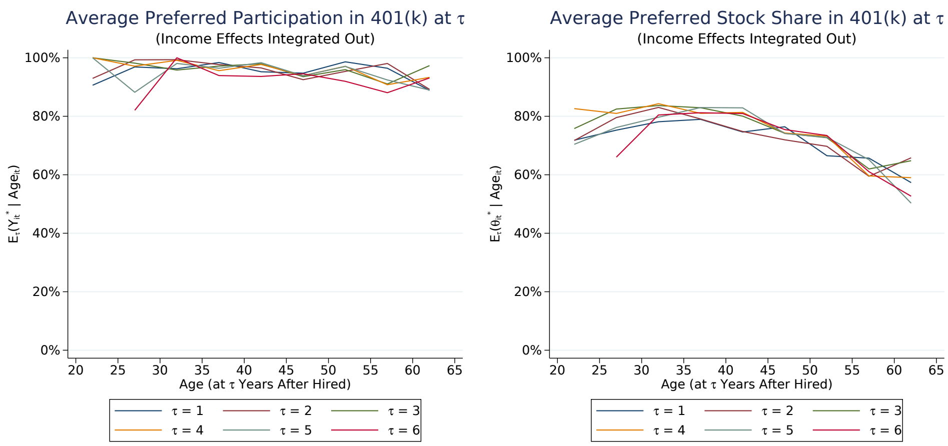


Figure A14. Estimated Preferences Under Weaker Identifying Assumption

Panel A: Money Market to TDF Sample



Panel B: Opt-In to TDF Sample

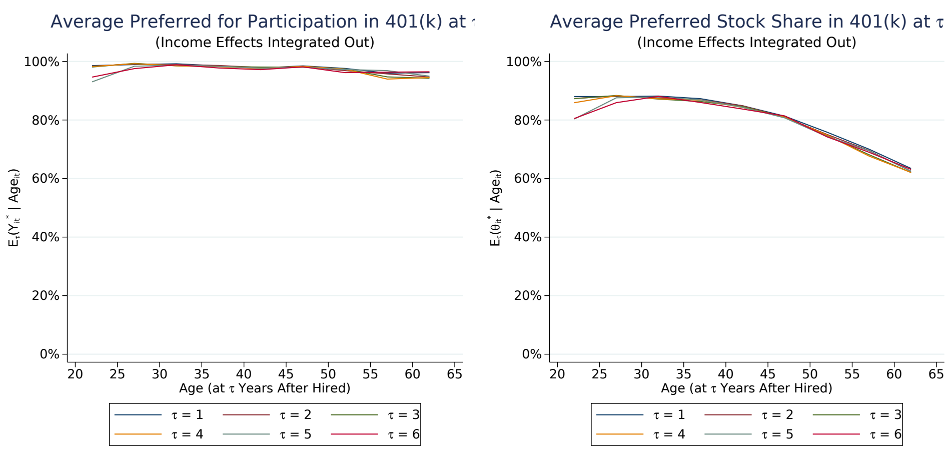
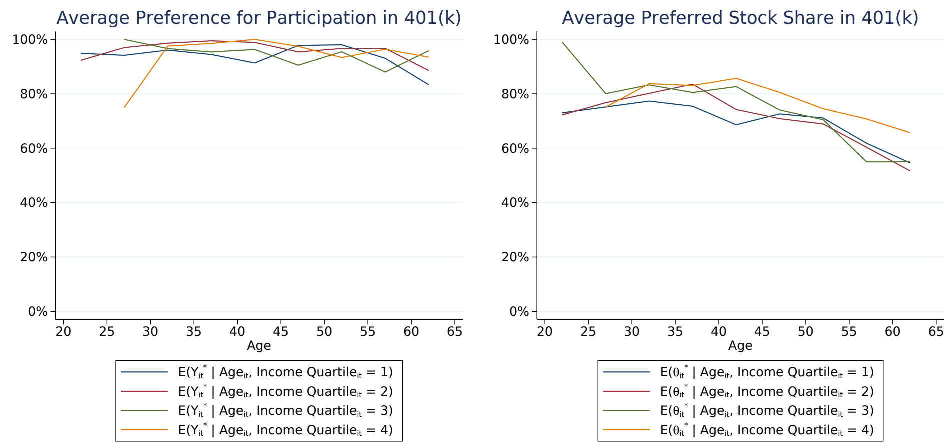


Figure A15. Preferences over the Life Cycle by Income Quartiles

Panel A: Money Market to TDF Sample



Panel B: Opt-In to TDF Sample

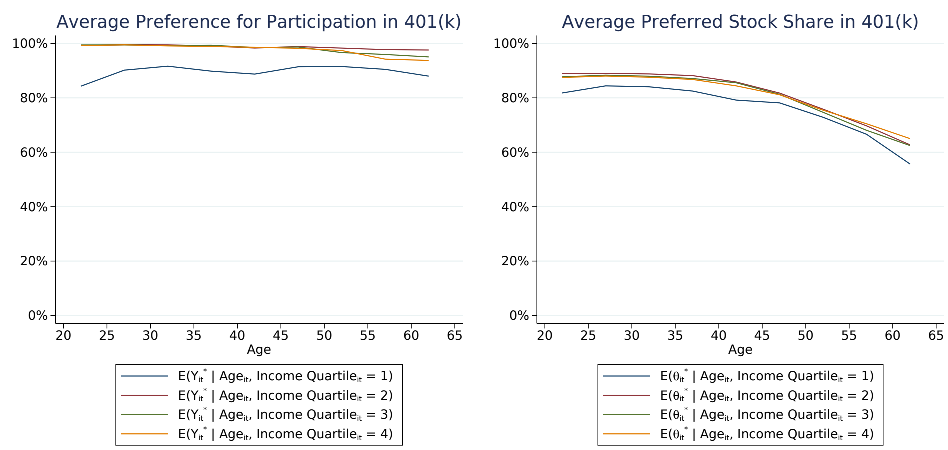


Table A3. Earnings Process Estimates

Age component				Stochastic component of earnings			
δ_0	δ_1	δ_2	δ_3	ρ	$\sigma^2_{\xi_0}$	σ^2_{ξ}	σ^2_{ι}
2.813	0.121	−0.00183	6.91×10^{-6}	0.9332	0.1749	0.0298	0.0538

Notes: 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.

Figure A16. Age Component of Annual Labor Market Transitions

Figure A17. Tenure Component of Annual Labor Market Transitions

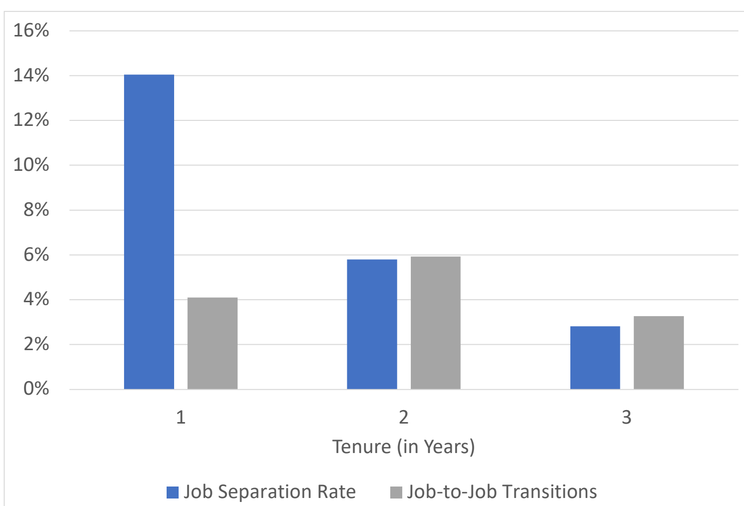
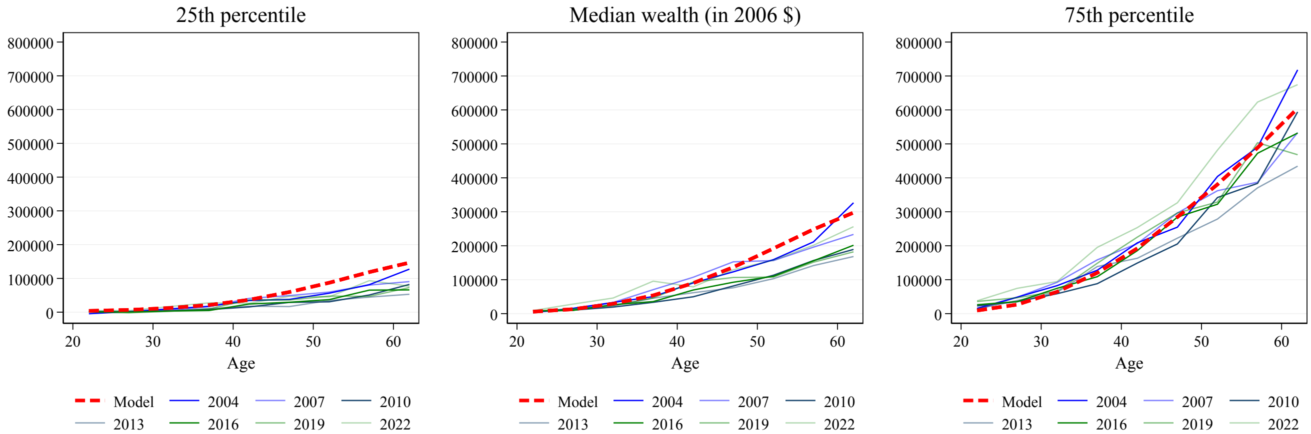
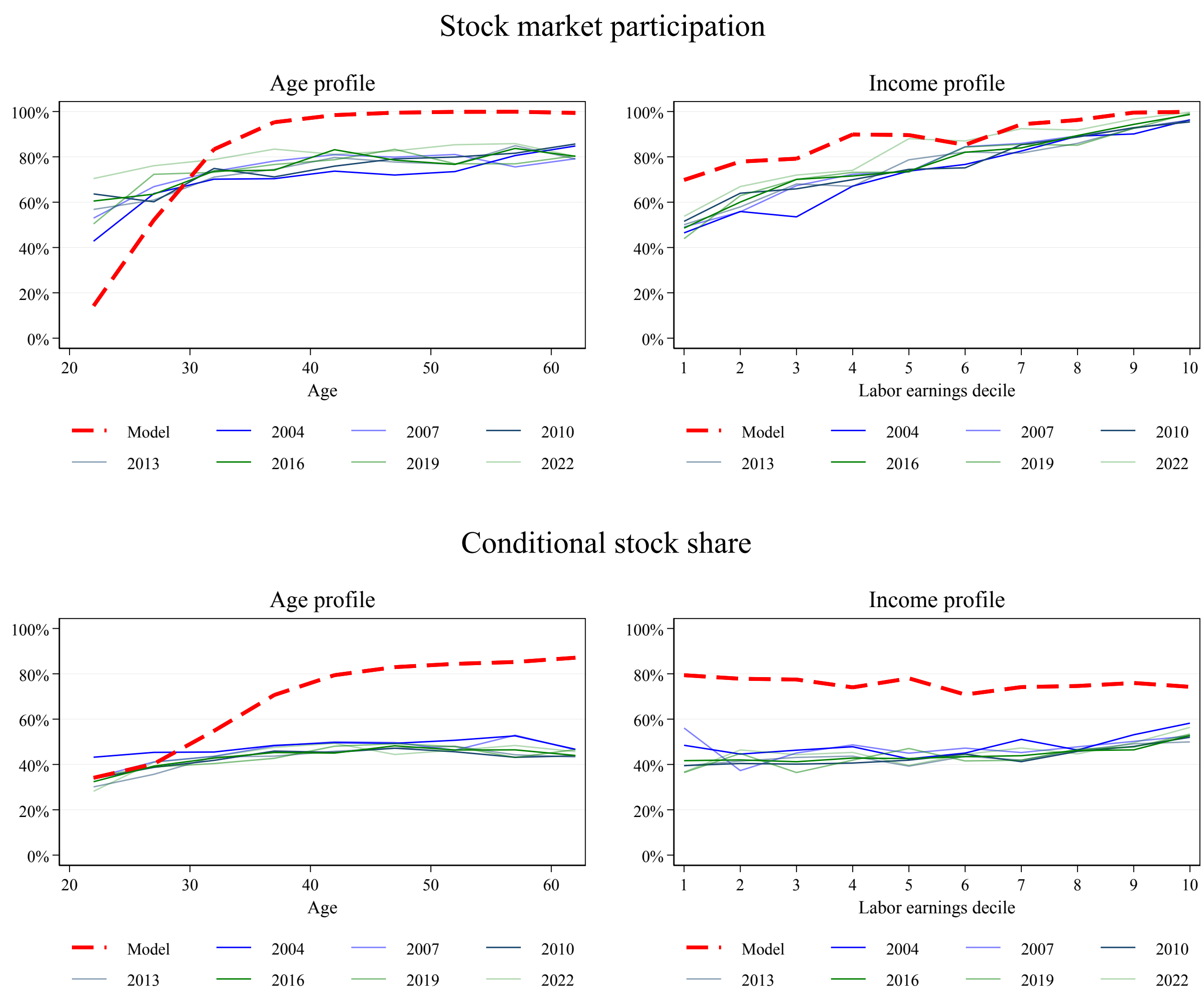


Figure A18. Comparison of Model and SCF: Wealth Accumulation



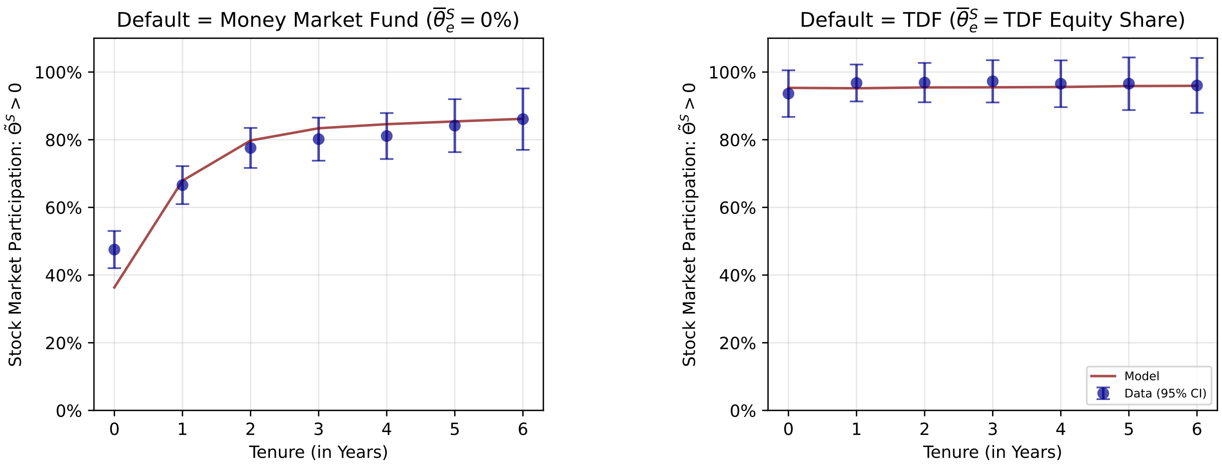
Notes: This figure compares wealth accumulation in the model with that in different waves of the SCF. Each panel plots how different percentiles of the wealth distribution vary with age. The dashed red line corresponds to the model, where wealth corresponds to the sum of retirement wealth and liquidity wealth. The solid lines correspond to wealth from different survey waves in the SCF, which is computed as household net worth divided by two if the household is married. The sample in the SCF is all individuals between ages 22 and 64 who participate in or have access to an employer-sponsored retirement savings account. All values are converted to 2006 dollars using the CPI, and SCF values are adjusted for survey weights.

Figure A19. Comparison of Model and SCF: Portfolio Choices



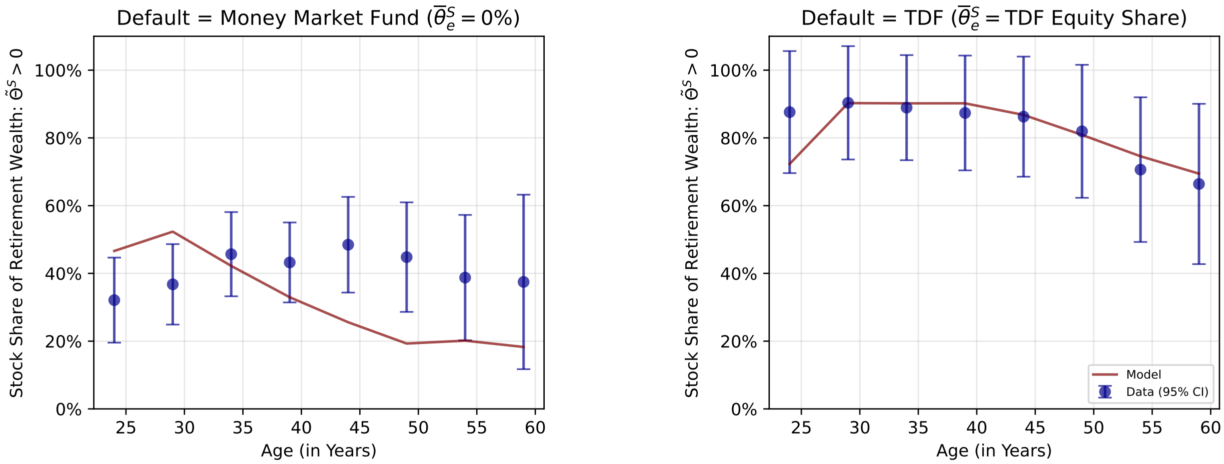
Notes: This figure compares stock market participation and conditional equity shares in the model with that in different waves of the SCF. The top two panels focus on stock market participation rates; the bottom two focus on conditional stock shares. Each panel plots how the relevant variable varies with age or decile of labor earnings. The dashed red line corresponds to the model, where stock market participation is based on the retirement account, and equity shares are computed as a fraction of total wealth, including both liquid and retirement wealth. The solid lines correspond to wealth from different survey waves in the SCF, where equity shares are computed as a fraction of financial wealth. The sample in the SCF is all individuals between ages 22 and 64 who participate in or have access to an employer-sponsored retirement savings account. All values are converted to 2006 dollars using the CPI, and SCF values are adjusted for survey weights.

Figure A20. CRRA Model Fit: Stock Market Participation in 401(k) from Quasi-Experiment #1



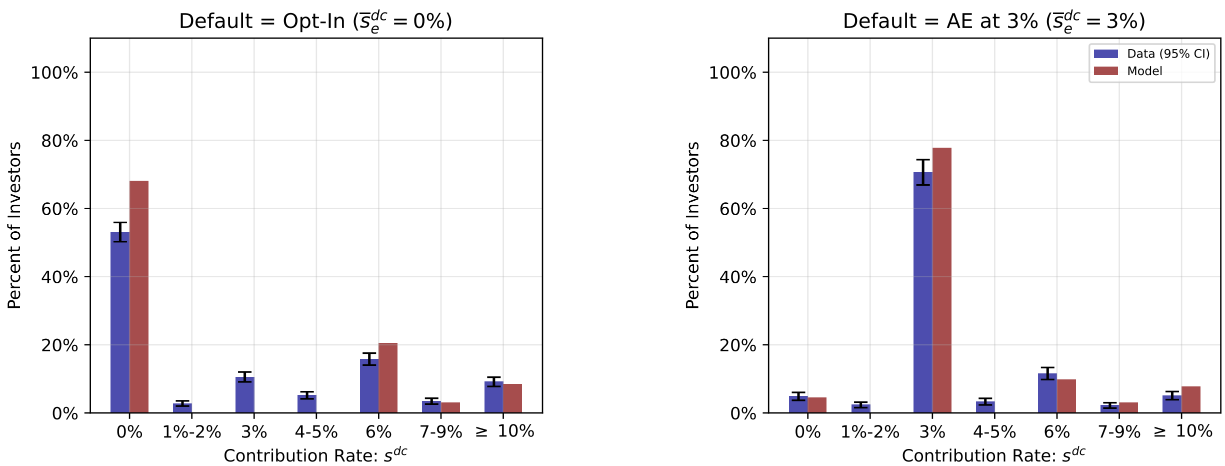
Notes: This figure presents the fit of our model on the response of stock market participation inside the current employer retirement account for our first quasi-experiment. The data moments in this figure correspond to the moments from our first quasi-experiment in the left half Figure 2 Panel A for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

Figure A21. CRRA Model Fit: Stock Shares by Age in First-Year of Tenure



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

Figure A22. CRRA Model Fit: Contribution Rates in First-Year of Tenure



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