Internet Appendix for "What Drives Investors' Portfolio Choices? Separating Risk Preferences from Frictions"

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ABSTRACT

This Internet Appendix contains the following additional materials supporting the main text. Section I: Table of parameters for the life-cycle model presented in Section III in the main article. Section II: Additional details, proofs, and derivations of results in Section II in the main article. Section III: Details on solution algorithm for the model presented in Section III in the main article. Section IV: Details on first-stage estimation of the model presented in Section III in the main article. Section V: Details on second-stage estimation procedure for the model in Section III in the main article. Section VI: Additional figures and tables referenced in the main text and this appendix.

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I. Life-Cycle Model Parameters

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

II. Proofs of Nonparametric 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

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

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,

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

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:

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

□

III. 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 five grid points. We place tenure on a grid with three components (i.e., one year of tenure, two years of tenure, and three or more years of tenure). We place average lifetime income on a grid with five 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 two times larger in each dimension and found that our moments used for estimation changed by no more than an average of 0.95%.[2]

Discretization of choice variables. We have four 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 ten 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 equiva-

[2] 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.

lently 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, 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.[3] 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 Section V below, we parallelize the estimation across 32 nodes using a total of over 3,000 CPUs.

[3]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 $\gamma = \sigma$.

IV. First-Stage Estimation Details

A. 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 two adults and one 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.

B. 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 (IA1). 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.

$$\Upsilon_e(t, ten) = 1 - \sum_{j=0}^{T^R - t} \left(\prod_{k=1}^{j-1} \left(1 - \pi^{EU}_{t+k,ten+k} - \pi^{JJ}_{t+k,ten+k}\right) \right) \left(\pi^{EU}_{t+j,ten+j} + \pi^{JJ}_{t+j,ten+j}\right) \left(1 - vst_e(ten + j)\right) \tag{IA1}$$

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 third year of tenure.

C. 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 five annual income brackets $\{\tilde{\kappa}^{\tau}_i\}_{i=1}^{5} = \{\$5,150; \$7,550; \$30,650; \$74,200; \$154,800\}$.[4] 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.

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

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

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

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

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[5]

D. *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

[5] 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.

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 et al. (2010). The empirical income process is given in equation (IA2), which is the empirical counterpart of the model earning process in equation (7) with one additional term: serially uncorrelated measurement error $\iota_{i,t} \sim N\left(0, \sigma_\iota^2\right)$.

$$\ln w_{i,t} = \delta_0 + \delta_1 a_{i,t} + \delta_2 a_{i,t}^2 + \delta_3 a_{i,t}^3 + \underbrace{\phi_{i,t}}_{\eta_{i,t}+\iota_{i,t}} \tag{IA2}$$

The estimation has two steps. In the first step, We estimate the parameters of the deterministic component of earnings $\left(\{\delta_j\}_{j=0}^3\right)$—a cubic in age. In the second step, We use the residual from regression (IA2) to estimate the five parameters governing the stochastic component of earnings: the coefficient of autocorrelation in earnings shocks (ρ), the variances of the first earnings innovation ($\sigma_{\xi_0}^2$), the variance of subsequent innovations (σ_ξ^2), and the variance of measurement error (σ_ι^2). We estimate these five parameters by minimizing the distance between the empirical variance-covariance matrix of earnings residuals and its theoretical counterpart implied by the statistical model. The resulting estimates are provided in Table IAIII.

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 (IA3)) or moves to non-employment (given in equation (IA4)) 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 three years of tenure):

$$\pi^{JJ}(a, ten) = \sum_{k=1}^{6} \alpha_k^{JJ} a^k + \sum_{j=1}^{3} \iota_k^{JJ} 1\{(ten = j)\} \tag{IA3}$$

$$\pi^{EU}(a, ten) = \sum_{k=1}^{6} \alpha_k^{EU} a^k + \sum_{j=1}^{3} \iota_k^{UE} 1\{(ten = j)\} \tag{IA4}$$

The probability that an unemployed investor finds a job, given in equation (IA5), is defined as a sixth-order polynomial in age.

$$\pi^{UE}(a) = \sum_{k=1}^{6} \alpha_k^{EU} a^k \tag{IA5}$$

We estimate equations (IA3), (IA4), and (IA5) using a linear probability regression. Estimates for the age component of labor market transitions are reported in Figure IA16. Estimates for the tenure component are reported in Figure IA17.

V. 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.

A. *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.

B. *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.

C. *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.

D. 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.

VI. Additional Figures and Tables

Table IAI. 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

This table provides summary statistics from the 2007, 2010, 2013, and 2016 waves of the SCF, 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. (2023) 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.

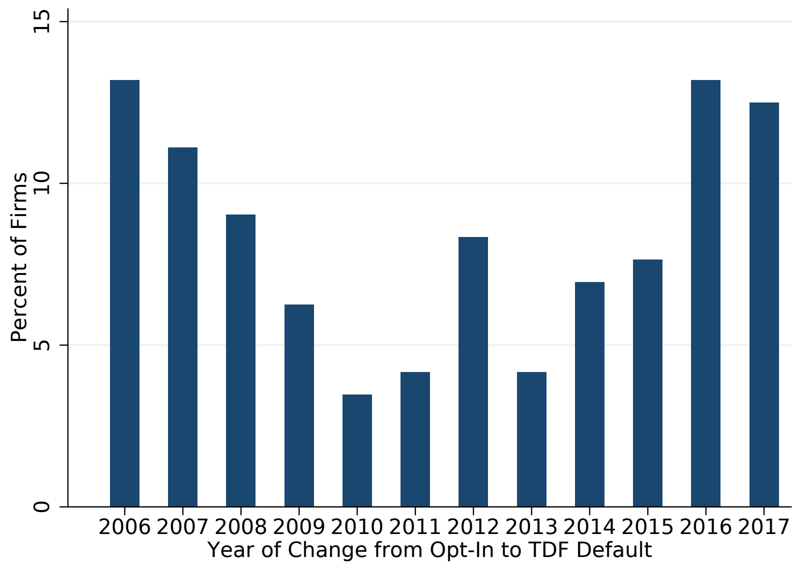


Figure IA1. Distribution of treatment and control groups by year: Opt-in to TDF sample.

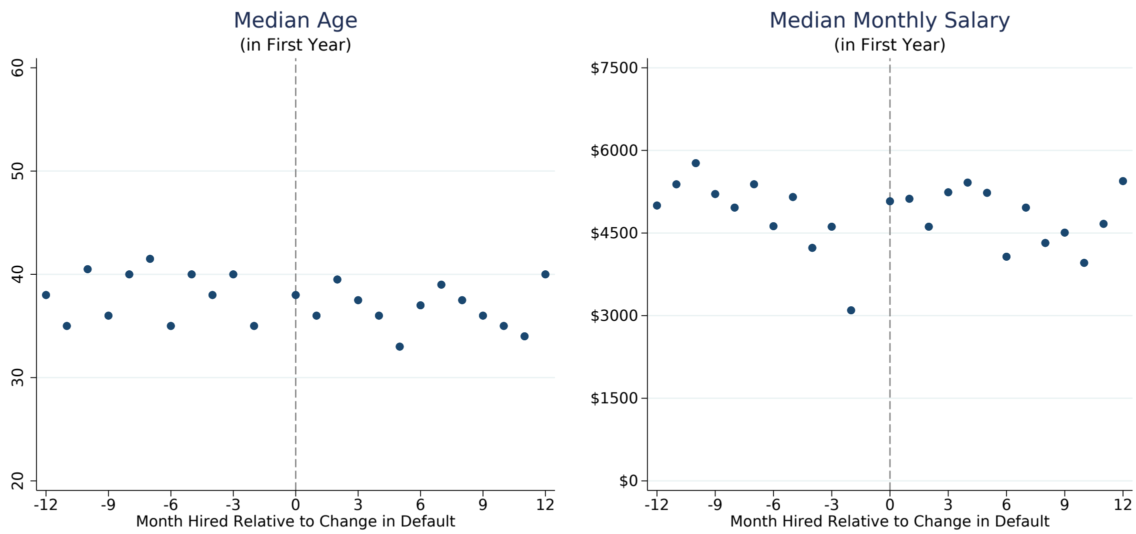


Figure IA2. Balance checks: Money market to TDF sample.

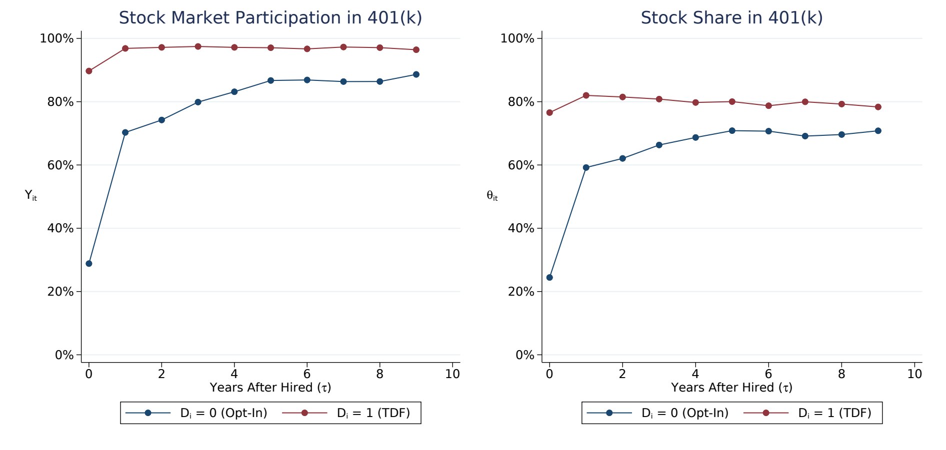


Figure IA3. Observed portfolio choice response: Opt-in-to-TDF sample. This figure plots the observed portfolio responses for employees hired under an opt-in regime and those automatically enrolled in a target date fund.

Table IAII. Observed portfolio choice response: regression.

Panel A: Money-market-to-TDF sample

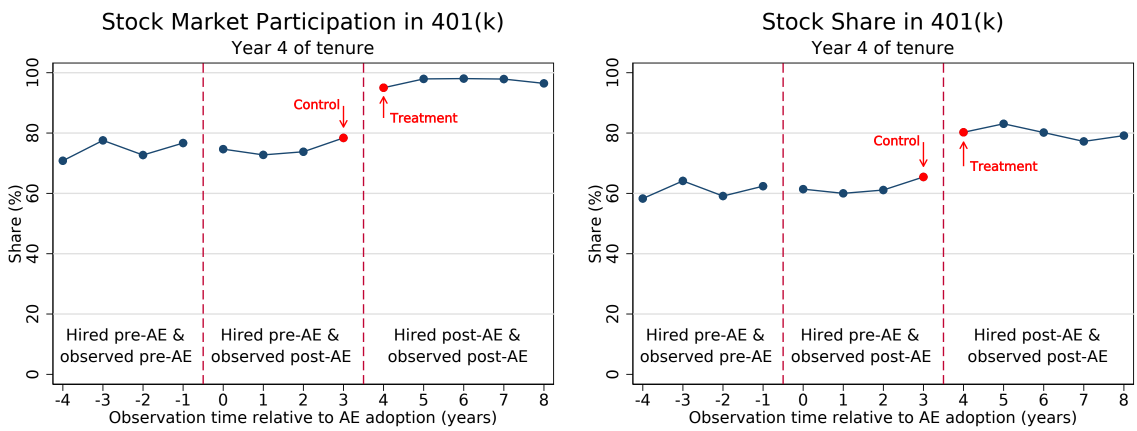
	Stock Market Participation in 401(k): Y_{it}				Stock Share in 401(k): θ_{it}			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Constant	76.50	76.42	76.94	76.63	58.90	58.83	59.43	59.21
	(5.971)	(5.095)	(3.673)	(2.797)	(4.912)	(4.280)	(3.404)	(2.824)
Default Has Stocks: D_i	19.92	20.06	19.12	19.68	21.50	21.62	20.55	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

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.

Panel A: Peer effects



Panel B: Compositional change

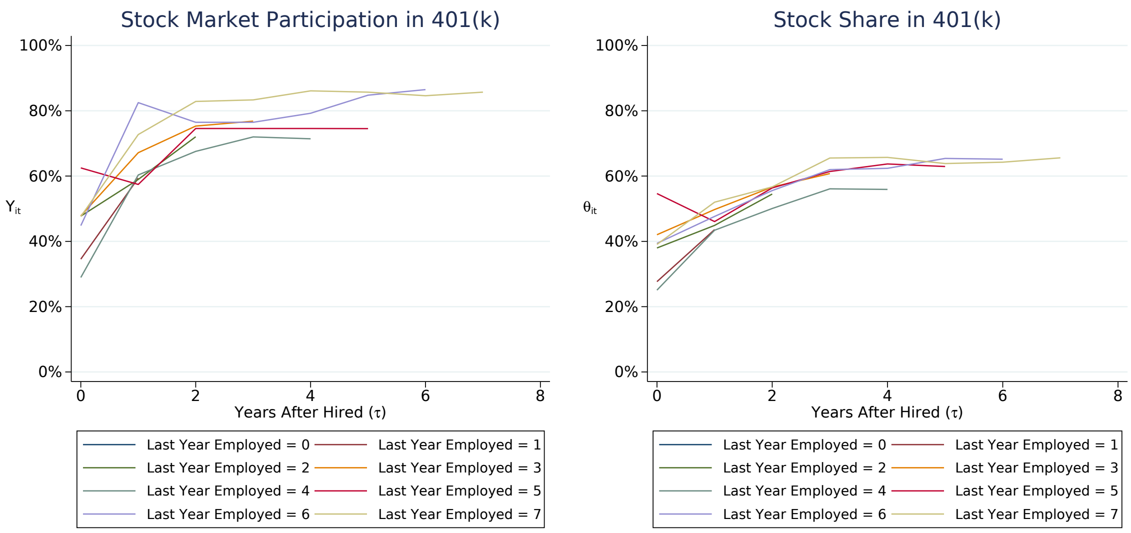
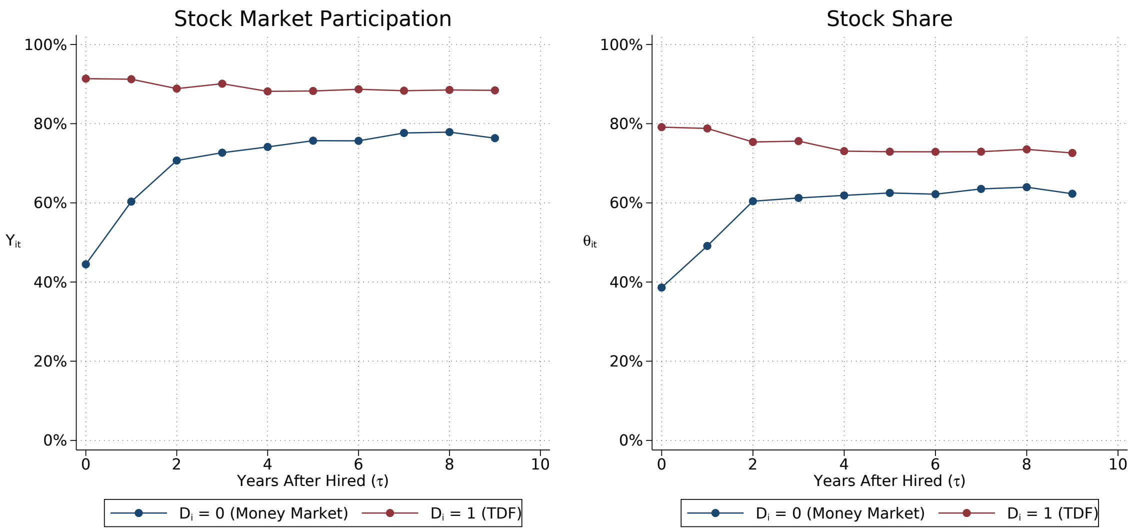


Figure IA4. Robustness of portfolio choice response: Money market-to-TDF sample.

Panel A: Money market to TDF sample



Panel B: Opt-in to TDF sample

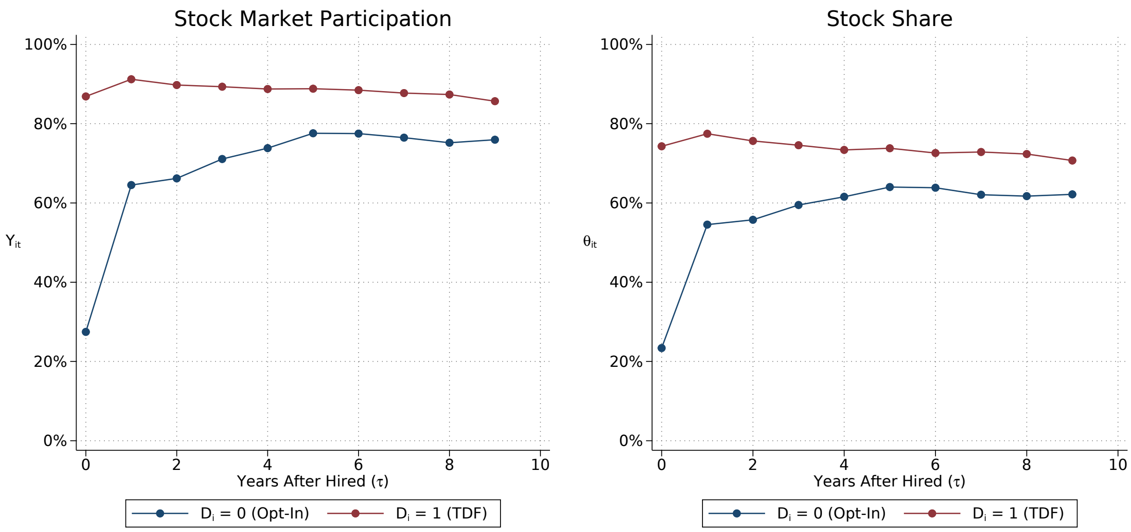
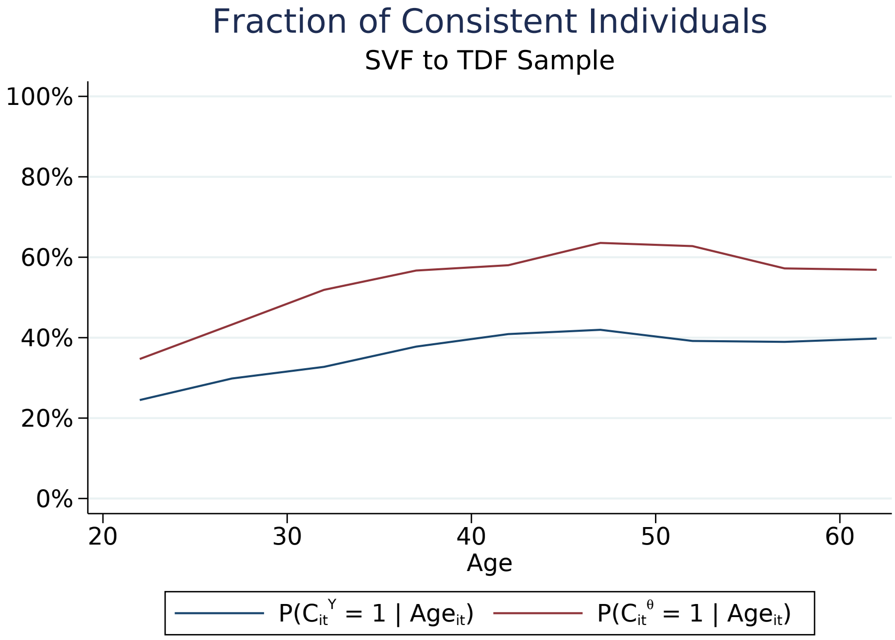


Figure IA5. Robustness of portfolio choice response: Portfolio choices for new contributions to 401(k).

Panel A: Money market to TDF sample



Panel B: Opt-in to TDF sample

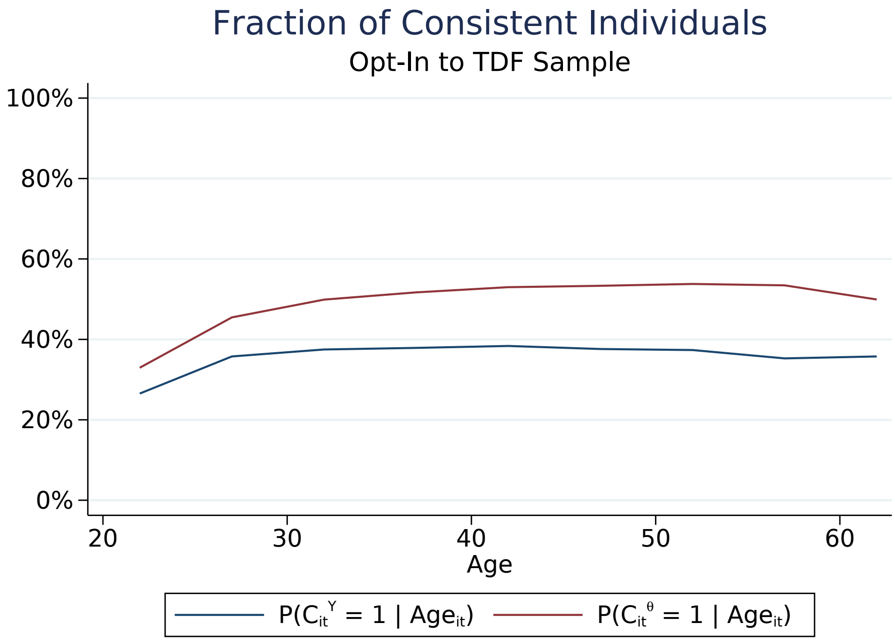


Figure IA6. Fraction of consistent investors by age.

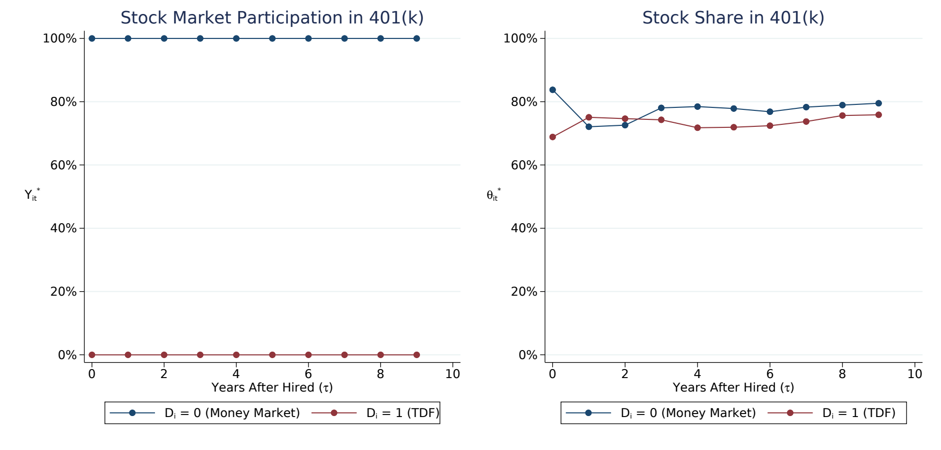


Figure IA7. Preferences of consistent investors by default: Money market to TDF sample.

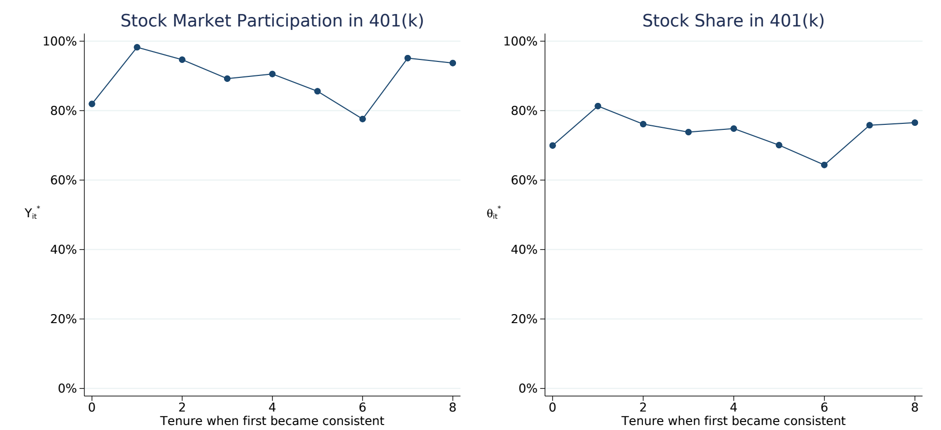
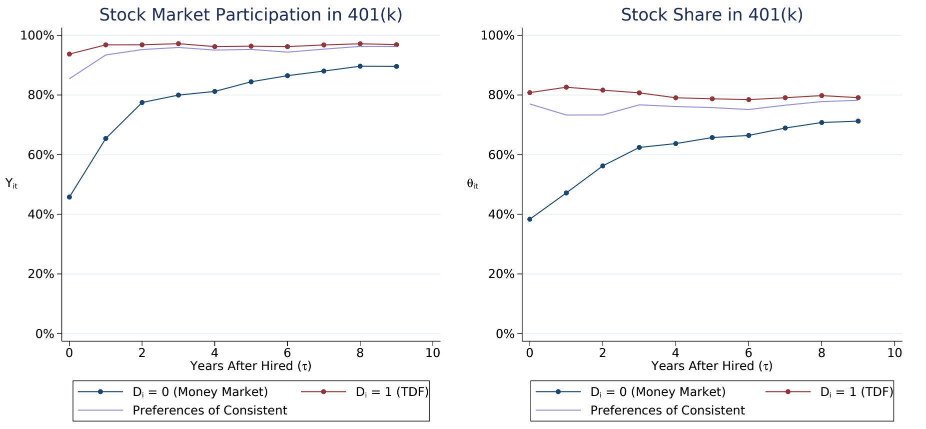


Figure IA8. Preferences of consistent investors by tenure of consistency: Opt-in to TDF sample.

Panel A: Money market to TDF sample



Panel B: Opt-in to TDF sample

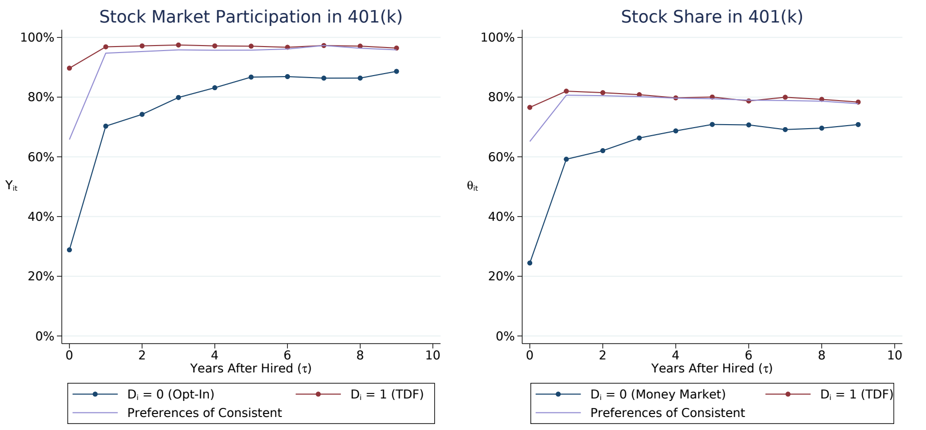
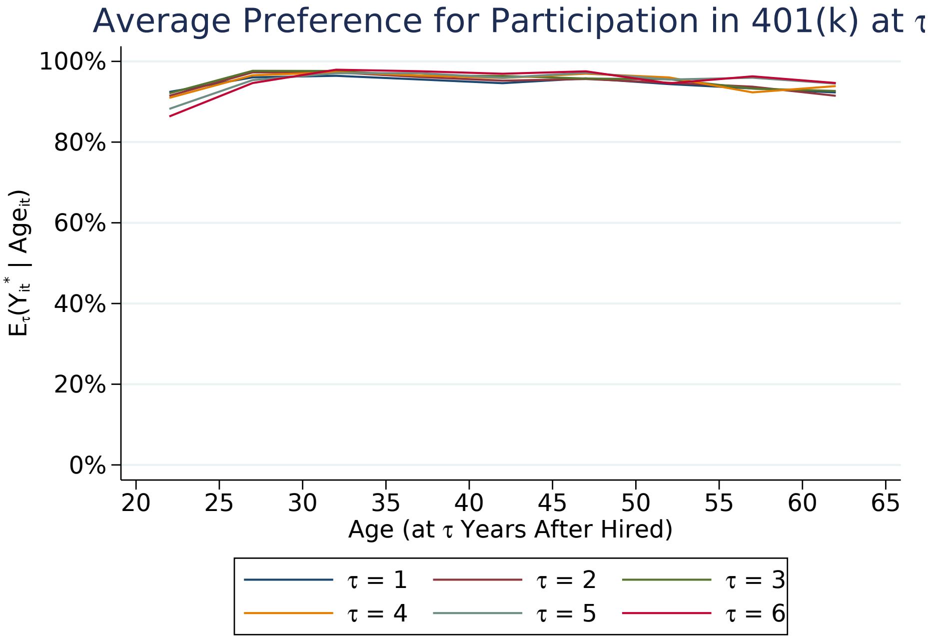


Figure IA9. Preferences of consistent investors. This figure plots the same data as in Figure 2 but includes our point estimates for the consistent investors under Assumptions 1–4 for stock market participation within 401(k) plans and Assumptions 1–3 and 5 for the stock share of retirement wealth. Under Assumption 6, these estimates provide an estimate of the preferences of the entire population.

Panel A: Stock market participation



Panel B: Stock share of retirement wealth

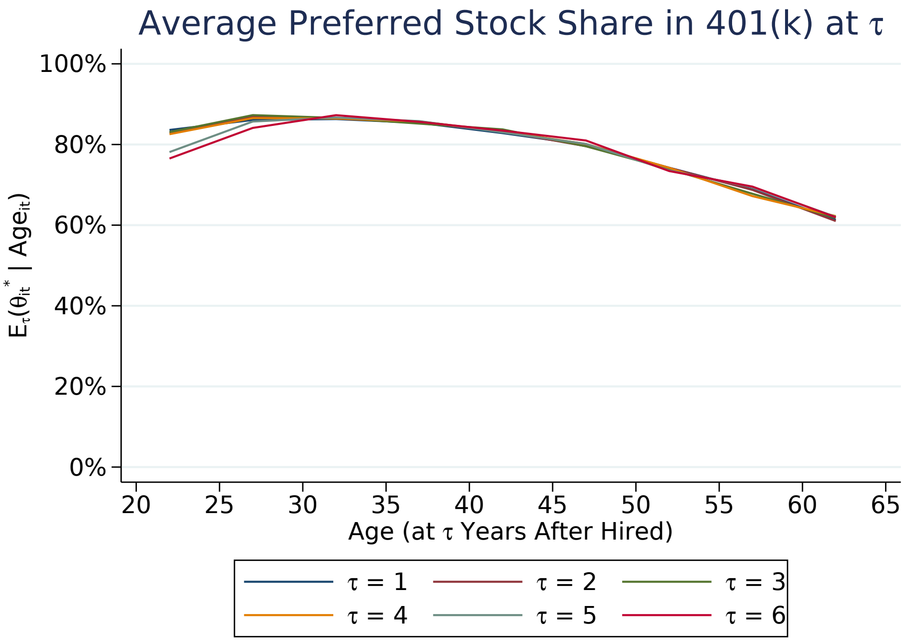
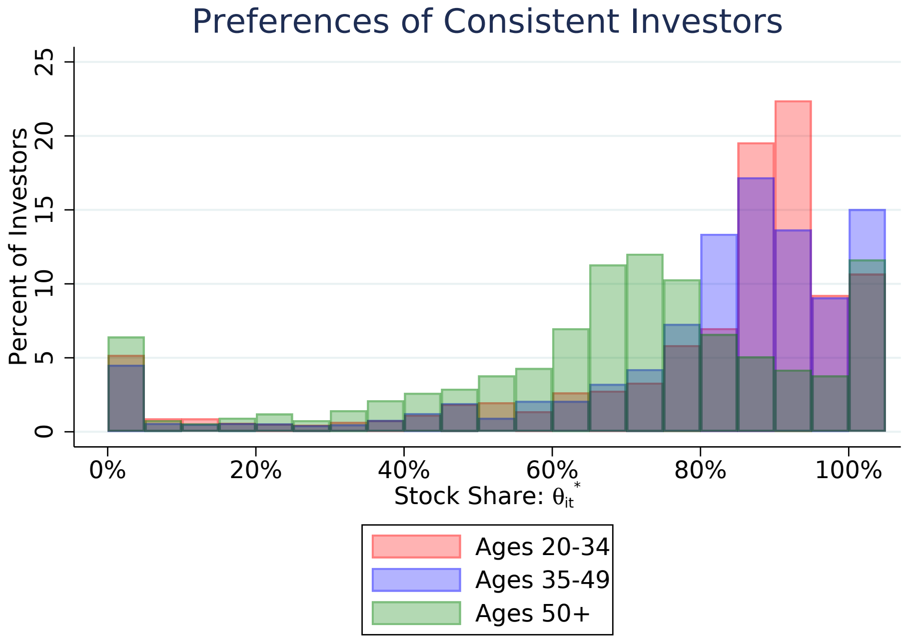


Figure IA10. Estimated preferences by tenure: Opt-in to TDF sample.

Panel A: Money market to TDF sample



Panel B: Opt-in to TDF sample

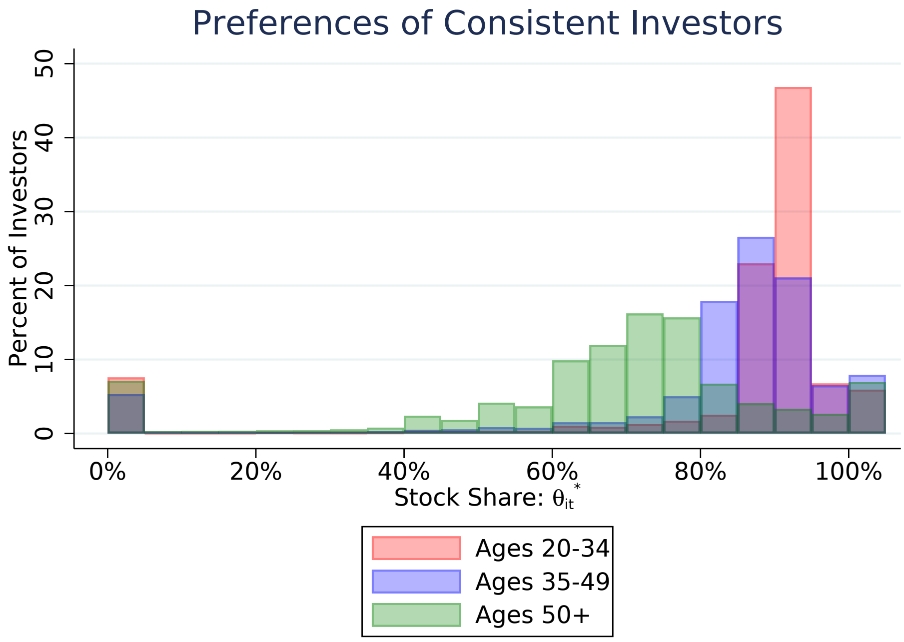
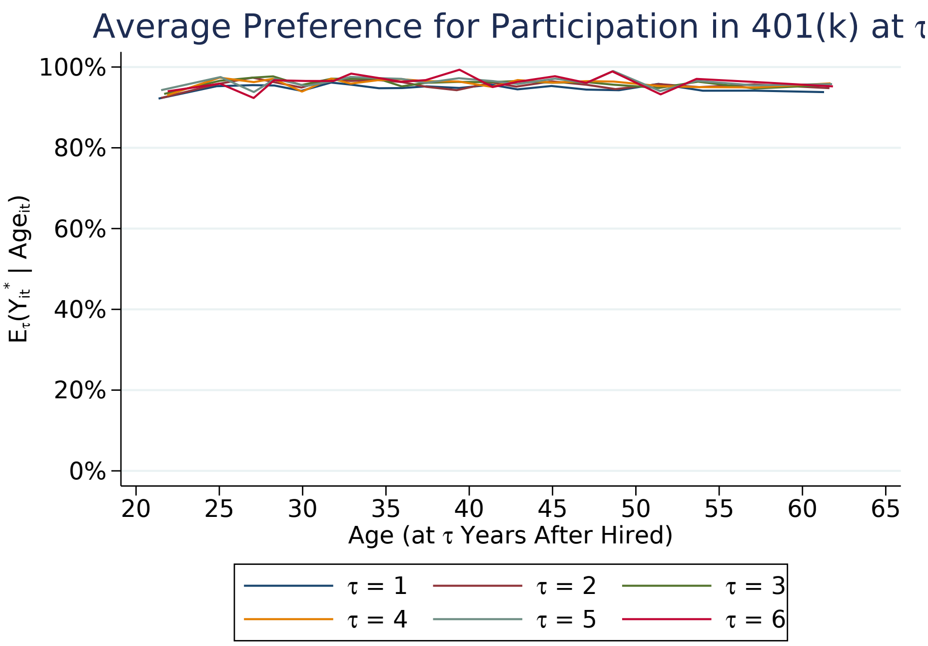


Figure IA11. Preference heterogeneity among consistent investors.

Panel A: Participation



Panel B: Stock share of retirement wealth

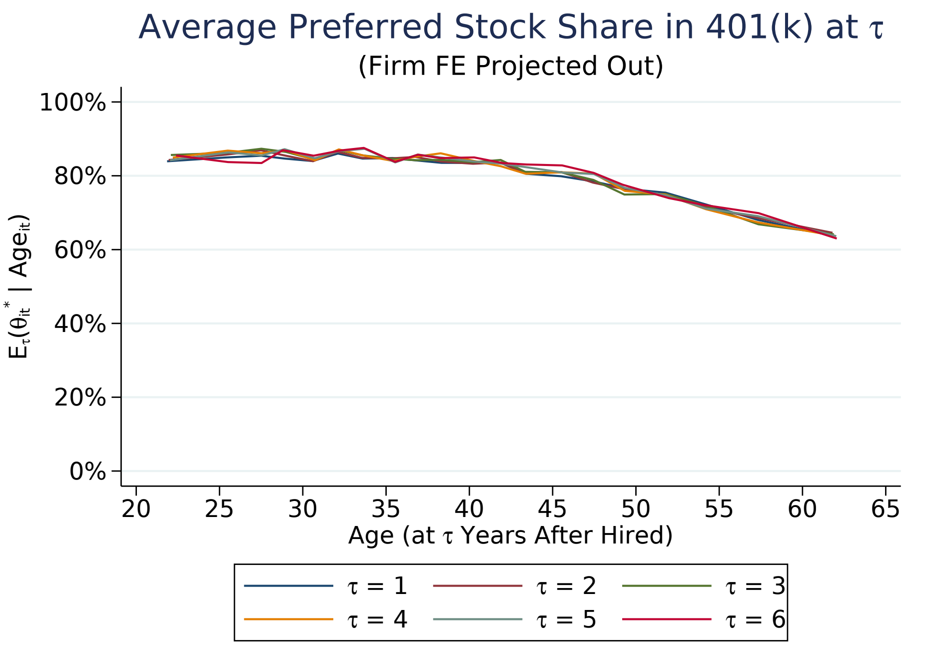
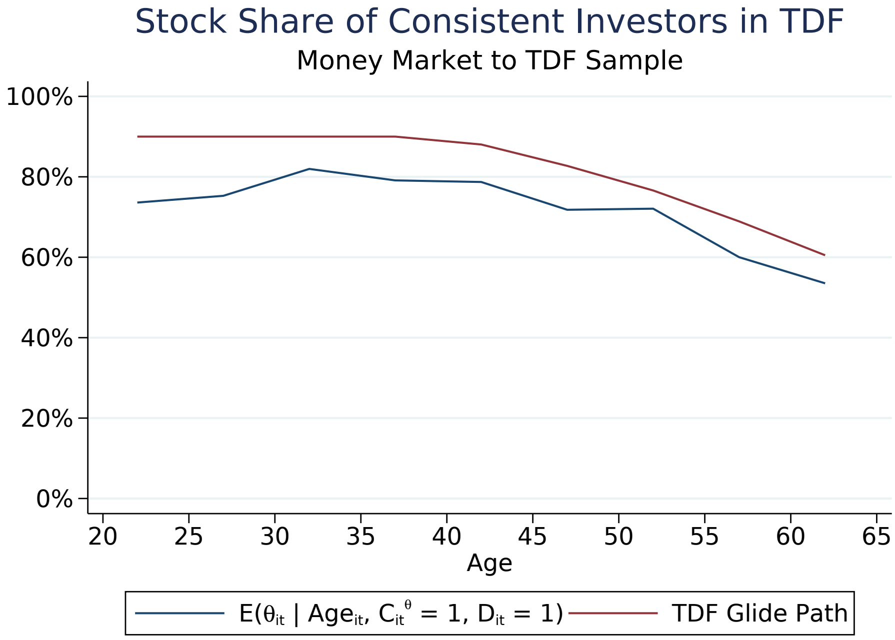


Figure IA12. Robustness of preferences over the life cycle: Opt-in to TDF sample.

Panel A: Money market to TDF sample



Panel B: Opt-in to TDF sample

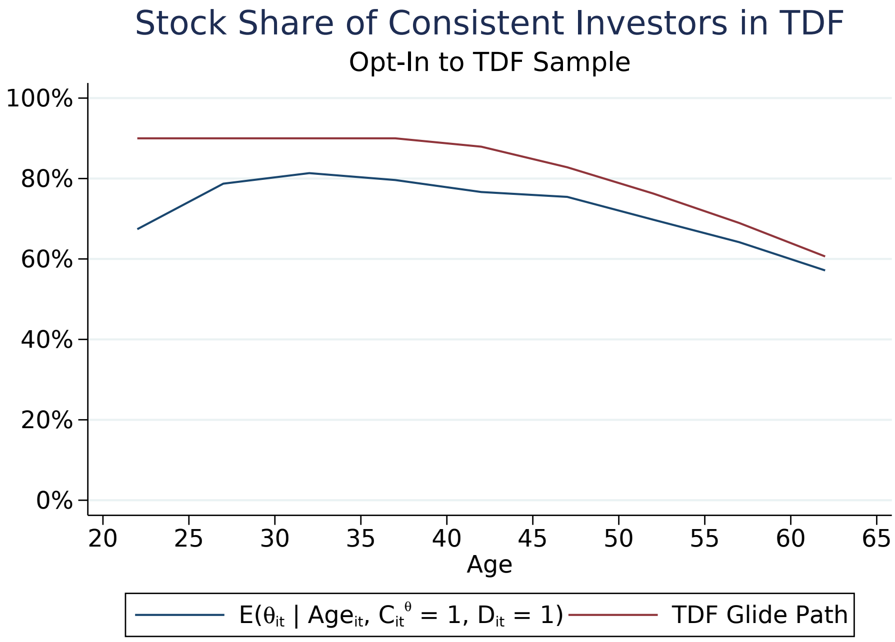
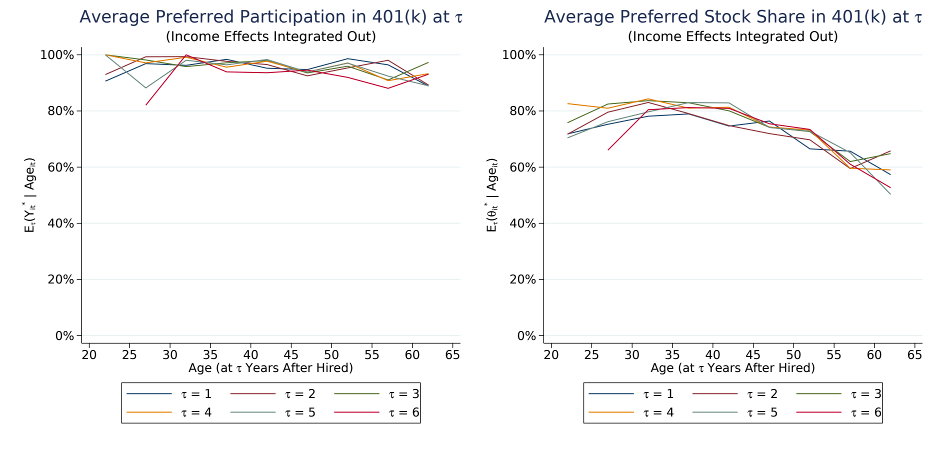


Figure IA13. Life-cycle preferences of consistent investors defaulted into TDF.

Panel A: Money market to TDF sample



Panel B: Opt-in to TDF sample

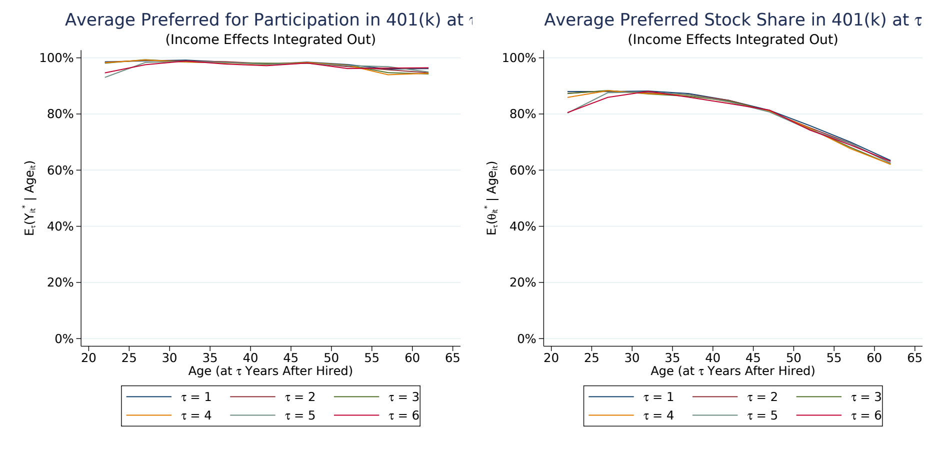
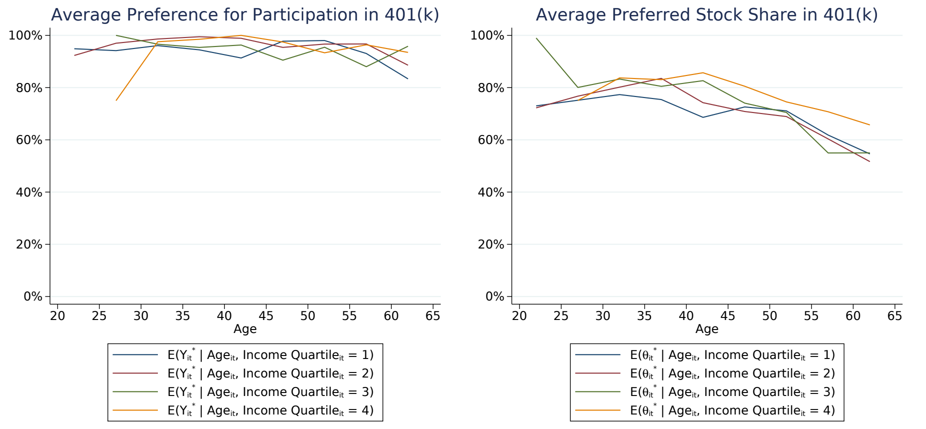


Figure IA14. Estimated preferences under weaker identifying assumption.

Panel A: Money market to TDF sample



Panel B: Opt-in to TDF sample

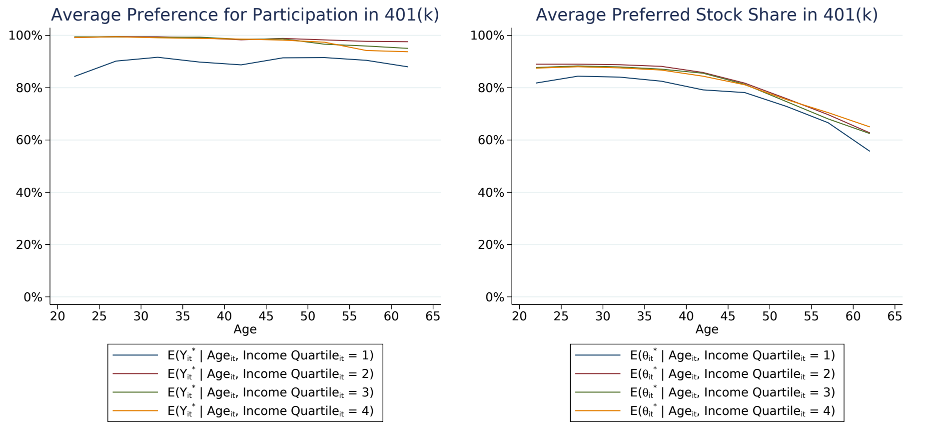


Figure IA15. Preferences over the life-cycle by income quartiles.

Table IAIII. 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

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.

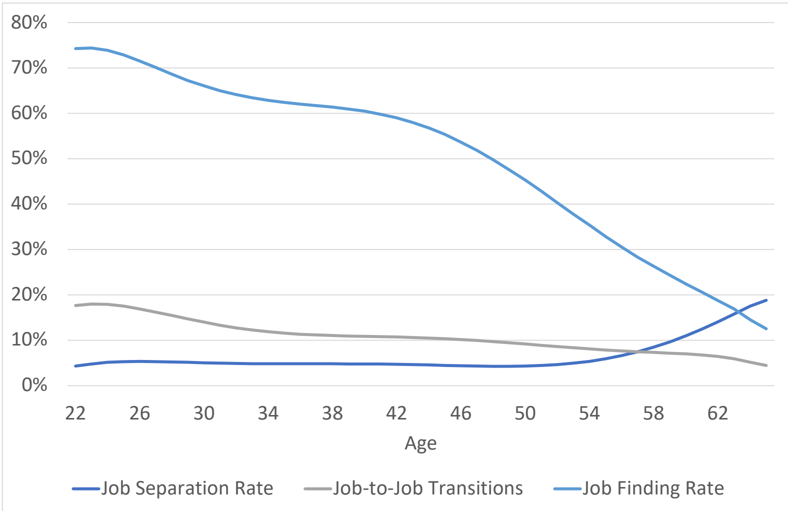


Figure IA16. Age component of annual labor market transitions.

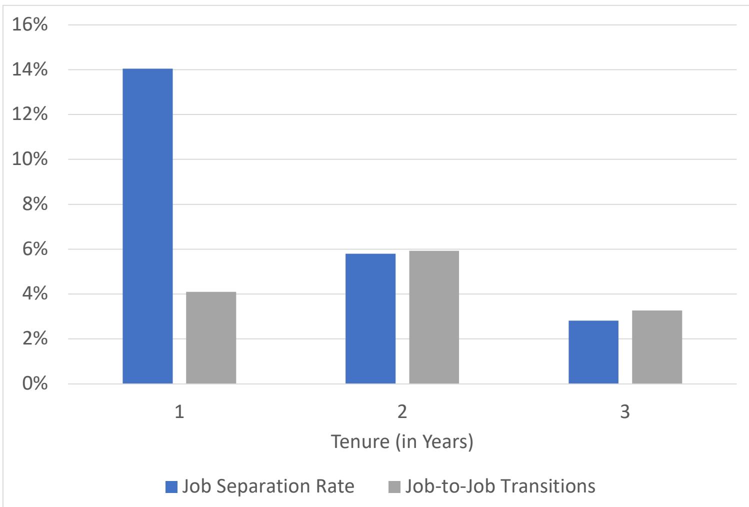


Figure IA17. Tenure component of annual labor market transitions.

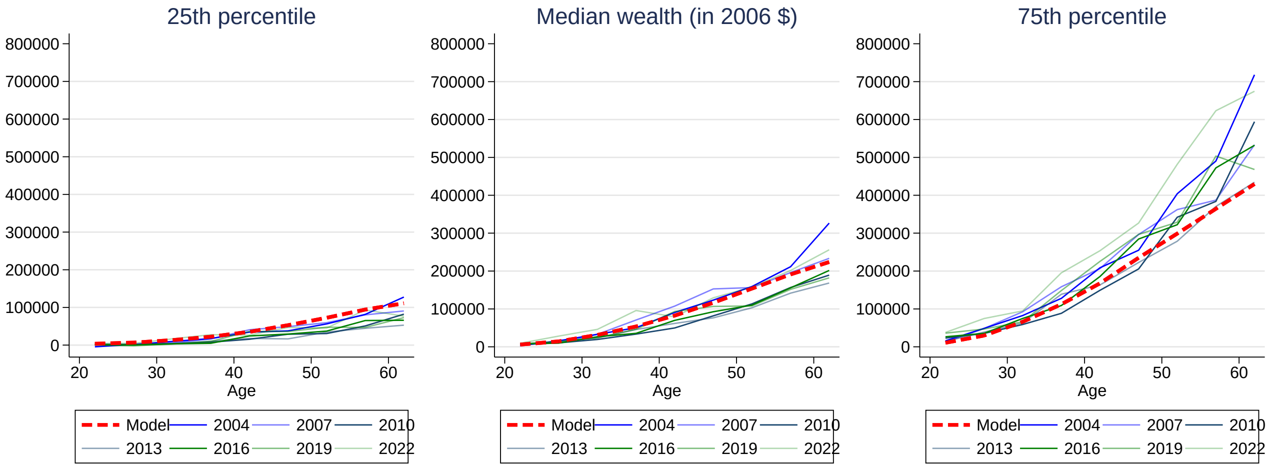


Figure IA18. Comparison of model and SCF: Wealth accumulation. This figure compares wealth accumulation in the model with that in different waves of the SCF. Each panel plots how different percentiles of the wealth distribution vary with age. The dashed red line corresponds to the model, where wealth 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.

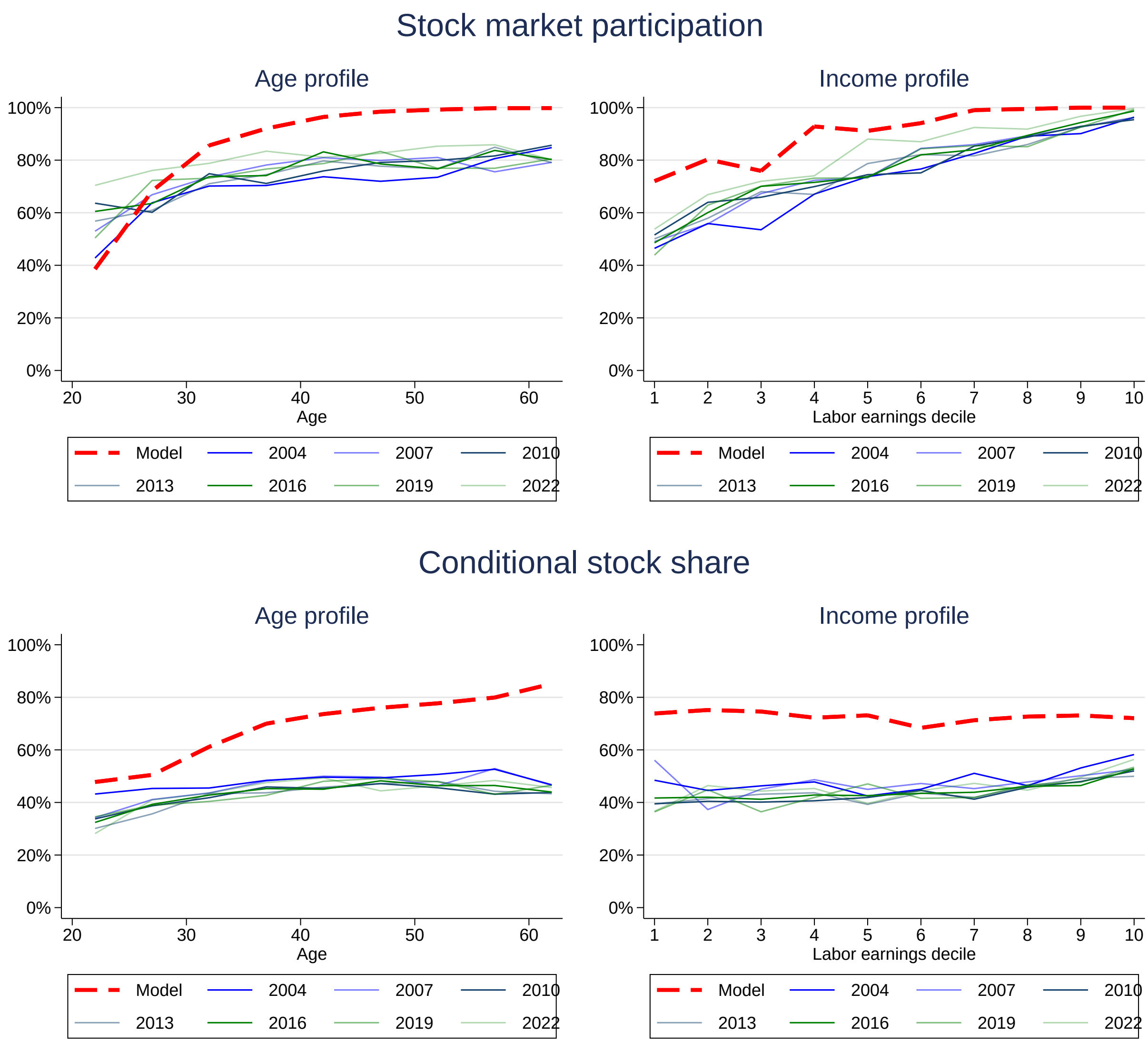


Figure IA19. Comparison of model and SCF: Portfolio choices. This figure compares stock market participation and conditional equity shares in the model with that in different waves of the SCF. The top two panels focus on stock market participation rates; the bottom two focus on conditional stock shares. 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.

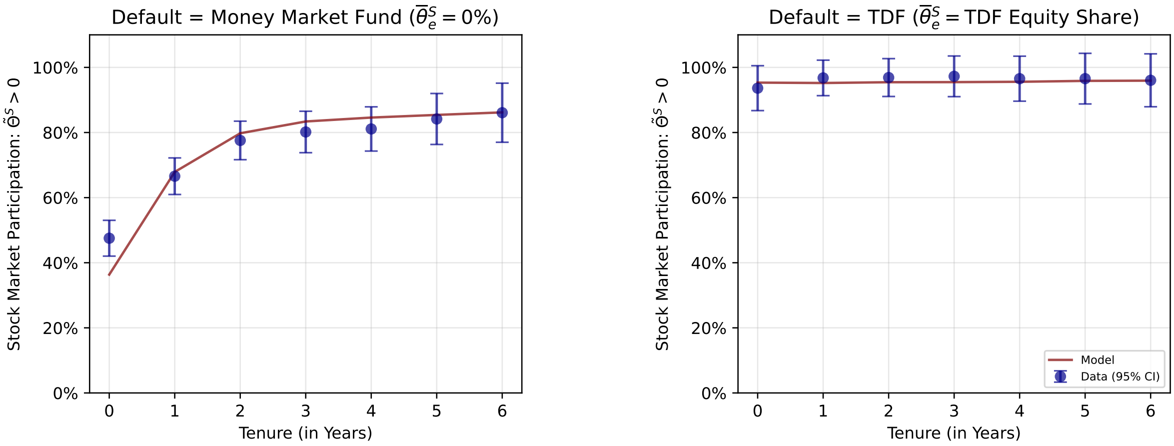


Figure IA20. CRRA model fit: Stock market participation in 401(k) from quasi-experiment #1. This figure presents the fit of our model on the response of stock market participation inside the current employer retirement account for our first quasi-experiment. The data moments in this figure correspond 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 III.

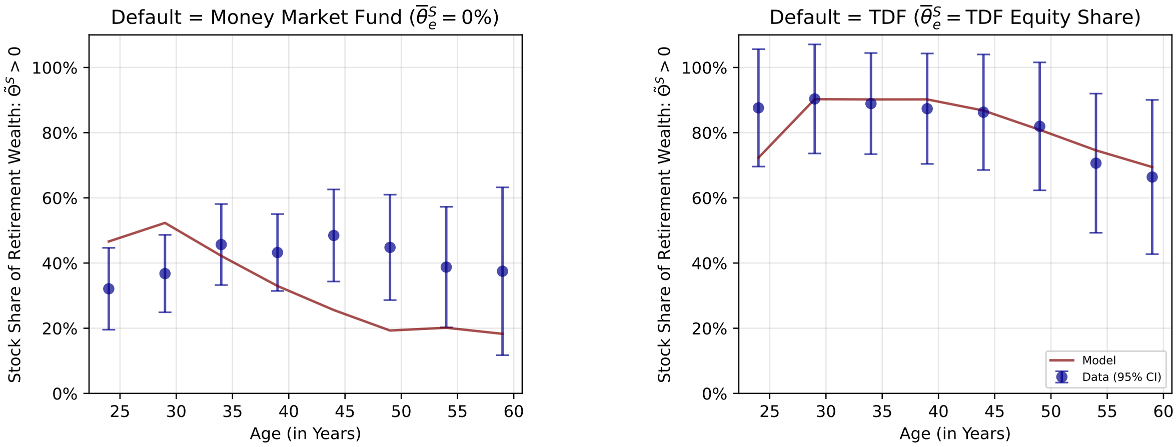


Figure IA21. CRRA model fit: Stock shares by age in first-year of tenure. This figure presents the fit of our model on the age profile of equity shares inside the current employer retirement account for the treatment and control groups in our first quasi-experiment separately. The data moments are calculated 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 III.

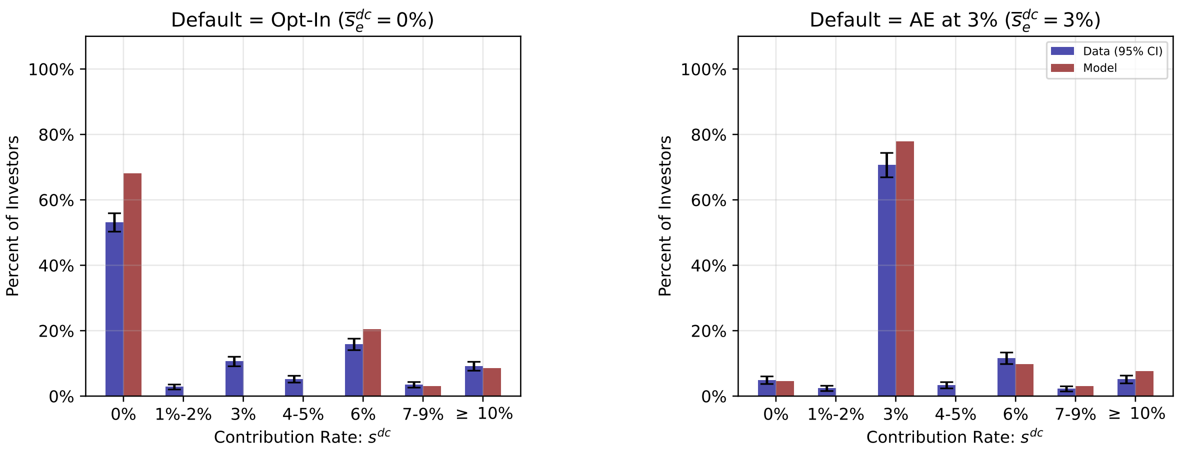


Figure IA22. CRRA model fit: Contribution rates in first-year of tenure. This figure presents the fit of our model on the distribution of contribution rates in investors' first-year of tenure. The amount of investors at 0%, 3%, 6%, and greater than 10% is targeted in the estimations reported in Table III. 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 III.

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