Online Appendix for
Default Options and Retirement Saving Dynamics

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A Parameters Definition

Table A.1 summarizes all the model parameters introduced in the paper (excluding the appendices).

Table A.1: Summary of model parameters

	Preference Parameters		**Assets**
δ	Discount factor	R^{dc}	Rate of return on DC wealth
σ	Elasticity of intertemporal substitution	$R^{liq}\left(\,\right)$	Rate of return on liquid assets
k	Switching cost	$1+r$	Interest rate on positive asset holdings
	State variables	$1+r^{cc}$	Interest rate on unsecured debt
X_t	Vector of all state variables	$\underline{l}_a$	Borrowing limit
a	Age		**Defined Contribution (DC) Account**
emp_t	Employment status	$E\left(\,\right)$	Distribution of DC account types
ten_t	Tenure	$ec^e\left(\,\right)$	Employer DC contribution
e	Employer DC plan type	$match^e$	Employer matching rate
θ	Labor productivity	cap^e	Threshold on employer matching
ae	Average lifetime earnings	$\Upsilon_e\left(\,\right)$	Vesting risk-adjustment
l	Liquid assets		**Labor Market**
dc	DC wealth stock	$\pi^{JJ}\left(\,\right)$	Job-to-job transition probability
d	Default contribution rate	$\pi^{EU}\left(\,\right)$	Unemployment transition probability
$F\left(\,\right)$	Joint distribution of θ, emp, e	$\pi^{UE}\left(\,\right)$	Out-of-unemployment transition probability
	Choices	$\{\delta_i\}_{i=0}^{3}$	Deterministic component of earnings
c	Consumption	w	Labor earnings
s	DC contribution rate	ρ	Autocorrelation in earnings shocks
$draw$	DC withdrawal rate	ξ	Earnings innovation if continuously employed
	Utility	$\sigma^2_{\xi_1}$	Variance of the first earnings innovation
$u_a\left(\,\right)$	Utility function	σ^2_{ξ}	Variance of subsequent innovations
$V\left(\,\right)$	Value function	ζ	Earnings innovation after job-to-job transition
$V^S\left(\,\right)$	Value function cdt. on DC contrib. s	μ^{JJ}	Avg. wage gain after a job-to-job transition
	Demographics	ς_t	Earnings innovation out of unemployment
A	Maximum age	μ^{UE}	Avg. wage loss out of unemployment
A^R	Retirement age	ι	Measurement error in earnings
m_a	Mortality risk	σ^2_{ι}	Variance of measurement error
n_a	Equivalence scale	η	Earnings innovation plus measurement error
	Aggregate budget constraint		**Tax and benefit system**
$\overline{Y}$	Employers' aggregate budget constraint	$tax^i\left(\,\right)$	Tax on income
$Pf\left(\,\right)$	Aggregate employer profits	τ^k	Tax on capital returns
$W\left(\,\right)$	Aggregate wages	$limit_a$	Tax limit on DC contributions
$Mtc\left(\,\right)$	Agg. employer matching contributions	pen_a	Tax penalty for early DC withdrawals
$\bar{y}\left(\,\right)$	Avg. individual income under opt-in	$ui\left(\,\right)$	Unemployment insurance benefit
		$ss\left(\,\right)$	Public pension income

B Additional Evidence for the Empirical Section

B.1 Additional details on the event-study sample construction

Plan selection. The event-study sample includes 401(k) plans that satisfy the following criteria:

- The plan must have adopted auto-enrollment for new hires with a default contribution rate of either 3% or 6% of salary.
- The plan must have a minimum of five years of data, starting from the year prior to the adoption of the auto-enrollment policy (t-1) and a minimum of three years of data after the policy adoption (t+3). This ensures that the opt-in and auto-enrollment cohorts are observed for at least 36 months of tenure.
- The plan must have new hires in at least six of the twelve months prior to and six of the twelve months after the adoption of the auto-enrollment policy. This excludes smaller plans with few employees hired during the event-study window and plans with hiring concentrated in a small number of months.
- The plan must offer an employer match for employee contributions up to 6% of salary throughout the event-study period. This is the most common matching cap both in this dataset and for nearly half of U.S. 401(k) plans (Arnoud et al., 2021).

Sample restrictions. I further restrict the sample to include continuously-employed workers who satisfy the following three criteria. The goal of these restrictions is to ensure compliance with the auto-enrollment treatment.

(i) I exclude employees hired in the month of auto-enrollment adoption (month 0).

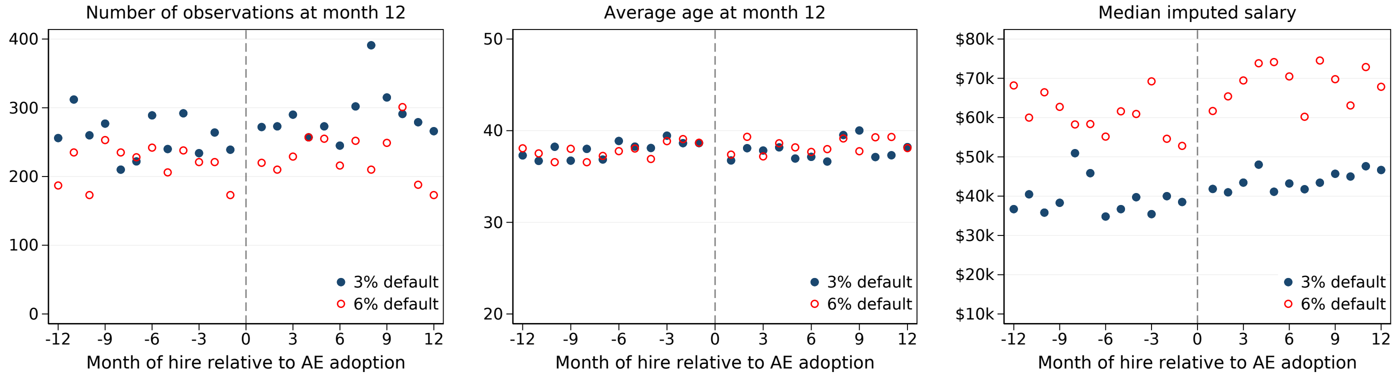
(ii) I exclude employees hired under auto-enrollment but auto-enrolled more than 3 months after their date of hire.

(iii) I exclude employees who are auto-enrolled despite being hired prior to the adoption of the auto-enrollment policy.

The resulting sample is described in Table 1. I show in Appendix B.2.3 that the empirical results are similar without these three sample restrictions, but the effects are more difficult to interpret due to imperfect compliance with the policy.

Balance check. I define the month of hire relative to the adoption window as each successive 31 calendar days relative to the month of auto-enrollment adoption. Following the approach initiated by Madrian and Shea (2001), I compare employees hired in the 12 months prior to the month of auto-enrollment adoption (opt-in cohorts) to those hired in the 12 months after the policy adoption (auto-enrollment cohorts). Figure A.1 shows that both cohorts are balanced in terms of number of observations, age and salary.

Figure A.1: Observable characteristics: Auto-enrollment vs. opt-in cohort (12th month of tenure)



Notes: The horizontal axis shows the normalized month of hire relative to the time of auto-enrollment adoption. In the left panel, each dot corresponds to the number of observations for employees in their 12th month of tenure by date of hire relative to the month of the policy adoption. The middle panel corresponds to the average age. The right panel corresponds to estimated annual median salary. Salary information is available only for employees with a positive contribution rate, and I assume that all nonparticipating employees have below-median salaries.

Main variables. Below, I discuss the definition of the main variables:

- Participation is defined as an employee's making a positive contribution to the 401(k) plan in a given month. Participation rates in the first few months of tenure are biased upward because I do not observe workers who never joined the 401(k) plan and left their employer before the month of December of their first year of tenure. After 12 months of tenure, every nonparticipating employee has been observed at least once in December.

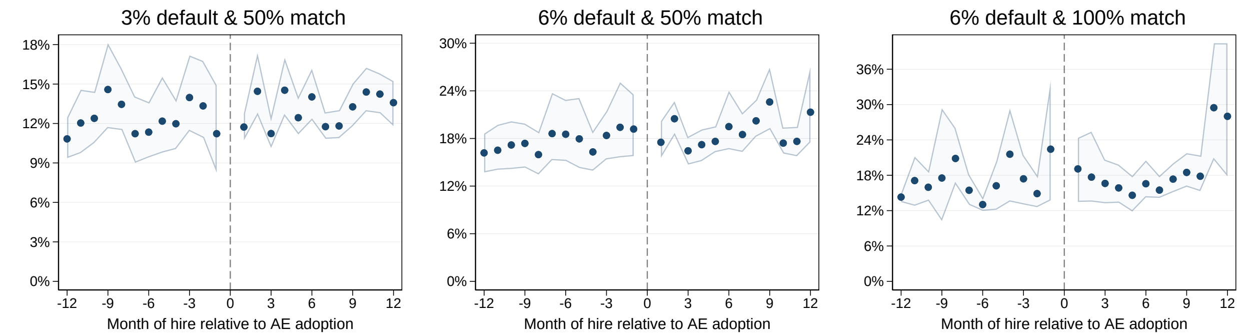
- Cumulative contributions are computed as the sum of all employee (or combined employee and employer) contributions made to the 401(k) plan since the date of hire divided by the employee's current annual salary. Values are winsorized when the ratio of cumulative contributions to cumulative earnings is above 1 (i.e., implying a savings rate above 100%).

- Earnings information is available only for employees with a positive contribution rate. When computing median earnings, I assume that all nonparticipating employees have below-median earnings.

B.2 Additional evidence on Fact II

B.2.1 Plans with different matching formulas

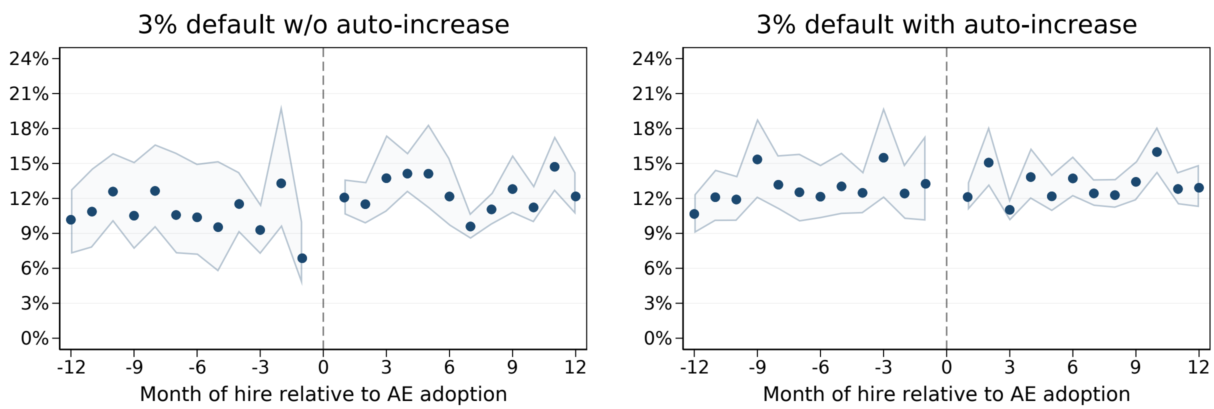
Figure A.2: Effect of auto-enrollment on cumulative employee contributions after 36 months of tenure by employer matching formula



Notes: The horizontal axis shows the normalized month of hire relative to the month of auto-enrollment adoption. Each panel shows average cumulative employee 401(k) contributions observed in the 36th month of tenure divided by individuals' annual salary for plans with different employer matching formulas. The left (middle) panel corresponds to plans with a 50% match rate up to 6% of salary and a 3% (6%) auto-enrollment default contribution rate. The right panel corresponds to plans with a 100% match rate up to 6% of salary and a 6% auto-enrollment default contribution rate. Shaded areas correspond to the bootstrapped 95% confidence intervals stratified at the plan level for each series.

B.2.2 Plans with and without an auto-escalating default option

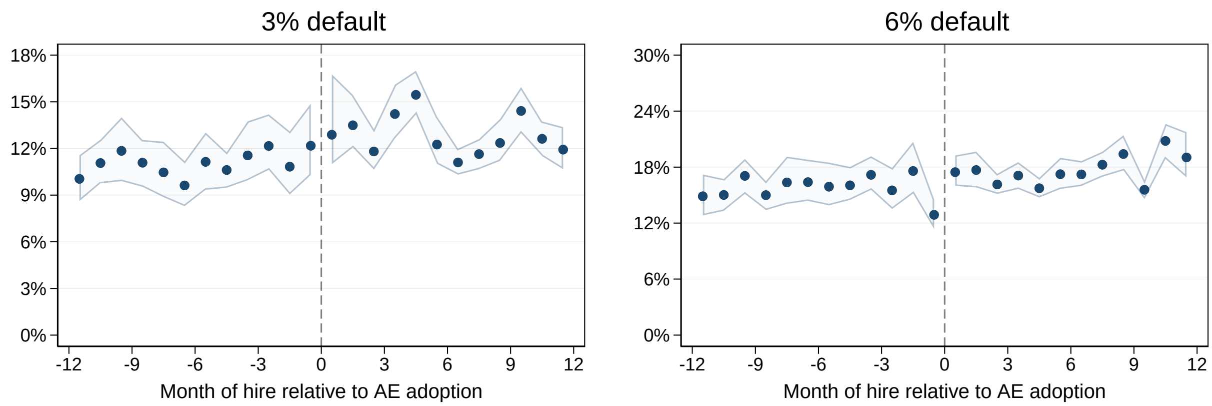
Figure A.3: Effect of auto-enrollment on cumulative employee contributions after 36 months of tenure with and without auto-escalation



Notes: The horizontal axis shows the normalized month of hire relative to the month of auto-enrollment adoption. The left (right) panel shows average cumulative employee 401(k) contributions observed in the 36th month of tenure divided by individuals' annual salary in plans adopting auto-enrollment at 3% without (with) an auto-escalating default contribution rate. Shaded areas correspond to the bootstrapped 95% confidence intervals stratified at the plan level for each series.

B.2.3 Results without baseline sample restrictions

Figure A.4: Effect of auto-enrollment on cumulative employee contributions after 36 months of tenure without the baseline sample restrictions

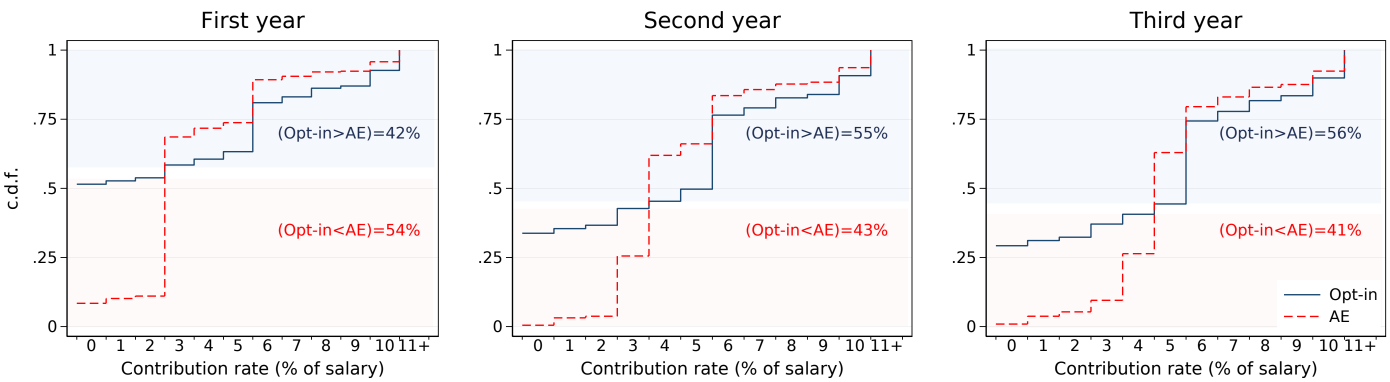


Notes: The horizontal axis shows the normalized month of hire relative to the calendar date of auto-enrollment adoption. The left (right) panel shows average cumulative employee 401(k) contributions observed in the 36th month of tenure divided by individuals' annual salary in plans adopting auto-enrollment with a 3% (6%) default contribution rate. Event-study without the three sample restrictions described in Appendix B.1. Shaded areas correspond to the bootstrapped 95% confidence intervals stratified at the plan level for each series.

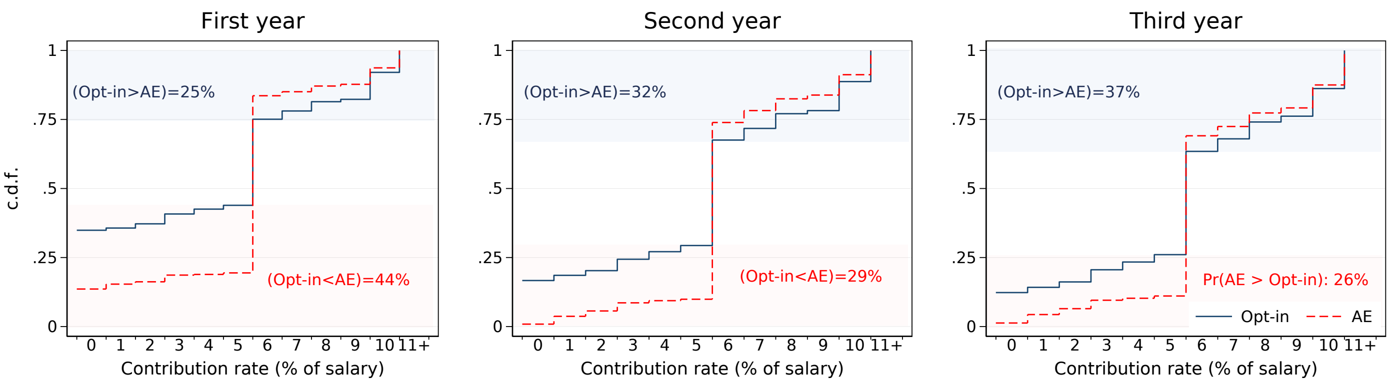
B.3 Additional evidence on Fact V

Figure A.5: Distribution of contribution rates over tenure

(a) Plans with a 3% default with auto-escalation



(b) Plans with a 6% default



Notes: Each line corresponds to the cumulative distribution function (CDF) of contribution rates as a % of salary recorded in December of the employee's first year (left panels), second year (middle panels), and third year (right panels) of tenure. The solid line corresponds to employees hired in the 12 months prior to the adoption of auto-enrollment (the opt-in cohort), and the dashed lines correspond to the distribution for employees hired in the 12 months following auto-enrollment adoption (the AE cohort).

B.4 Additional evidence for Fact VI

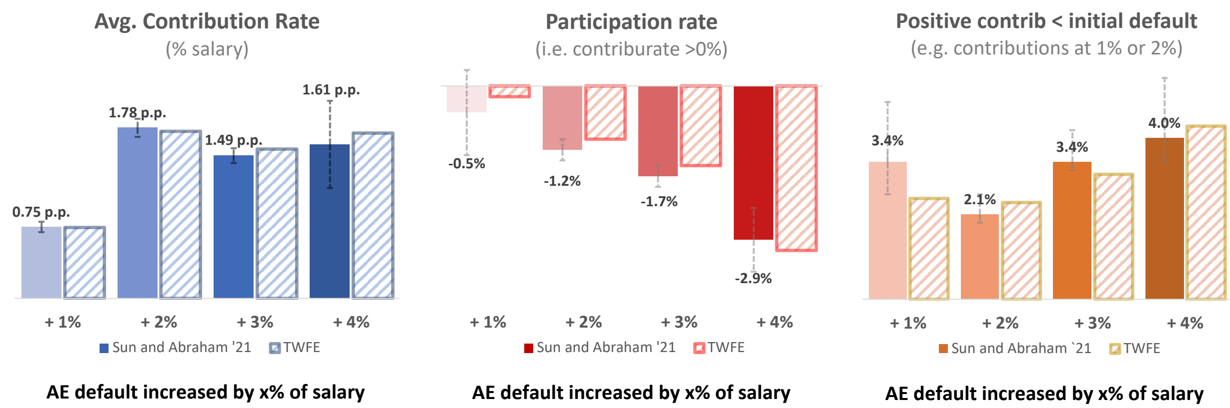
Figure A.6 shows that the evidence presented in Fact VI is robust to my using the dynamic event-study approach of Sun and Abraham (2021), which is robust to treatment effect heterogeneity. Table A.2 shows the regression coefficient estimates under both approaches.

Table A.2: Effect of a higher auto-enrollment default on participation and contributions

	Average contribution rate (share of salary)			**Participation (i.e. contribution > 0)**			**Positive contribution below initial default**		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	TWFE	TWFE	SunAbraham	TWFE	TWFE	SunAbraham	TWFE	TWFE	SunAbraham
Increase in the default (p.p.)	0.613			-0.006			0.012		
	(0.071)			(0.001)			0.003		
Increase in default = 1%		0.742	0.747		-0.002	-0.005		0.025	0.034
		(0.063)	(0.054)		(0.007)	(0.008)		(0.012)	(0.015)
Increase in default = 2%		1.748	1.784		-0.01	-0.012		0.024	0.021
		(0.14)	(0.095)		(0.004)	(0.002)		(0.006)	(0.005)
Increase in default = 3%		1.563	1.494		-0.015	-0.017		0.031	0.034
		(0.148)	(0.078)		(0.004)	(0.002)		(0.01)	(0.008)
Increase in default = 4%		1.728	1.611		-0.031	-0.029		0.043	0.040
		(0.413)	(0.456)		(0.011)	(0.006)		(0.018)	(0.015)
Ln(age)	1.155	1.159	1.158	-0.005	-0.005	-0.005	-0.004	-0.004	-0.004
	(0.173)	(0.173)	(0.172)	(0.002)	(0.002)	(0.01)	(0.003)	(0.003)	(0.002)
Ln(tenure)	0.328	0.331	0.332	0.014	0.014	0.014	0.01	0.01	0.01
	(0.050)	(0.051)	(0.051)	(0.01)	(0.01)	(0.002)	(0.002)	(0.002)	(0.003)
Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Plan FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Observations	764,006	764,006	764,006	764,006	764,006	764,006	764,006	764,006	764,006
R-squared	0.149	0.149	0.149	0.014	0.014	0.014	0.074	0.074	0.075

Notes: Each column reports coefficients from a regression where the dependent variable is the outcome in the column heading. The coefficients correspond to the difference between employees hired before and after each firm increased its auto-enrollment default contribution rate. Each data point corresponds to an employee observed in her first 12 months of tenure, and after the end of the auto-enrollment grace period. Columns 1, 2, 4, 5, 7 and 8 are estimated using a two-fixed effect regression, while columns 3, 6 and 9 are the result of the dynamic event-study estimator of Sun and Abraham (2021). Standard errors clustered at the firm level are in parentheses.

Figure A.6: Effect of a higher auto-enrollment default on participation and contributions



Notes: Each column reports coefficients from a two-way fixed effect regression (solid shading) or the dynamic event-study approach of Sun and Abraham (2021) (diagonal stripes) for employees observed in their first 12 months of tenure and after the end of the auto-enrollment grace period. The independent variables are dummies equal to one for employees hired after the default contribution rate was increased by 1, 2, 3, or 4 percentage points in 101 US 401(k) plans. The sample also includes employees in 245 never-treated 401(k) plans with no change to their auto-enrollment default option. Controls include year fixed effects, plan fixed effects, log tenure (in days), and log age. Standard errors are clustered at the plan level.

B.5 Additional evidence on Fact VII

In this appendix, I provide additional evidence on the effect of auto-enrollment after a job transition, as described in Section 3.7.

First, I run the same specification as in Table 3 under the assumption that the policy rollout started before the actual policy implementation date in 2012. The results of these placebo tests, reported in columns 2 to 8 of Appendix Table A.3, are all insignificant at the 5% level for both the participation and contribution outcomes, and a single coefficient is significant at the 10% level. These results help validate the empirical strategy and suggest that the estimates capture the effect of the auto-enrollment rollout rather than the effect of an employee's having moved from a larger to a smaller employer.

Table A.3: Auto-enrollment effect after a job transition

	Actual policy	Placebo tests						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Beginning of policy rollout	2012	2005	2006	2007	2008	2009	2010	2011
				Panel A – Participation rate				
AE to non-AE employer	-0.128	0.077	0.034	0.014	0.016	0.053	0.016	-0.061
	(0.055)	(0.058)	(0.037)	(0.051)	(0.049)	(0.058)	(0.051)	(0.086)
AE to AE employer	0.010	0.001	0.007	0.014	0.008	0.016	0.028	0.021
	(0.019)	(0.017)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.017)
				Panel B – Contribution rate (in percentage of pay)				
AE to non-AE employer	-0.546	-0.001	-0.018	0.261	-0.139	0.003	-0.269	-0.209
	(0.226)	(0.209)	(0.187)	(0.541)	(0.221)	(0.244)	(0.217)	(0.336)
AE to AE employer	-0.039	-0.013	-0.026	-0.04	-0.001	0.052	-0.026	-0.035
	(0.068)	(0.093)	(0.073)	(0.064)	(0.062)	(0.068)	(0.099)	(0.069)
Employee characteristics	✓	✓	✓	✓	✓	✓	✓	✓
$\text{Size}_{e'} \times \text{Size}_e$	✓	✓	✓	✓	✓	✓	✓	✓
Employer×Year FEs	✓	✓	✓	✓	✓	✓	✓	✓
Observations	37120	37120	37120	37120	37120	37120	37120	37120

Notes: Each cell reports coefficients from a regression whose dependent variable is a dummy for workers' participation status in the retirement savings plan (Panel A) or contribution rate in percentage points of pensionable pay (Panel B). The sample contains job switchers in their first year of tenure. The coefficients correspond to the effect of the automatic enrollment mandate in the previous employer on contributions when the current employer is not subject to the auto-enrollment requirement (AE to non-AE employer) and when the current employer is subject to automatic enrollment (AE to AE employer). In column 1, I assign an enrollment regime to each employer (i.e., opt AE or non-AE) based on the U.K. national auto-enrollment policy rollout schedule (in Appendix H). In columns 2 to 8, I assign enrollment regimes based on a (placebo) policy rollout schedule that starts earlier than the actual policy. I assume that the policy rollout started in the year reported in the column heading. Controls for employees' characteristics include controls for log salary and log tenure in the current job, log salary and log tenure when the employee is last observed in the previous job, a dummy for gender, and a third-order polynomial in age. The sample is restricted to private-sector workers between the ages of 22 and 60. Standard errors clustered by current employer are in parentheses. Data source: U.K. ASHE waves 2006 to 2017.

In the model, I interpret the difference in participation and contribution rates between those who were previously auto-enrolled and those who were not as reflecting a wealth effect (more saving in the previous job reduces the need to save in the current job). However, previously auto-enrolled workers may be better informed about the future roll-out of the policy and may expect to eventually be automatically enrolled by their new employer. They may therefore choose not to opt into their new employer's retirement savings plan because they expect to be automatically enrolled soon anyway. This mechanism should affect mainly those whose new employer will soon become subject to the auto-enrollment mandate. To test this hypothesis in Table A.4, columns 3 and 6, I interact the variable for a transition to an opt-in employer with a dummy equal to 1 if the new employer is expected to become subject to automatic enrollment within the next 12 months. While the results are noisy and not statistically significant, previously auto-enrolled workers who do not expect to be auto-enrolled in their new job within a year reduce their participation by 7.5 percentage points and their contributions by 0.12% of income, in line with the model predictions in 7.2 (a model-implied drop in participation of 9.6% and in contributions of 0.11% of salary). The drop in participation and contributions for those whose employer was scheduled to adopt auto-enrollment within 12 months is significantly larger (participation drops by an additional 11.6 percentage points and contributions by an additional 0.93% of income), which suggests that differential expectations about the policy rollout may play a role.

Table A.4: Auto-enrollment effect after a job transition

	Participation rate			**Contribution rate**		
	(1)	(2)	(3)	(4)	(5)	(6)
AE to non-AE employer	-0.065	-0.128	-0.075	-0.267	-0.538	-0.122
	(0.031)	(0.055)	(0.052)	(0.108)	(0.227)	(0.266)
AE to non-AE employer ×			-0.116			-0.927
AE to be adopted within a year			(0.092)			(0.517)
$\text{Size}_{e'} \times \text{Size}_e$		✓	✓		✓	✓
Employee characteristics	✓	✓	✓	✓	✓	✓
Employer×Year FE	✓	✓	✓	✓	✓	✓
Observations	37120	37120	37120	37120	37120	37120

Notes: Each cell reports coefficients from a regression whose dependent variable is a dummy for workers' participation status in the retirement savings plan (columns 1, 2 and 3) or contribution rate in percentage points of pensionable pay (columns 4, 5, and 6). The sample contains job switchers in their first year of tenure. I assign an enrollment regime to each employer (i.e., AE or non-AE) based on the U.K. national auto-enrollment policy rollout schedule (in Appendix H). The coefficients for "AE to non-AE employer" correspond to the effect of the automatic enrollment mandate in the previous employer on contributions when the current employer is not subject to the auto-enrollment requirement. In columns 3 and 6, the variable "AE to be adopted within a year" is a dummy equal to 1 if the current employer is expected to be subject to automatic enrollment in the 12 months following the date of observation. Controls for employees' characteristics include controls for log salary and log tenure in the current job, log salary and log tenure when the employee is last observed in the previous job, a dummy for gender, and a third-order polynomial in age. The sample is restricted to private-sector workers between the ages of 22 and 60. Standard errors clustered by current employer are in parentheses. Data source: U.K. ASHE waves 2006 to 2017.

C A theoretical framework for comparing alternative theories

I begin with a simple theoretical framework to compare the predictions of different behavioral theories that can potentially explain inertia at the savings default. This is a simplified version of the full model developed in Section 4.

A worker contributes a fraction s of her wage w to a retirement savings account. She faces a default contribution rate d and selects an optimal contribution choice s^* from a discrete set S such that:

$$s^* = \underset{s \in S}{\operatorname{argmax}} \left\{ U\left(s, d\right) + \delta V_{t+1}\left(s\right) \right\}$$

where δ is the intertemporal discount factor, U is flow utility, and V_{t+1} is the continuation value, which is strictly increasing in contributions to the retirement savings account. I use this framework to compare the predictions of three possible explanations of the default effect: switching costs, loss aversion and psychological anchoring.

C.1 A model of switching costs fits the empirical evidence

A first explanation for the default effect is that employees have to incur real or behavioral costs to depart from the savings default. As discussed later in Section 4, these switching costs can capture a broad class of neoclassical and behavioral explanations of the default effect such as the cost of completing a form or seeking out advice from a professional adviser, as well as the cognitive cost of paying attention or finding the optimal saving choice.

I assume that workers incur a cost k to choose a contribution rate other than the default:

$$U\left(s, d\right) = \begin{cases} u\left(\left(1 - s\right) w - k\right) & \text{if } s \neq d \\ u\left(\left(1 - s\right) w\right) & \text{if } s = d \end{cases}$$

where the utility function u is increasing and strictly concave in take-home pay $\left(1 - s\right) w$.

Proposition 1 shows that, in line with the empirical evidence, increasing the default contribution rate in a model with a fixed switching cost causes more people to drop out of the retirement savings plan entirely or to contribute at the lowest rates.[1]

Proposition 1. *If V_{t+1} is concave, increasing the default contribution rate from $\underline{d}$ to $\overline{d}$ weakly increases contributions strictly below $\underline{d}$ in a model with a fixed switching cost.*

To understand the intuition behind Proposition 1, consider an employee whose preferred contribution rate is 1% of salary. When the default contribution rate is 3%, this employee may stay at

[1] This pattern of behavior, dubbed the "drop-out" effect" by Caplin and Martin (2017), has been documented in other settings. For instance, in the case of charitable giving (Altmann et al., 2019) and tips for taxi rides (Haggag and Paci, 2014), increasing the default led more people to not contribute at all.

the default to avoid incurring the switching cost because the default option is close enough to her preferred contribution rate. However, if the contribution rate is raised to 6%, the same employee may choose to incur the cost and switch to 1% because the higher default is further away from her preferred contribution rate. Therefore, this employee reduces her contribution rate from 3% to 1% when the default is increased from 3% to 6%. [2] Later, in Section 7.1, I show that the switching cost model not only makes the right qualitative prediction but also predicts the magnitude of employees' response to increasing the default.

C.2 Loss aversion yields the opposite prediction

Loss aversion is a common explanation for individuals' propensity to stay at the status quo (Samuelson and Zeckhauser, 1988). Employees may perceive the default as a reference point around which gains and losses are evaluated. For instance, they may perceive an actively chosen additional contribution to the retirement savings plan as a loss in take-home pay, whereas resources that are automatically contributed to the savings account may not feel like losses. To capture this idea, I adopt a functional form similar to that in DellaVigna et al. (2017) and define flow utility as:

$$U(s,d) = \begin{cases} u\left((1-s)\,w\right) + \eta\left(v(s) - v(d)\right) & \text{if } s < d \\ u\left((1-s)\,w\right) + \eta\lambda\left(v(s) - v(d)\right) & \text{if } s \geq d \end{cases}$$

where $v(.)$ is decreasing in the contribution rate and reflects gain–loss utility.[3] An employee who contributes below the default contribution rate has more resources than her reference level and experiences gain utility $v(s) - v(d) > 0$ with weight $\eta \geq 0$. An employee who contributes above the default has fewer resources than her reference level and experiences loss utility $v(s) - v(d) < 0$ with a weight $\eta\lambda$. The parameter $\lambda \geq 1$ captures loss aversion.

Proposition 2 shows that, under loss-averse preferences, increasing the default contribution rate reduces the fraction of employees contributing at the lowest rates.

Proposition 2. *Under loss-averse preferences, increasing the default contribution rate from* $\underline{d}$ *to* $\overline{d}$

[2] The proof relies on the assumption that V_{t+1} is concave in the retirement contribution rate. This assumption may not always hold because of the discrete nature of the contribution choice decision. In practice, if there is enough uncertainty about the future, the continuation value V_{t+1} is generally concave.

[3] A natural candidate functional form is $v = u\left((1-s)\,w\right)$, where take-home pay serves as a consumption reference point. This specification satisfies the condition that v is decreasing in s.

weakly decreases contributions strictly below $\underline{d}$:

$$Pr\left(s^{*}<\underline{d}\,|\,d=\underline{d}\right)\geq Pr\left(s^{*}<\underline{d}\,|\,d=\overline{d}\right)$$

To understand the intuition behind Proposition 2, consider a plan that has increased its default contribution rate from 3% to 6% of salary. Contributions at 4%, 5%, or 6% of salary no longer feel like losses. Thus, these contributions become relatively more desirable than contributions at 0, 1%, and 2% of income (which are in the gain domain under both default contribution rates).

C.3 Psychological anchoring makes yields the opposite prediction

People may perceive the default contribution rate as a psychological anchor. Following Bernheim et al. (2015), I assume that the anchoring parameter χ shifts workers' preferences toward the value that would rationalize the default as an optimal choice. I assume that workers act as if they were more (less) patient when contributing below (above) the default. The value of contributing s when the default is d is equal to:

$$\begin{cases} u\left(\left(1-s\right)w\right)+\left(\delta+\chi\right)V_{t+1}\left(s\right) & \text{if } s<d \\ u\left(\left(1-s\right)w\right)+\delta V_{t+1}\left(s\right) & \text{if } s=d \\ u\left(\left(1-s\right)w\right)+\left(\delta-\chi\right)V_{t+1}\left(s\right) & \text{if } s>d \end{cases}$$

This specification also captures the idea of cognitive dissonance: participants shift their time preference to rationalize why the default may be optimal for them. Similarly to the case with loss aversion, Proposition 3 shows that a model of psychological anchoring predicts that increasing the default contribution rate reduces contributions at the lowest rates.

Proposition 3. *When the default serves as a psychological anchor, increasing the default contribution rate from $\underline{d}$ to $\overline{d}$ weakly decreases contributions strictly below $\underline{d}$:*

$$Pr\left(s^{*}<\underline{d}\,|\,d=\underline{d}\right)\geq Pr\left(s^{*}<\underline{d}\,|\,d=\overline{d}\right)$$

Proposition 3 demonstrates that anchoring contributions at a higher level should always lead employees to contribute and participate more (not less).

D Baseline Model and Calibration – Additional Details

D.1 Individual Maximization Problem

Individuals maximize their discounted intertemporal utility with an exponential discount factor δ. In what follows, I introduce the recursive optimization problem in periods of retirement, employment, and unemployment. This dynamic optimization problem is characterized by 9 state variables: age (a), employment status (emp), tenure (ten_t), employer DC plan type (e), labor productivity (θ), average lifetime earnings (ae), liquid assets (l), DC wealth (dc) and the default contribution rate (d). The vector of state variables is denoted $X_t = [a_t, emp_t, ten_t, e_t, \theta_t, ae_t, l_t, dc_t, d]$. There is uncertainty over survival to the next period (with mortality probability (m_a)), the stochastic component of earnings (θ), employment status (emp), and the type of the future employer after a job change (e). The joint distribution of earnings, employment and employer types is denoted $F(\theta_t, emp_t, e_t)$.

Individual problem in retirement (after age 65). The only source of uncertainty in retirement is mortality risk. Retired individuals decide every period how much to hold in the liquid asset and how much to withdraw from the DC account.

$$V_t(X_t) = \max_{draw_t \in [0,1],\, l_{t+1} \geq \underline{l}_a} u_a(c_t) + \delta(1 - m_a) V_{t+1}(X_{t+1})$$

$$s.t.\ l_{t+1} = R^{liq}(l_{t+1}) \left[ss\left(ae_{A^{ret}}\right) + draw_t dc_t + l_t - c_t - tax_t^i \right]$$

$$dc_{t+1} = R^{dc}\left((1 - draw_t) dc_t\right)$$

Individual problem when employed. People are employed following a job-to-job transition, an unemployment-to-employment transition or while in continuous employment. They face earnings and employment risk and decide how much to save in liquid wealth or borrow through unsecured credit and how much to contribute to the DC account. The decision is in two steps.

In the first step, for every possible DC contribution choice s in the discrete set S, the worker solves for the optimal amount of liquid wealth or unsecured debt to hold subject to the intertemporal budget constraint 3. The value of choosing a contribution rate s is thus given by:

$$V_t^s(X_t) = \max_{l_{t+1} \geq \underline{l}_a} u_a\left(c_t - \mathbb{1}_{(s_t \neq d_t)} k\right) + \delta(1 - m_a) \int V_{t+1}(X_{t+1})\, dF(\theta_t, emp_t, e_t)$$

$$s.t.\ l_{t+1} = R^{liq}(l_{t+1}) \left[(1 - s_t) w_t + l_t - c_t - tax_t^i \right] \tag{3}$$

In the second step, the worker selects a DC contribution rate s subject to a tax limit on DC contributions:

$$V_t(X_t) = \max_{s_t \in S} \{V_t^s(X_t)\}$$

$$s.t.\ s_t w_t \leq limit_a$$

$$dc_{t+1} = R^{dc}(dc_t + s_t w_t + ec_t^e)$$

Individual problem when unemployed. After an unemployment shock, people receive constant unemployment benefits and face uncertainty about finding a job and the wage and type of DC plan in their future job. They decide how much liquid wealth or unsecured debt to hold and how much to withdraw from the DC account.

$$V_t(X_t) = \max_{draw_t \in [0,1],\, l_{t+1} \geq \underline{l}_a} u_a(c_t) + \delta(1 - m_a) \int V_{t+1}(X_{t+1})\, dF(\theta_t, emp_t, e_t)$$

$$s.t.\ l_{t+1} = R^{liq}(l_{t+1})\left[ui_t + draw_t(1 - pen_a)\, dc_t + l_t - c_t - tax_t^i\right]$$

$$dc_{t+1} = R^{dc}(1 - draw_t)\, dc_t$$

D.2 Labor market parameters

Data. I use the Survey of Income and Program Participation (SIPP) to estimate of the wage earnings process and labor market transition probabilities. For each individual in the panel, we observe data on income, employment status and her employer's identity for each week. I use the 1996 panel of the SIPP, which contains data from December 1995 to February 2000, and aggregate the data to quarterly frequency. I focus on an individual's primary job (defined as the job where she works the most hours). I restrict the sample to individuals aged 22 to 65 years old and exclude full-time students and business owners. Following Borella et al. (2018), I use data on both male and female respondents. I use the publicly available replication files provided by Menzio et al. (2016b) to build the SIPP panel and use a broadly similar definition of labor market transition variables. I assign employment status based on individuals' responses in the first week of each quarter. An individual is classified as employed if she reports having a job. I record a job-to-job transition if the identity of an individual's employer is different in two successive quarters. I record a job separation if an individual is employed at the beginning of a quarter and not employed at the beginning of the subsequent quarter. Job separations include early retirement (before age 65) decisions.

Earnings process. I estimate the labor earnings process for workers staying in the same job using a standard two-step minimum distance approach similar to the approaches of Guvenen (2009) and Low et al. (2010). The empirical income process is given in equation (4). It is the empirical counterpart of the model earning process with one additional term: serially uncorrelated measurement error $\iota_{i,t} \sim N\left(0, \sigma_\iota^2\right)$.

$$\ln w_{i,t} = \delta_0 + \delta_1 a_{i,t} + \delta_2 a_{i,t}^2 + \delta_3 a_{i,t}^3 + \underbrace{\eta_{i,t}}_{\theta_{i,t}+\iota_{i,t}} \tag{4}$$

The estimation has two steps. In the first step, I estimate the parameters of the deterministic component of earnings $\left(\{\delta_j\}_{j=0}^3\right)$—a cubic in age. In the second step, I use the residual from regression (4) to estimate the four parameters governing the stochastic component of earnings: the coefficient of autocorrelation in earnings shocks (ρ), the variances of the first earnings innovation ($\sigma_{\xi_1}^2$), the variance of subsequent innovations (σ_ξ^2), and the variance of measurement error (σ_ι^2). I estimate these four parameters by minimizing the distance between the empirical variance–covariance matrix of earnings residuals and its theoretical counterpart implied by the statistical model. The parameters of the income process that I estimate (given in Table A.5) are in line with other results from the literature. In particular, I estimate very persistent income innovations, almost following a unit root, with a coefficient of autocorrelation $\rho = 0.974$.

Table A.5: Earnings process estimates

Age-income profile				**Stochastic component of earnings**			
δ_0	δ_1	δ_2	δ_3	ρ	$\sigma_{\xi_1}^2$	σ_ξ^2	σ_ι^2
1.632	0.094	-0.00107	$3.9e^{-7}$	0.974	0.184	0.0125	0.10

Notes: Quarterly earnings process estimated with 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.

Earnings after a transition. I estimate the median change in log salary following a job-to-job transition (μ^{JJ}) to be equal to 0.048. I estimate that job transitions following a period of unemployment are associated with a loss in earnings. I 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). I calibrate average quarterly earnings to be equal to $\overline{w} = \$9,250$.

Labor transition probabilities. I use SIPP micro-data to estimate quarterly job-to-job (π^{JJ}) and job-to-nonemployment (π^{EU}) transition probabilities by age, income, and tenure and job finding rates (π^{UE}) by age and income. The initial unemployment rate is set equal to 22%, which is the share not employed at age 22 in SIPP. The probability that a worker switches to another job is determined by equation (5), and the probability that she moves to nonemployment is determined by equation (6):

$$\ln\left(\frac{\pi^{JJ}\left(a_i,\theta_i,ten_i\right)}{1-\pi^{JJ}\left(a_i,\theta_i,ten_i\right)}\right)=\sum_{k=1}^{3}\alpha_k^{JJ}a_i^k+\varrho^{JJ}\ln\left(\frac{w_i}{\overline{w}_a}\right)+\sum_{j=1}^{9}\iota_k^{JJ}\mathbb{1}_{(ten_i=j)} \tag{5}$$

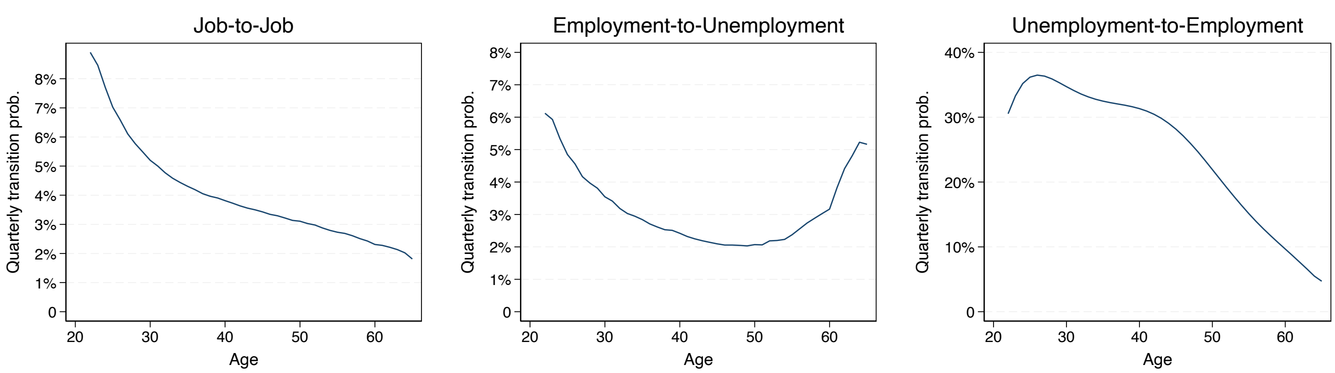
$$\ln\left(\frac{\pi^{EU}\left(a_i,\theta_i,ten_i\right)}{1-\pi^{EU}\left(a_i,\theta_i,ten_i\right)}\right)=\sum_{k=1}^{3}\alpha_k^{EU}a^k+\varrho^{EU}\ln\left(\frac{w_i}{\overline{w}_a}\right)+\sum_{j=1}^{9}\iota_k^{EU}\mathbb{1}_{(ten=j)} \tag{6}$$

The probability that an unemployed individual finds a job, given in equation (7), is defined as a fifth-order polynomial in age.

$$\pi^{UE}\left(a\right)=\sum_{k=1}^{5}\alpha_k^{UE}a^k \tag{7}$$

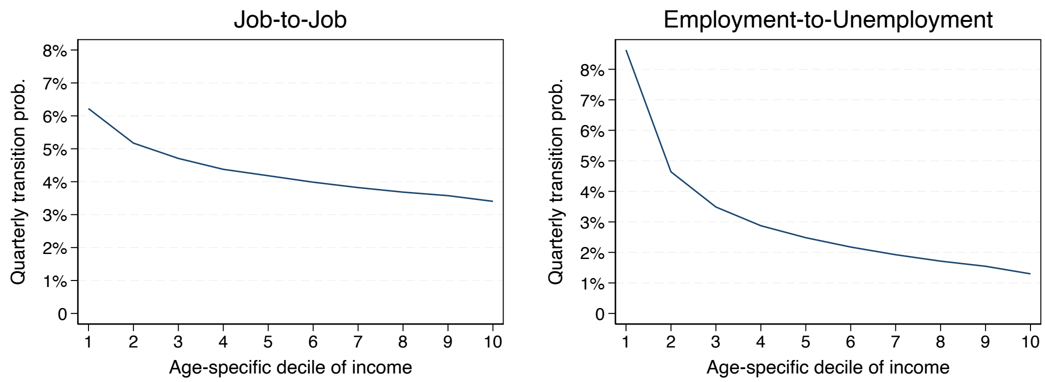
I estimate equations (5) and (6) with a logistic regression and equation (7) with a linear probability regression. Figures A.7, A.9, and A.9 show, respectively, the age, income and tenure profiles of labor market transitions in the SIPP that are implied by the estimated models.

Figure A.7: Age component of quarterly labor market transitions



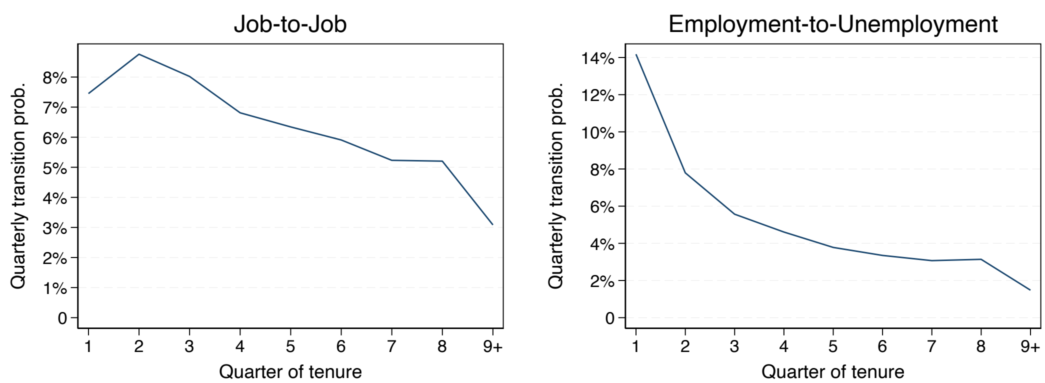
Notes: The graphed series plot the predicted age profile of labor market transitions in the SIPP sample estimated based on regression equations (5), (6), and (7).

Figure A.8: Income component of quarterly labor market transitions



Notes: The graphed series plot the predicted income profile of labor market transitions in the SIPP sample estimated based on regression equations (5) and (6).

Figure A.9: Tenure component of quarterly labor market transitions



Notes: The graphed series plot the predicted tenure profile of labor market transitions in the SIPP sample estimated based on regression equations (5) and (6).

D.2.1 Demographics

Survival probabilities. Survival probabilities for each age are calibrated to the U.S. Social Security 2014 period life table.[4]

Equivalence scale. Changes in household composition over the lifecycle are captured by an equivalence scale in the utility function. I use the equivalence scale by age estimated by Lusardi et al. (2017b). Using Panel Study of Income Dynamics (PSID) data from 1984 to 2005, Lusardi et al. (2017b) estimate $z(j_t, k_t) = (j_t + 0.7k_t)^{0.75}$, where j_t and k_t are, respectively, the average

[4] In the data, death probabilities are given at yearly frequency, while individuals make decisions every quarter in the model. I assume that the quarterly death probability is equal to 0.25 times the annual probability.

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, I use publicly available replication files from Lusardi et al. (2017b) and aggregate the data across education groups.

D.2.2 Tax and benefit system

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

$$y_t^{tax} = \begin{cases} (1-s_t)\,w_t & if\; emp_t \in \{E, JJ\} \\ ui_t + draw_t dc_t & if\; emp_t = U \\ ss\,(ae_{A^{ret}}) + draw_t dc_t & if\; emp_t = Ret \end{cases}$$

Individuals' 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 individual filling as single and claiming the standard deduction. The tax formula has 5 annual income brackets: $\{\tilde{\kappa}_i^{\tau}\}_{i=1}^{5} = \{\$\,5,150\,;\,\$\,7,550\,;\,\$\,30,650\,;\,\$\,74,200\,;\,\$\,154,800\}$.[5] Quarterly tax brackets are defined as: $\kappa_i^{\tau} = \frac{1}{4}\tilde{\kappa}_i^{\tau}$. The quarterly income tax liability is equal to:

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

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

$$ss\,(ae_{A^{ret}}) = 3 \times \max\{si\,;\,\tilde{ss}\,(ae_{A^{ret}})\}$$

[5] Note that the first bracket corresponds to the standard deduction amount in 2006.

where $\tilde{ss}$, the monthly Social Security benefit, is increasing in average lifetime earnings $ae_{A^{ret}}$ up to a maximum monthly benefit:

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

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 θ_t stays constant during an unemployment spell. I set $\omega = 0.40$, which is the average replacement rate across all U.S. states (U.S. Department of Labor, 2018). In the U.S., unemployment benefits may be reduced by a claimant's retirement income. The Unemployment Compensation Amendments of 1976 require that all retirement income be offset against unemployment compensation. There are differences in how states implement the offset, and generally, for withdrawals from a 401(k), only the amount contributed by the employer offsets unemployment benefits (see Franco (2004) for differences across U.S. states). For simplicity, I assume that the employer contribution portion of an early withdrawal is always equal to the employer match rate. This simplifying assumption is valid assuming that participants contribute below the matching threshold and that contributions are fully vested. The adjusted unemployment benefits for an individual unemployed since period $t - x$ are given by:

$$ui_t = \max\left\{0 ; \omega w_t\left(\theta_{t-x}\right) - draw_t dc_t \times match_e\right\}$$

D.2.3 Assets

Asset returns and limits. I set the annual (riskless) rate of return at 3%, which is equal to the long-term nominal yield on government bonds over the sample period between 2006 to 2017.[6] The annual interest rate on unsecured credit is set at $R^{cc} = 11.52\%$, the value estimated by Laibson et al. (2024) for the interest rate on credit card debt adjusted for both bankruptcy and inflation. The borrowing constraint prior to retirement is fixed and set equal to 74% of average quarterly earnings ($\underline{l}_{a<A^{ret}} = 0.74\overline{w}$). This is the average credit card limit estimated by Kaplan and Violante (2014) in

[6] R is assumed to be exogenous, and I abstract from the equilibrium determination of the interest rate for two reasons. First, the effect of auto-enrollment policies on aggregate savings is small, and second, the effect of the policy is concentrated on low-income individuals (who hold a relatively small share of aggregate assets).

the Survey of Consumer Finances. Unsecured borrowing is not allowed in retirement: $\underline{l}_{a \geq A^{ret}} = 0$.[7]

Asset taxation. In line with IRS rules for 2006, the maximum contribution limit for tax-deferred retirement contributions ($limit_a$) is set equal to \$3,750 per quarter (\$15,000 annually) for individuals younger than 50 years old and \$5,000 after that in 2006 dollars. The tax penalty for early DC withdrawals (pen_t) is equal to 10% before age $59^{1/2}$ and to zero afterward.[8] Capital income is taxed at a rate τ^k of 15%, which implies that the annual return (net of tax) on liquid wealth is 2.55%.

Vesting schedule. An employee 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 $vst_e\left(ten\right)$ determines the percentage of employer contributions that an employee keeps if she separates at a given tenure level. For instance, under a cliff vesting schedule, vst_e is equal to zero before the end of the vesting period and to one afterward. Modeling the vesting schedule explicitly would introduce an additional continuous state variable to the dynamic problem: the amount of nonvested DC wealth. Instead, I adjust employer contributions by a factor $\Upsilon_e\left(t, \theta, ten\right)$ proportional to the risk of losing unvested employer contributions. The adjustment factor $\Upsilon_e\left(t, \theta, ten\right)$ is given in equation (8). 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 is equal to one afterward. Importantly, this specification captures the fact that vesting matters more for employees who—based on their age and tenure—are more likely to separate from their employer.

$$\Upsilon_e\left(t, \theta, ten\right) = 1 - \sum_{j=0}^{T^R - t} \left(\prod_{k=1}^{j-1} \left(1 - \pi^{EU}_{t+k, ten+k} - \pi^{JJ}_{t+k, ten+k}\right) \right) \left(\pi^{EU}_{t+j, ten+j} + \pi^{JJ}_{t+j, ten+j}\right) \left(1 - vst_e\left(ten + j\right)\right) \tag{8}$$

Employer contributions adjusted for "vesting risk" ($\widetilde{ec}_e$) are given by equation (9).

$$\widetilde{ec}_{e,t}\left(\tau_t, \theta, ten_t\right) = \Upsilon_e\left(t, \theta, ten_t\right) \times ec_e\left(\tau_t, ten_t\right) \tag{9}$$

On average, in the estimation sample, employer matching contributions are initially vested at 44%, and this share increases over tenure. The average vested share reaches 73% after the end of

[7]This assumption is similar to the approach in Kaplan and Violante (2014). Absent this no-borrowing-in-retirement constraint, older individuals in the model borrow excessively because their high mortality risk reduces their repayment liability.

[8]Workers who separate from their employer after reaching age 55 can make penalty-free withdrawals from their current 401(k) plan. However, this exemption does not extend to funds in 401(k) plans from previous employers or to funds that have been rolled over into an IRA, which are still subject to a 10% early withdrawal penalty until age $59^{1/2}$. In the model, the majority of retirement wealth is represented by assets accumulated in jobs from which separation occurred before age 55.

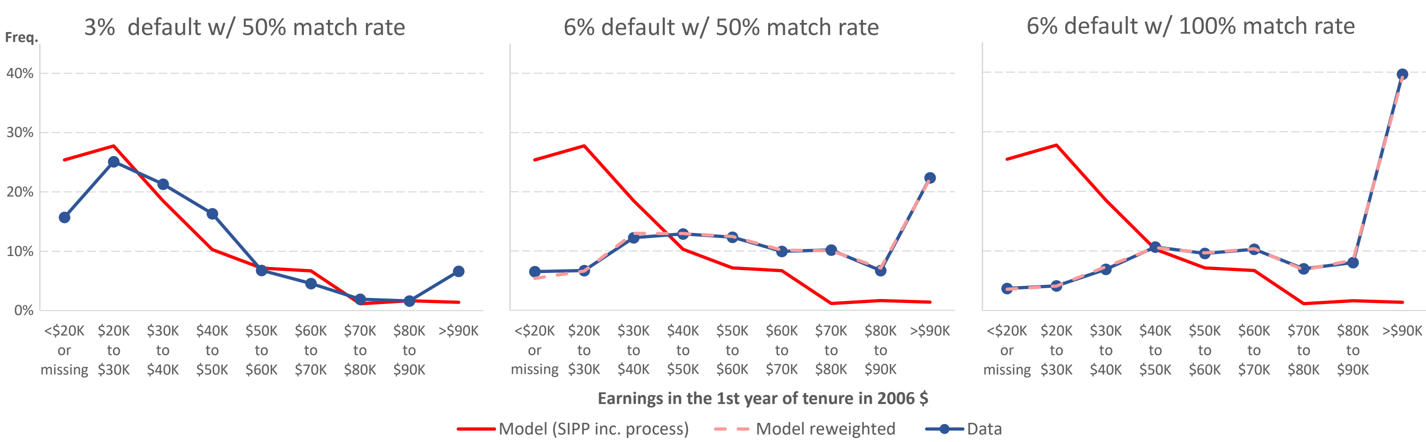
the second year of tenure. I assume that all matching contributions are fully vested starting from the 9th quarter of tenure.

E Estimation with a 6% Default Contribution Rate

E.1 Reweighting approaches

Figure A.10 shows the distribution of labor earnings for employees in their first year of tenure in the model and in the three estimation samples. As shown in the left panel, the baseline income process estimated in nationally representative data from the Survey of Income Programs and Participation (SIPP) generates a distribution of earnings similar to the one observed for auto-enrolled employees in plans adopting a 3% default with a 50% match rate up to 6% of salary.[9] The figure also shows that employees in plans with a 6% default and a 50% match rate, and to a greater extent those with a 6% default and a 100% match rate, have significantly higher earnings and that the income process estimated in the SIPP data offers a poor fit for the distribution of earnings in these two samples with a higher default option. To address this issue, I consider two approaches.

Figure A.10: Income distribution for auto-enrolled workers: Model vs. data



Notes: Each panel corresponds to the probability distribution function of first-year earnings (in 2006 $) accross nine income bins. The "Model (SIPP inc. process)" corresponds to the distribution of earnings in the simulated data based on the income process estimated in SIPP data. The "Model reweighted" series corresponds to the simulated data reweighted to match the empirical earnings distribution as described in Appendix E.1. The "Data" series corresponds to auto-enrolled employees hired in the 12 months following the policy adoption.

In the first approach, I reweight observations in the simulated data to match the empirical

[9] I focus on the distribution of earnings among the auto-enrolled because I observe earnings only for workers making positive contributions to the 401(k) plan. Since participation among the auto-enrolled is above 95%, I have earnings data for over 95% of auto-enrolled workers.

distribution of earnings in the samples with a 6% default and, respectively, a 50% and a 100% match rate. The weight assigned to a simulated observation with earnings in group k is equal to $weight_k = \frac{sh_k^{data}}{sh_k^{sim}}$, where sh_k^{data} and sh_k^{sim} are the shares of observations with income in group k in, respectively, the data and the model simulation. That is, I give more weight to observations with a higher simulated income in computing the simulated moments. Preference parameter estimates using this approach are reported in columns 6 through 8 of Table 4 and the values of sh_k^{data} and sh_k^{sim} are plotted in Figure A.10.

The second approach allows for heterogeneous preferences. I consider two types of agents: (i) standard agents with the baseline preference estimates (i.e., the values estimated in column 1 of Table 4) and the distribution of earnings generated by the income process estimated in SIPP data and (ii) high-earners, who are allowed to have different preferences. I simulated the model twice, once with the baseline preference parameters and once with the high-earners preference parameters. I set the share of high earners to $\alpha^H = 45\%$ and I calculate the simulated moment conditions by applying a weight of $1 - \alpha^H$ on observations simulated under the baseline preferences, and a weight of $\alpha^H weight_k^H$ on observations with earnings in group k simulated under the preferences of the high earners. These weights are chosen such that the reweighted distribution of simulated earnings matches the empirical distribution of earnings in Figure A.10. That is, the reweighted share of simulated observations in income group k (i.e., the weighted sum of sh_k^B, the simulated shares under baseline preferences and sh_k^H, the simulated shares under the preferences of the high earners) is equal to the empirical share of observation in income group k (sh_k^{Data}):

$$\begin{gathered} sh_k^{Data} = \left(1 - \alpha^H\right) \times sh_k^B + \alpha^H \times weight_k^H \times sh_k^H \\ \Rightarrow weight_k^H = \frac{sh_k^{Data} - \left(1 - \alpha^H\right) \times sh_k^B}{\alpha^H \times sh_k^H} \end{gathered}$$

I confirm in Figure A.10 that the reweighted distributions of simulated earnings match the empirical distributions in the two samples with a 6% default. In Table A.6, I report the preference parameter estimates for high-earners in the two samples with a 6% default contribution rate.

Both approaches yield similar results; workers in plans with a 6% default contribution are estimated to have significantly higher discount factors than those in plans adopting a 3% default. The switching cost estimated under a 6% default is lower in plans with a 100% match rate and larger in plans with a 50% match rate.

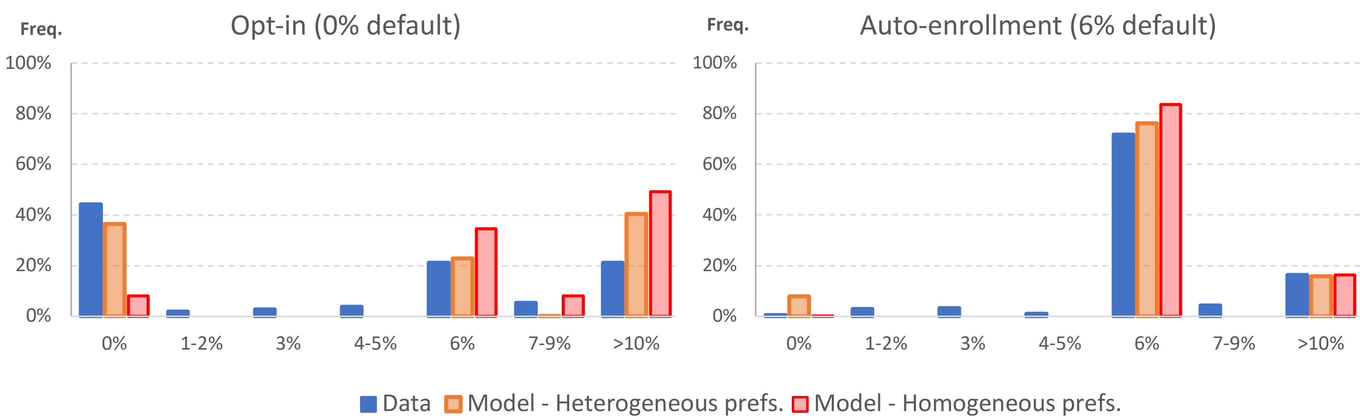
Table A.6: Preference parameter estimates for high-earners

	(1) Switching cost (k)	(2) Quarterly disc. factor (δ)	(3) EIS (σ)
6% default & 50% match rate	\$ 289	0.999	0.586
	(70)	(0.002)	(0.242)
6% default & 100% match rate	\$ 99	0.998	0.761
	(24)	(0.002)	(0.488)

Notes: Preference estimates for high-earners (i.e., 45% of simulated observations) following the reweighting approach outlined in Section E.1. The remaining 55% of observations are simulated under the baseline preference parameter values from column 1 of Table 4 and the baseline earnings distribution. Standard errors adjusted for measurement error in the estimation of the income process are in parentheses.

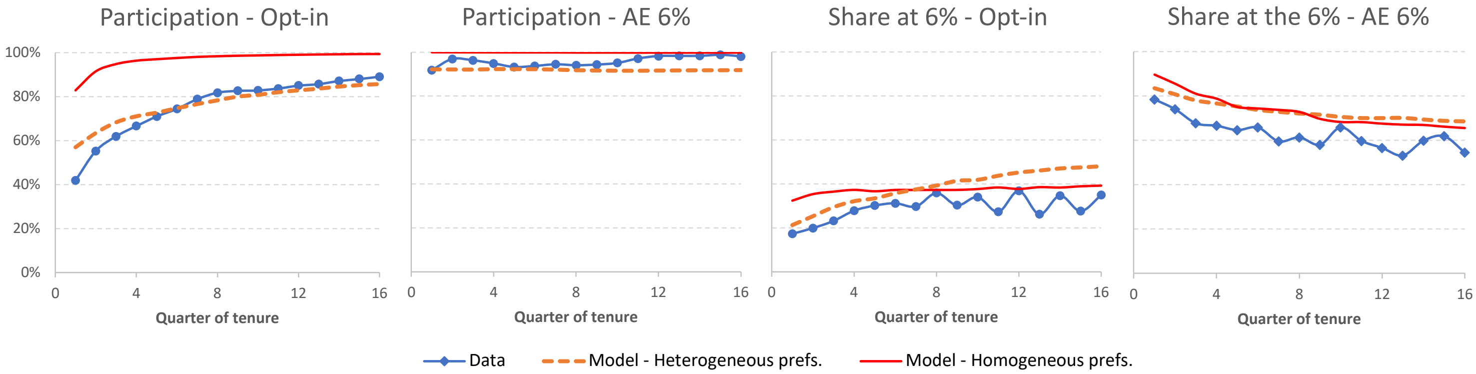
E.2 Model fit: Sample of plans with a 6% default and a 50% match rate up to 6%

Figure A.11: Empirical and simulated distributions of contribution rates in the first 12 months of tenure



Notes: The left (right) panel shows contribution rates of individuals hired in the 12 months before (after) the introduction of auto-enrollment at 6% for new hires in plans with a 50% match rate up to 6% of salary. The model series corresponds to simulations for identical individuals under a 0% and a 6% default.

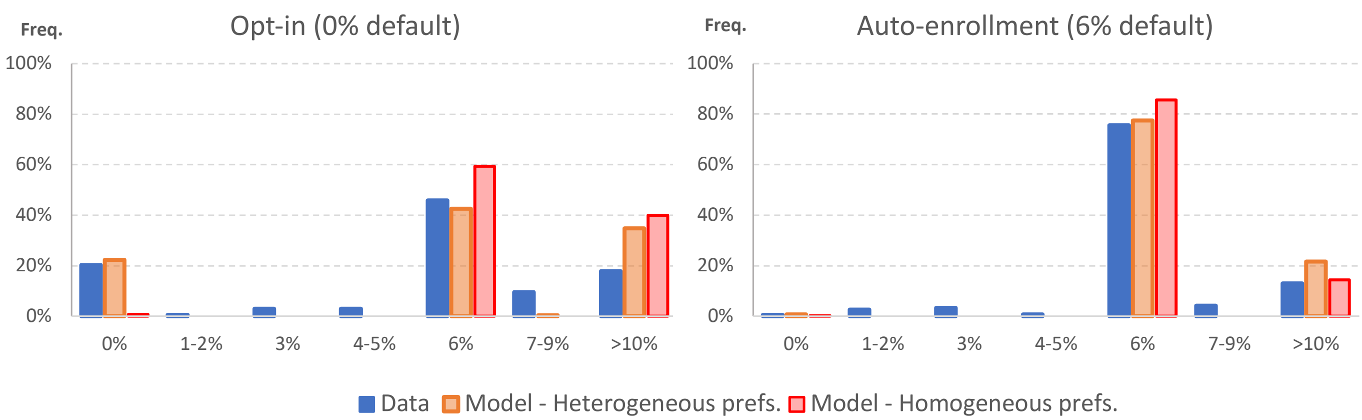
Figure A.12: Empirical and simulated contribution behavior over 4 years of tenure



Notes: The two left (right) panels show the 401(k) participation rate (the share who contribute exactly 6% of salary) for workers hired in the 12 months before and 12 months after the adoption of auto-enrollment at 6% for new hires in plans with a 50% match rate up to 6% of salary. The model series are simulations for identical individuals under a 0% and a 6% default.

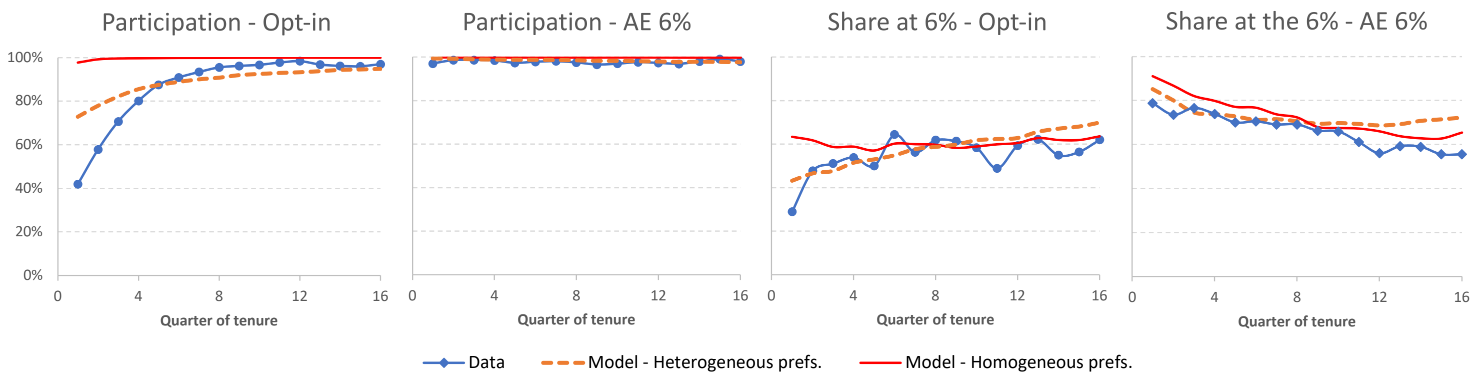
E.3 Model fit: Sample of plans with a 6% default and a 100% match rate up to 6%

Figure A.13: Empirical and simulated distributions of contribution rates in the first 12 months of tenure



Notes: The left (right) panel shows the contribution rates of individuals hired in the 12 months before (after) the introduction of auto-enrollment at 6% for new hires in plans with a 100% match rate up to 6% of salary. The model series corresponds to simulations for identical individuals under a 0% and a 6% default.

Figure A.14: Empirical and simulated contribution behavior over 4 years of tenure



Notes: The two left (right) panels show the 401(k) participation rate (the share who contribute exactly 6% of salary) for workers hired in the 12 months before and 12 months after the adoption of auto-enrollment at 6% for new hires in plans with a 100% match rate up to 6% of salary. The model series are simulations for identical individuals under a 0% and a 6% default.

E.4 Robustness of the preference estimates

In this Appendix, I assess the robustness of the switching cost estimates. I fix either δ or σ and re-estimate the remaining two preference parameters. Estimation results are reported in Table A.7. I estimate a larger switching cost—around \$380—when I fix the quarterly discount factor to be lower (i.e., $\delta = 0.96$, implying an annual discount factor of $\delta^4 = 0.85$) or when I fix the elasticity of intertemporal substitution to be lower (i.e., $\sigma = 0.2$ implying a coefficient of relative risk aversion of 5). In contrast, when I fix the EIS to be higher, I estimate a lower switching cost than in the baseline: \$210. The model's fit worsens in these specifications relative to the baseline reported in column 1 as reflected by a larger goodness-of-fit measure).

Table A.7: Preference parameter estimates

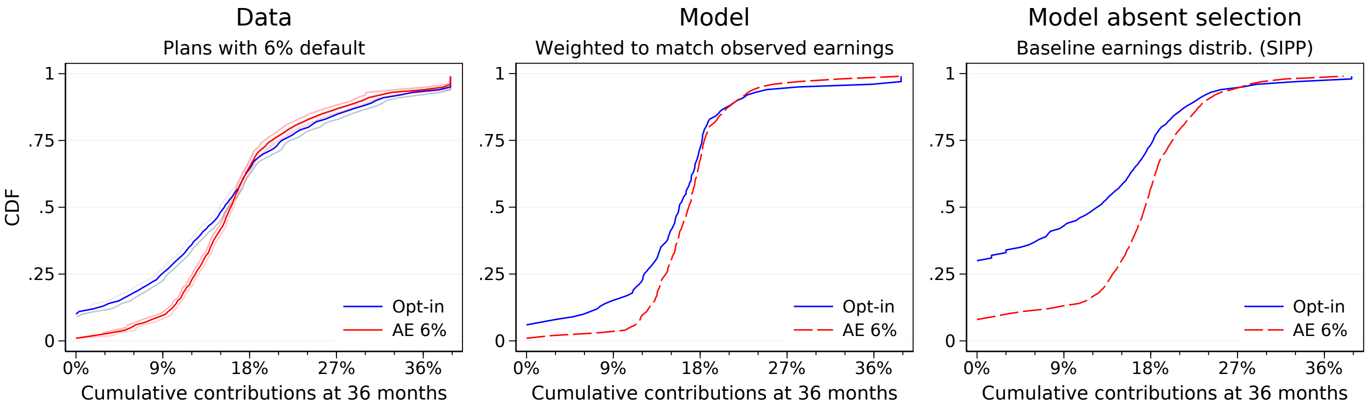
	Auto-enrollment at 3% & 50% match rate			
	(1)	(2)	(3)	(4)
	Baseline	Fixed $\sigma = 1.25$	Fixed $\sigma = 0.2$	Fixed $\delta = 0.96$
	(i.e., col 1 of Table 4)	(i.e., RRA: $\sigma^{-1} = 0.8$)	(i.e., RRA: $\sigma^{-1} = 5$)	(i.e., annual freq: δ^4=0.85)
Switching cost (k)	\$ 235	\$ 210	\$ 383	\$ 371
	(31)	(7)	(68)	(48)
Quarterly disc. factor (δ)	0.989	0.990	0.978	0.96
	(0.002)	(0.001)	(0.006)	–
EIS (σ)	0.520	1.25	0.20	0.189
	(0.085)	–	–	(0.007)
Goodness of fit	323	582	684	5,098

Notes: preferences are estimated with data from plans with a 3% default and a 50% match rate up to 6% of salary. Column 1 report the baseline estimate from column 1 of Table 4. Columns 2 and 3 (Column 4) fix the value of the EIS (discount factor) and estimate the remaining two preference parameters. I use the identity weighting matrix and standard errors adjusted for measurement error in the estimation of the income process are in parentheses. I construct the same goodness-of-fit measure as in Laibson et al., 2024.

E.5 Correcting for selection in the sample of plans with a 6% default

As described in Section 5.7, I use the model to assess the effect of a higher default absent these two sources of selection. The left panel of Figure A.15 corresponds to the observed CDFs in plans with a 6% default. The middle panel, corresponds to model simulations when simulated observations are reweighted to match the distribution of earnings observed in the plans with a 6% default and a 50% match rate. Finally, the right panel corresponds to the model prediction under the baseline income process estimated in SIPP data.

Figure A.15: Heterogeneity in the effect of auto-enrollment at 6%: Data vs Model



Notes: Each line corresponds to the simulated cumulative distribution function (CDF) of cumulative employee 401(k) contributions divided by individuals' annual salary after 36 months of tenure. The left panel corresponds to the empirical distribution in plans adopting a 6% default. The Model series correspond to simulated data using the baseline preference estimates from column 1 of Table 4. In the middle panel, the simulated observations are reweighted to match the empirical distribution of earnings in plans with a 6% default and a 50% match rate following the procedure outlined in Appendix E.1. In the right panel, earnings are simulated based on the income process estimated in SIPP data.

F Model Extensions

F.1 Present-biased preferences

Several empirical studies have documented that measures of time inconsistency correlate with the propensity to stay at the default option in retirement savings plans (Blumenstock et al., 2018; Brown et al., 2016; Brown and Previtero, 2020, Goda et al., 2020). Under present-biased preferences, workers procrastinate on changing their contribution rate because the switching cost is paid in the present while the benefits of retirement saving are in the future (O'Donoghue and Rabin, 1998; Carroll et al., 2009; DellaVigna 2009 and 2018). There are two different approaches for modeling the role of present-biased preferences.

A first view is that contribution choices reflect only the regular discount factor δ because contribution changes are implemented by employers with a delay—usually at the beginning of the next pay period. As noted by Carroll et al. (2009), this implies that a contribution rate choice serves as a commitment to save in the future, starting from the next paycheck. Under this view, introducing present bias acts in a similar way to assuming a higher switching cost: it reduces the probability of switching but does not affect the contribution choice conditional on the employee's making an active decision. In the absence of a source of variation in my data that would allow me to separately identify this form of present bias from switching costs, I interpret my baseline estimates as capturing the combined effect of present bias and other forms of switching costs.

A second view is that present bias directly affects contribution preferences. Workers choose low contribution rates because they do not want to reduce their consumption in the present and believe (mistakenly) that they will contribute more later. I explore the role of this specification of present bias by introducing in the model an additional discount factor $\beta \leq 1$ between the present and all future periods (Laibson, 1997). I assume that workers are naive about their future selves' present bias. The objective function for a present-biased worker V^{PB} is given by equation (10), where V_{t+1} is the value function in the baseline exponential discounting case.

$$V_t^{PB}(X_t) = \max_{s_t \in S, l_{t+1}} u_a\left(c_t - \mathbb{1}_{(s_t \neq d_t)}.k\right) + \beta\delta\left(1 - m_a\right) \int V_{t+1}\left(X_{t+1}\right) dF\left(\theta_t, emp_t, e_t\right) \tag{10}$$

I calibrate the short-term discount factor $\beta = 0.5$, which is the value estimated by Laibson et al. (2024) in a lifecycle setting, and re-estimate the model's three other preference parameters following the same procedure outlined in Section 5. The results are reported in Table A.8. My estimates of the preference parameters are very close to those estimated by Laibson et al. (2024) in a different setting with different data: I estimate a long-term quarterly discount factor of 0.997 (or 0.988 at annual frequency), which is close to the estimate in Laibson et al. (2024) of 0.99, while my EIS estimate of 0.64 is only slightly lower than the estimate of the inverse of relative risk aversion in Laibson et al. (2024) of 0.77.

Table A.8: Preference parameter estimates – Quasi-hyperbolic time preferences

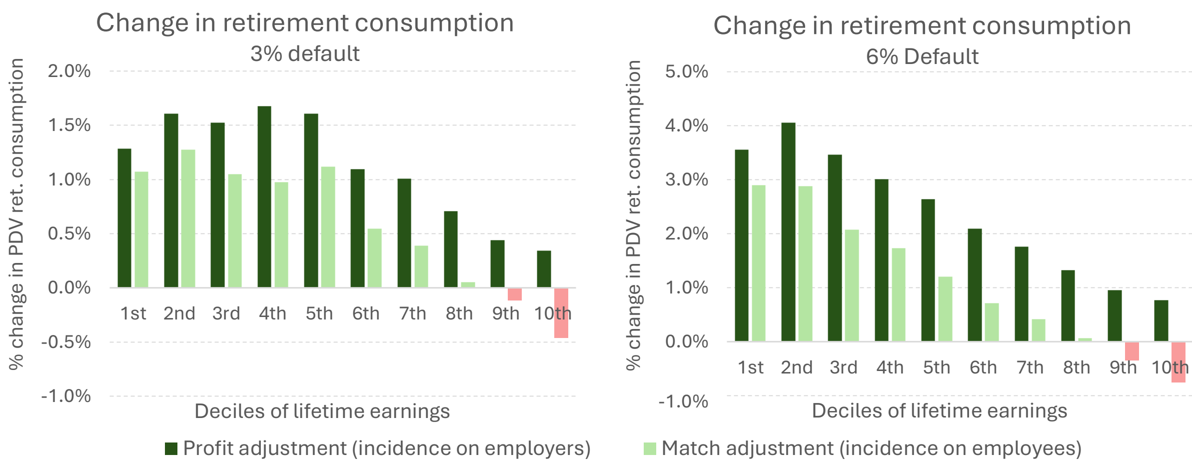
	(1) Baseline model $\beta = 1$	(2) Naive present bias $\beta = 0.5$
k	\$ 235	\$ 179
	(31)	(38)
δ	0.989	0.997
	(0.002)	(0.001)
σ	0.452	0.640
	(0.085)	(0.069)

Notes: Column 1 reproduces the baseline estimates from column 1 of Table 4. Column 2 shows preference estimates with naive quasi-hyperbolic discounting and a short term discount factor set equal to $\beta = 0.5$, the value estimated by Laibson et al. (2024).

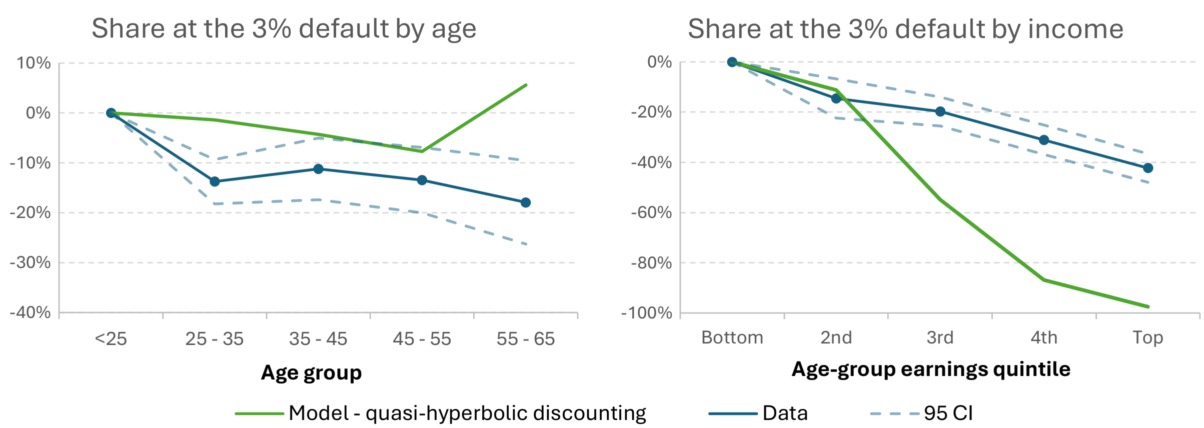
As shown in the top panel of Figure A.16, the model estimated with quasi-hyperbolic time preferences generates a qualitatively similar heterogeneity in the long-term savings gains from an auto-enrollment policy adopted by all employers. However, as shown in the bottom panel, this specification does a worse job capturing the heterogeneity in default effects by age an income.

Figure A.16: Lifetime impact and heterogeneous responses to auto-enrollment - Quasi-hyperbolic time preferences

(a) Effect of a universal auto-enrollment policy on retirement consumption



(b) Heterogeneity in default effects by age and income



Notes: In Panel (a) , each bar corresponds to the model-predicted percentage change in the present discounted value of consumption between ages 65 and 90 under an auto-enrollment policy adopted by all employers relative to that under an opt-in regime. I use the risk-free interest rate (3%) for discounting retirement consumption. The policies are simulated under the baseline preference estimates from column 2 of Table A.8. Dark-shaded bars correspond to the results based on the assumption that the incidence of the policy falls on employers, while the light-colored bars correspond to the results based on the assumption that employers reduce the 401(k) matching rate to satisfy their budget constraint. In Panel (b), each point corresponds to the coefficients of the interaction terms of auto-enrollment status (based on a worker's date of hire) with income and age group dummies, estimated according to equation (2). The dependent variable is a dummy equal to 1 if, conditional on participating, a worker observed in her first year of tenure contributes exactly 3% (the auto-enrollment default contribution rate).

F.2 Proportional switching costs

As an extension of the baseline model, I consider the case where the switching cost is proportional to each worker's labor earnings. For instance, this specification captures the fact that, if changing the DC contribution rate takes time, the opportunity cost of time is higher for highly paid workers. I introduce a switching cost $\tilde{k}$ that is proportional to earnings:

$$u_a \left(c_t - \mathbb{1}_{(s_t \neq d_t)} \tilde{k}.w_t \right)$$

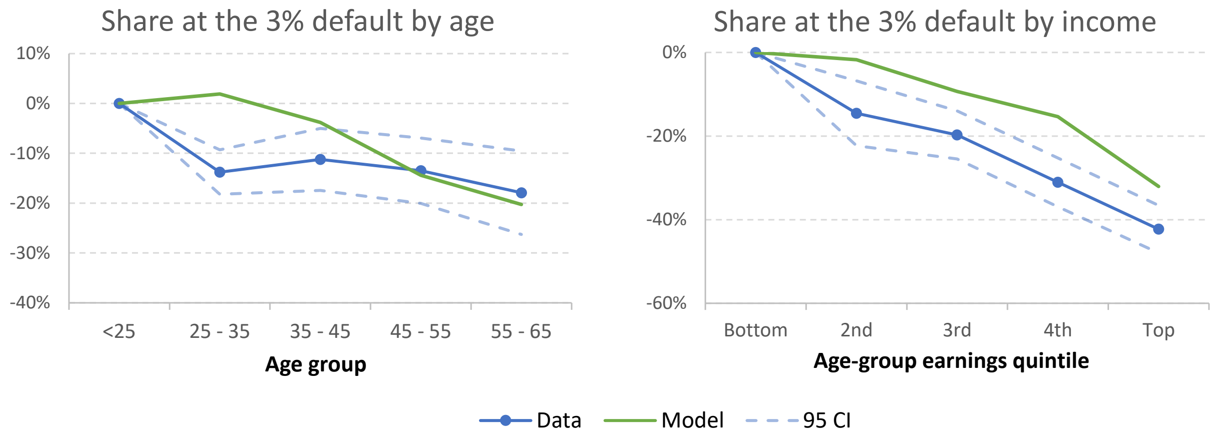
I present estimation results in Table A.9. I estimate $\tilde{k}$ to be equal to 3.16% of quarterly income (i.e., equivalent to \$ 311 at the average earnings level). Under this specification, high-income workers are more likely to stay at the default compared to the baseline model because the switching cost is now larger for them (Figure A.17, right panel). As a consequence, the model with a proportional switching cost generates less correlation between income and the propensity to stay at the default option. While this assumption reduces the correlation between earnings and default behavior, high-income workers are still predicted to deviate from the default contribution rate more frequently than low-income workers because: (i) low-income workers face higher separation probabilities and, as a consequence, expect to stay in the firm for a shorter period, and (ii) high-income individuals have more to gain by contributing to the retirement savings plan because they face a higher marginal tax rate and expect a lower Social Security replacement rate.

Table A.9: Preference parameter estimates with switching costs proportional to earnings

(1) $\tilde{k}$	(2) δ	(3) σ
0.0336	0.987	\$ 0.454
(0.009)	(0.003)	(0.032)

Notes: Columns 1 to 3 present second-stage parameter estimates for the switching cost, the quarterly discount factor, and the elasticity of intertemporal subsitution under the assumption that the switching cost is a constant fraction of earnings.

Figure A.17: Heterogeneity in default effects by age and income – Proportional switching cost



Notes: Each point corresponds to the coefficients of the interaction terms of auto-enrollment status (based on a worker's date of hire) with income and age group dummies, estimated according to equation (2). The dependent variable is a dummy equal to 1 if, conditional on participating, a worker observed in her first year of tenure contributes exactly 3% (the auto-enrollment default contribution rate). The area between the dashed lines corresponds to the 95% confidence intervals of the empirical coefficients. Data source: Administrative 401(k) records from 34 U.S. firms.

F.3 No offset of unemployment benefits

In the baseline specification of the model, early withdrawals from the DC account reduce unemployment benefits. This modeling assumption is consistent with the Unemployment Compensation Amendments of 1976, which require that all retirement income be offset against unemployment compensation. However, there are differences across states in how this offset is implemented. In general, for withdrawals from a 401(k) plan, only the amount contributed by the employer offsets unemployment benefits. For instance, in New Jersey, 50% of retirement income, including *"benefits paid in a lump sum such as 401(k)"*, is subtracted from the unemployment benefit if both the claimant and the base-period employer contributed to the pension plan.[10]

However, the rules are complex and vary across states (see Franco (2004) for a discussion of differences across U.S. states). Depending on the specific way the offset is implemented by states' unemployment insurance agencies, unemployed individuals may be able to avoid this offset by first rolling over their 401(k) assets into an individual retirement account before withdrawing those resources. As a robustness check, I re-estimate the model under the assumption that 401(k) withdrawals do not offset unemployment insurance benefits. The estimated parameters, in Table A.10, are little affected by this alternative assumption: the contribution switching cost and the quarterly

[10]Source: https://nj.gov/labor/ui/content/faq.html

discount factor are estimated to be a little smaller (\$175 and 0.985 relative to baseline values of, respectively, \$235 and 0.989) and the EIS somewhat higher (0.801 relative to an estimate of 0.520 in the baseline model).

Table A.10: Preference parameter estimates with no offset of unemployment benefits

(1) k	(2) δ	(3) σ
\$ 175	0.985	\$ 0.801
(20)	(0.001)	(0.071)

Notes: Columns 1 to 3 present second-stage parameter estimates for the switching cost, the quarterly discount factor, and the elasticity of intertemporal subsitution under the assumption of no unemployment offset of early 401(k) withdrawals.

F.4 Discussion of the counterfactual policy analysis

While the model attempts to capture the main aspects of the retirement saving environment, it abstracts from a number of features. In this section, I discuss how the absence of some of these elements could affect the counterfactual policy exercise.

Endogenous labor supply. Employees may be able to undo some of the effect of auto-enrollment by adjusting their future labor supply or shifting the timing of their retirement by a few weeks or months. Introducing these additional margins of adjustment would likely reinforce the main findings of the paper: when employees can adjust both their future contributions and labor supply, the size of the switching cost needed to generate the observed inertia at the default and the long-term effect of auto-enrollment on wealth may become even smaller. However, since I am not able to estimate the causal effect of auto-enrollment on labor supply and retirement decisions in the data, I make the more conservative assumption that auto-enrollment has no effect on labor supply and retirement timing.

Default asset allocation. Under auto-enrollment, the default contribution rate is often combined with a default asset allocation. In this paper, I study the effect of changing the default contribution rate independently from the choice of a default asset allocation. Changing the default asset allocation could have a separate impact on wealth accumulation that is potentially large but beyond the scope of this paper.[11]

[11] Dahlquist et al. (2018) estimate large welfare gains from the implementation of an optimal default asset allocation

General equilibrium interest rate. A national auto-enrollment policy could raise aggregate saving and lead to a reduction in the equilibrium interest rate. Given the estimated value of the elasticity of intertemporal substitution (EIS), this general equilibrium channel would likely reduce the effect of auto-enrollment on individual saving. However, given my finding that auto-enrollment has a very modest impact on long-term asset accumulation and that this effect is concentrated at the bottom of the income distribution (a population that accounts for a small share of aggregate savings), this general equilibrium effect is likely to be very small.

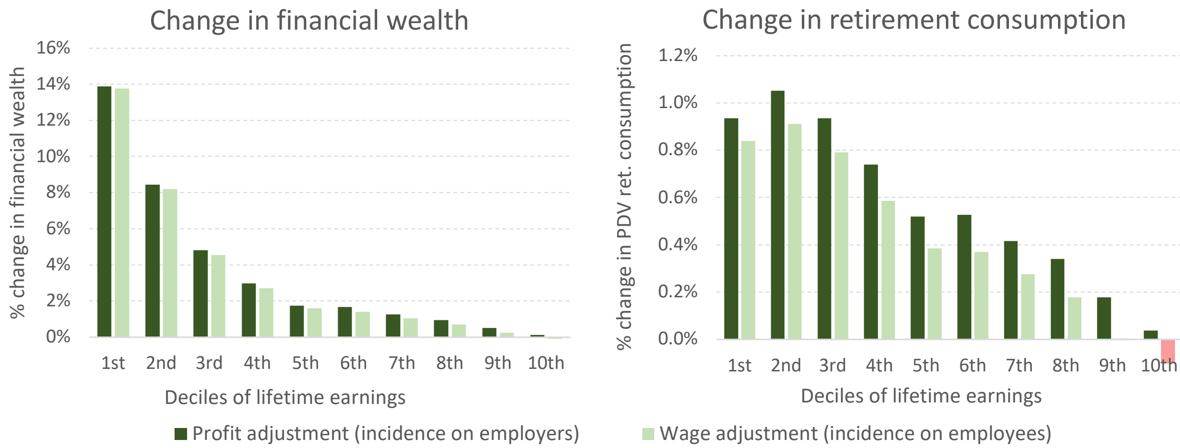
F.5 Alternative incidence assumption: Wage adjustment

Another possibility for satisfying the budget constraint is that employers reduce wages to offset higher matching costs. I assume that all wages are reduced by the same proportional factor to satisfy employers' aggregate budget constraint. Employers adjust the wage level to keep the total compensation bill $W\left(d^{SP}\right) + Mtc\left(d^{SP}\right)$ constant. I show in Figure A.18 simulation results on the effect of a universal auto-enrollment policy adopted by all employers over a lifetime under this incidence assumption.

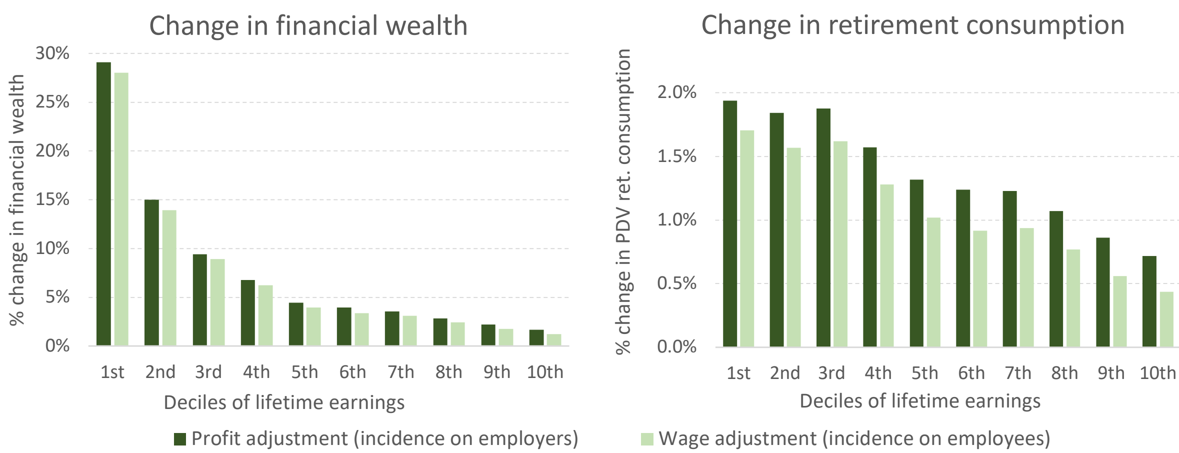
in the context of Swedish pension plans. Choukhmane and de Silva (2023) extend the model to a portfolio choice problem.

Figure A.18: Effect of auto-enrollment on financial wealth at age 65 and on retirement consumption

(a) Universal auto-enrollment policy at 3% over a lifetime



(b) Universal auto-enrollment policy at 6% over a lifetime

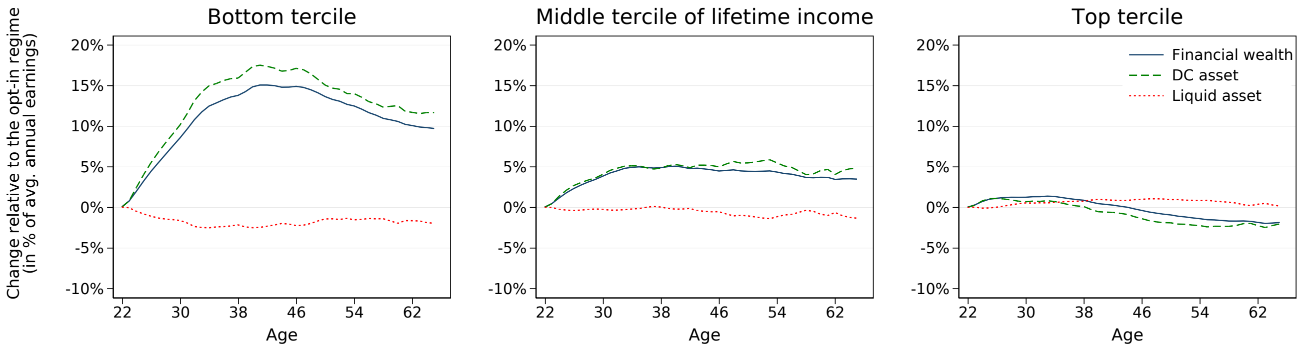


Notes: In the left (right) two panels, each bar corresponds to the model-predicted percentage change in financial wealth at age 65 (present discounted value of consumption between ages 65 and 90) under an auto-enrollment policy adopted by all employers relative to that under an opt-in regime. I use the risk-free interest rate (3%) for discounting retirement consumption. The policies are simulated under the baseline preference estimates from column 1 of Table 4 and the baseline distribution of earnings estimated in SIPP data. Dark-shaded bars correspond to the results based on the assumption that the incidence of the policy falls on employers, while the light-colored bars correspond to the results based on the assumption that employers reduce wages uniformly to satisfy their budget constraint.

F.6 Additional evidence on the lifecycle profile of auto-enrollment savings gains

F.6.1 3% default & match rate adjustment

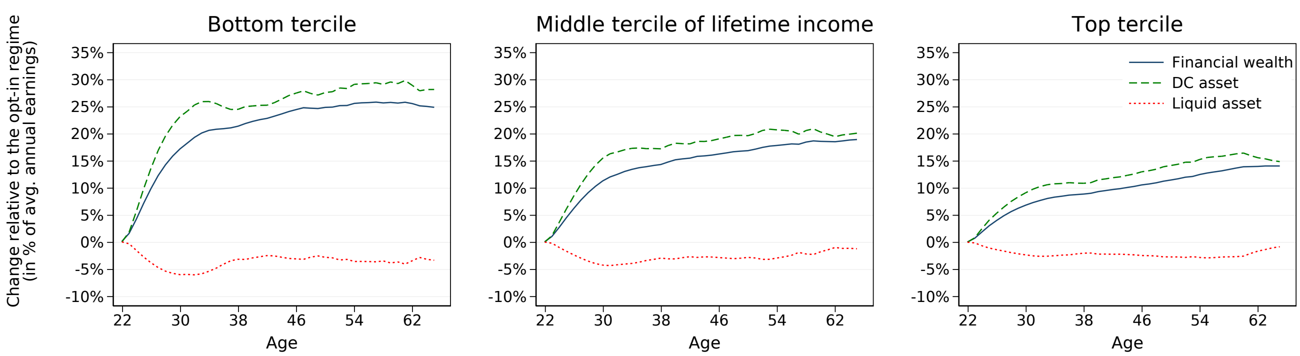
Figure A.19: Effect of auto-enrollment on lifecycle DC savings, liquid assets, and financial wealth



Notes: Each series corresponds to the model-predicted difference between assets under an auto-enrollment policy at 3% and those under an opt-in regime, adopted by all employers. Changes are expressed as a fraction of each simulated individual's average annual earnings between the ages of 22 and 65. The incidence of the policy is assumed to fall on employees, with employers reducing the 401(k) match rate to balance their budget.

F.6.2 6% default & incidence on employers

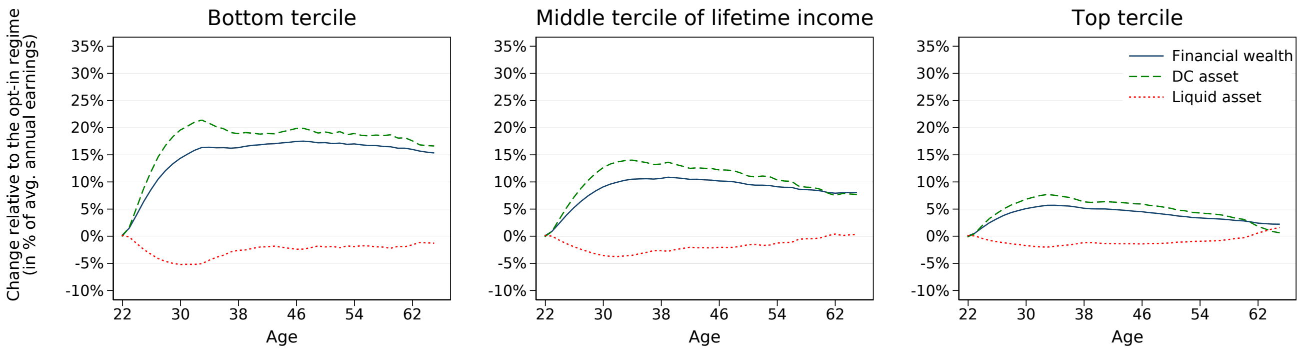
Figure A.20: Effect of auto-enrollment on lifecycle DC savings, liquid assets, and financial wealth



Notes: Each series corresponds to the model-predicted difference between assets under an auto-enrollment policy at 6% and those under an opt-in regime, adopted by all employers. Changes are expressed as a fraction of each simulated individual's average annual earnings between the ages of 22 and 65. The incidence of the policy is assumed to fall on employers, who reduce their profits to cover higher matching costs under auto-enrollment.

F.6.3 6% default & match rate adjustment

Figure A.21: Auto-enrollment's impact on lifecycle DC savings, liquid assets, and financial wealth



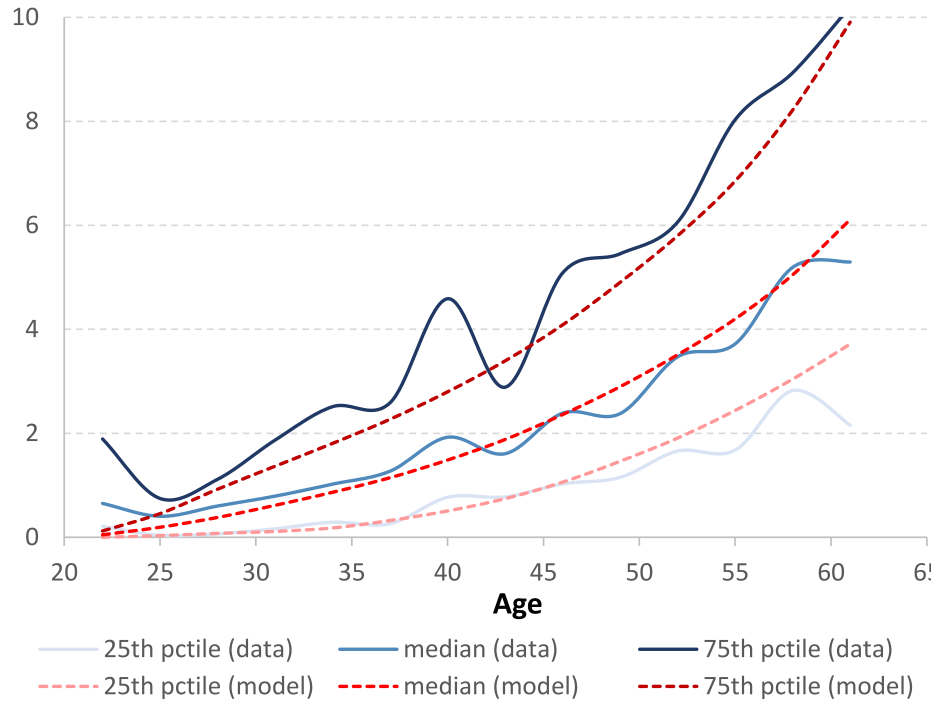
Notes: Each series corresponds to the model-predicted difference between assets under an auto-enrollment policy at 6% and those under an opt-in regime, adopted by all employers. Changes are expressed as a fraction of each simulated individual's average annual earnings between the ages of 22 and 65. The incidence of the policy is assumed to fall on employees, with employers reducing the 401(k) match rate to balance their budget.

G Additional Model Counterfactuals

G.1 Wealth accumulation over the lifecycle

While the model is estimated with 401(k) data only, my baseline estimates are also consistent with the evolution of total wealth accumulation over the lifecycle in the 2016 Survey of Consumer Finances (SCF). Because the wealth measures in the SCF are the household level, they are not directly comparable to the model simulations, which are at the individual level. Instead, I compare the evolution of wealth-to-income ratios over the lifecycle. Total wealth (or total net worth in the SCF) is defined as the sum of all assets net of all outstanding debts but excluding the expected value of future defined benefit and Social Security income. For comparability with the estimation sample, I restrict the SCF sample to households in which either the head or the spouse has any type of account-based pension plan in the current job. The evolution (and heterogeneity) in the observed wealth-to-wage income ratios are reported in Figure A.22 alongside the model predictions. Overall the model predicts well the evolution of wealth accumulation over the lifecycle.

Figure A.22: Ratio of net wealth to earnings by age: Data vs. model



Notes: The data series (straight lines) plot the ratio of total wealth to wage income by age of the head of household. Total wealth corresponds to the sum of all assets net of all outstanding debt. The sample is restricted to households where either the head or spouse has any type of account-based pension plan in the current job. The model series (dashed lines) correspond to the model simulation under an opt-in regime in all jobs. Total wealth in the model series corresponds to the sum of retirement and liquid assets net of unsecured debt liabilities. Data: Survey of Consumer Finances 2016.

H U.K. National Auto-enrollment Policy and Calibration

H.1 U.K. national auto-enrollment policy

The U.K. Pension Act of 2008 requires employers to automatically enroll their employees (with the option to opt-out) in a workplace pension scheme. The law sets the minimum combined employee plus employer default contribution rate at 2% of pensionable pay with a minimum employer contribution of 1%. Each employer was given a staging date based on its number of employees. The staging dates for each employer size are reported in Table A.11. Employers were required to enroll all employees aged between 22 and the stage pension age in a workplace pension plan by the staging date.[12] The auto-enrollment requirement applies to both new hires and nonparticipating seasoned

[12] Employers could apply to postpone the implementation of auto-enrollment by up to 3 months after the staging date. Since I do not observe whether a firm applied to use postponement, I treat the staging date as binding.

employees. I refer the reader to Cribb and Emmerson (2016) for more details on the policy and its rollout.

Table A.11: Auto-enrollment staging dates by employer size

Employer size	**Auto-enrollment staging date**	**Employer size**	**Auto-enrollment staging date**	**Employer size**	**Auto-enrollment staging date**
120,000+	October 1, 2012	2,000+	August 1, 2013	61+	August 1, 2014
50,000+	November 1, 2012	1,250+	September 1, 2013	60+	October 1, 2014
30,000+	January 1, 2013	800+	October 1, 2013	59+	November 1, 2014
20,000+	February 1, 2013	500+	November 1, 2013	58+	January 1, 2015
10,000+	March 1, 2013	350+	January 1, 2014	54+	March 1, 2015
6,000+	April 1, 2013	250+	February 1, 2014	50+	April 1, 2015
4,100+	May 1, 2013	160+	April 1, 2014	40+	August 1, 2015
4,000+	June 1, 2013	90+	May 1, 2014	30+	October 1, 2015
3,000+	July 1, 2013	62+	July 1, 2014		

Source: Cribb and Emmerson (2016).

H.2 U.K. calibration

In what follows, I detail the parametrization of the model in the U.K. validation exercise presented in Section 7.2. Other parameters are set equal to their value in the U.S. calibration.

Employer matching formulas. ASHE does not collect data on each employer's matching formula, and I am not aware of any representative evidence on the distribution of employer matching formulas in the U.K. To overcome this data limitation, I use data on the distribution of employee and employer contributions prior to the auto-enrollment rollout to back out each employer's matching formula. Because a cap on matching introduces a kink in the budget set, we should expect the distribution of contribution rates to feature excess mass at the employer matching threshold. Therefore, I hypothesize that the cap on the employer matching contribution is equal to the modal (positive) employee contribution rate in each firm. If this hypothesis is correct, employer contributions should increase in employee contributions up to the modal employee contribution rate in each firm, but not above this hypothesized cap on employer matching. I test and validate this hypothesis in Table A.12 by regressing employer contributions on employee contributions above and below the modal employee contribution rate. Columns 1 and 2 show that, up to the modal employee contribution, each percentage-point increase in contributions raises the employer contribution rate by half a percentage point. Columns 1 and 3 show that employee contributions above the modal contribution rate do not lead to significantly higher employer contributions. These results are consistent with employers offering a 50% match on contributions up to the modal contribution.

In the calibration of the model to the U.K. environment, I group employers into 5 types based on their employer contribution formula. Motivated by the evidence in Table A.12, I set the match rate equal to 50% for all employers with immediate vesting. I assume that employers have one of five different matching thresholds (cap_e), based on the five most common modal contribution rates observed in the data (and covering more than 80% of employees). The calibrated probability distribution of employer types is reported in Table A.13 and reflects the empirical distribution of modal employee contributions.

U.K. income profile. I estimate the age-income profile using earnings data for U.K. private sector workers aged 22 to 65 using ASHE data from between 1997 and 2016. I use the same regression specification used to estimate the income profile for U.S. workers. The estimation results are reported in Table A.14. For simplicity, I assume that labor market transitions in the U.K. calibration vary by age and tenure but not by income.

Table A.12: Relationship between employer and employee retirement contributions in the U.K.

	Employer contribution in % of pay		
	(1) Full sample	(2) Employee contrib. $\leq$ modal contrib.	(3) Employee contrib. $>$ modal contrib.
Employee contribution rate			
$\times$dummy (contrib.$\leq$modal)	0.500	0.504	
	(0.14)	(0.14)	
$\times$dummy (contrib.$>$modal)	0.229		0.155
	(0.158)		(0.123)
Modal contribution rate in the firm			
$\times$dummy (contrib.$\leq$modal)	0.471	0.499	
	(0.306)	(0.333)	
$\times$dummy (contrib.$>$modal)	0.923		0.812
	(0.408)		(0.407)
R-squared	0.146	0.143	0.111
Observations	21771	17856	3915

Notes: The outcome variable is the employer retirement contribution amount as a percentage of pensionable pay. The modal (positive) employee contribution is computed separately for each employer. I restrict the sample to firms with at least 50 observations in the three years prior to the auto-enrollment staging date. Data source: ASHE waves 2006 to 2016.

Table A.13: Probability distribution of employer types

	Threshold on matching (cap_e)				
	2%	3%	4%	5%	6%
Prob.	0.12	0.18	0.15	0.25	0.30

Notes: This table shows the probability distribution of match thresholds in the U.K. calibration of the model. This distribution is inferred from the empirical distribution of modal contribution rates in the three years prior to the auto-enrollment staging date. Data source: ASHE waves 2006 to 2016.

Table A.14: U.K. age-earnings profile

Age component			
δ_0	δ_1	δ_2	δ_3
5.306	0.255	−0.0043	0.0000219

Notes: Age-earnings profile estimated on a panel of workers continuously employed in the same job. Data source: ASHE waves 1997 to 2016.

Early withdrawals. Early withdrawals from a DC account are not allowed in the U.K. Thus, I impose a 100% tax penalty on early withdrawals $pen_a = 1$.

Income taxation. Individuals' income tax liability is calculated according to the U.K. income tax schedule of 2006 for an individual claiming the personal allowance for singles. The quarterly income tax liability is equal to:

$$tax_t^i = \begin{cases} 0 & if\ 4y^{tax} \leq £4,895 \\ 0.22\left(y^{tax} - \frac{4,895}{4}\right) & if\ £32,400 \geq 4y^{tax} > £4,895 \\ 0.22\left(\frac{32,400-4,895}{4}\right) + 0.40\left(y^{tax} - \frac{32,400}{4}\right) & if\ 4y^{tax} > £32,400 \end{cases}$$

Public pension. The U.K. State Pension provides public pension benefits similar to Social Security in the U.S. The relationship between average lifetime earnings and public pension entitlements is modeled to match the evidence in Figure 1 of O'Dea (2018), expressed in 2006 pounds.

Unemployment benefits. The main unemployment benefit in the U.K. is the Jobseeker's Allowance. In 2006, the quarterly allowance was equal to £ 746 for unemployed individuals older than 24.

H.3 Out-of-sample validation: job switchers in the context of the U.K. national auto-enrollment policy

Fact VII of Section 3 shows that auto-enrollment causes workers to contribute less in their next employer's opt-in retirement savings plan, with no significant effect when the new job has auto-enrollment. The model predicts a qualitatively similar response.

Model exercise. For each simulated individual, I change the enrollment regime faced in the first two jobs after a randomly drawn quarter t^{exp}. I assume that all employers have an opt-in enrollment regime prior to t^{exp}. I simulate the model under four scenarios: (i) AE to non-AE: auto-enrollment in job number 1 (in period t^{exp} for both new hires and seasoned nonparticipating employees) and opt-in in job number 2, (ii) non-AE to non-AE: opt-in in both jobs, (iii) AE to AE: auto-enrollment in both jobs, and (iv) non-AE to AE: opt-in in job number 1 and auto-enrollment in job number 2. From job number 3 after t^{exp}, all employers auto-enroll their new hires. I compute the difference in contributions in the first year of tenure at job number 2 between scenarios (i) and (ii) to obtain the model counterpart to the coefficient AEtononAE in Table A.3. I compare scenarios (iii) and (iv) to obtain the model counterpart to the coefficient AEtoAE in Table A.3.

Results. The model predicts that auto-enrolling workers in job number 1 causes them to participate 8.4% less in their first year when job number 2 has an opt-in regime. This prediction aligns well with the empirical estimate of 12.8% (*s.e.* 5.5%) lower participation in the next opt-in job (column 1 of Table 3). However, the model-predicted decline in the contribution rate of 0.1 p.p. of salary is smaller than the empirical estimate of a 0.55 p.p.(*s.e.* 0.226) of salary (column 2 of Table 3). Interestingly, the model predictions for both the participation and contribution rates are closer to the point estimates for new hires in jobs who do not expect be auto-enrolled in the next 12 months: a drop in participation of 7.5% (*s.e.* 5.2%) and in the contribution rate of 0.12 p.p. (*s.e.* 0.266) (see Appendix Table A.4, column 6). For employees moving from an auto-enrollment employer to another auto-enrollment employer (i.e., AE to AE relative to non-AE to AE), the model predicts a modest drop in participation of 2.8% and a small drop in contributions of 0.01 p.p. of salary. This is broadly consistent with the empirical finding of no statistically significant difference between previously auto-enrolled and previously non-auto-enrolled workers when the new employer has auto-enrollment (coefficient AE to AE in Table 3).

I Numerical procedure

Discretization. The model has four discrete and five continuous state variables that need to be discretized: labor productivity, tenure, liquid assets, retirement wealth, and average lifetime earnings. Labor productivity is placed on a grid with 7 elements using the method of Tauchen (1986). Tenure is placed on a grid with 9 elements (with all periods past the 9th quarter of tenure treated equally). Liquid assets and retirement wealth are discretized in a way that gives smaller gaps between successive entries on the grid at lower levels and are placed on a grid with 50 elements for each period of retirement and 16 elements for each period of working life. Average earnings are placed on a grid of 7 elements.

Consumption is not placed on a grid, and individuals can choose any feasible consumption level. 401(k) contribution rates are naturally discrete, and in the firms in the estimation sample, contributions are often restricted to below 15% of salary. Thus, I adopt a grid of contribution rates with 16 elements: 0%, 1%,...,15% of salary. Early withdrawals from the DC account are restricted to taking one of ten values. That is, unemployed individuals can withdraw 0%, 1%, 2%, 5%, 10%, 15%, 25%, 50%, 75% or 100% of their DC wealth. In retirement, DC withdrawals can take one of 101 values (0%, 1%,2%,...,99%, 100%).

Interpolation. To evaluate the value function at points not in the discrete subset of points in the discretized state space, I use linear interpolation in multiple dimensions. To limit approximation error despite having fairly coarse grids, I use a method proposed by Carroll (2022). I approximate a quasi-linear transformation of the value function. The transformed value function is closer to linear than the actual one, which implies that linear interpolation is more accurate despite my having few grid points. I verify the accuracy of my numerical procedure by simulating the model—at the parameter values in my baseline estimation—with more grid points and obtain similar results.

Optimization. I solve for the DC contribution and withdrawal choices using a grid search. Given a DC contribution or withdrawal choice, I solve for the liquid asset level (which implies the consumption level) using a golden section search.

Estimation. I estimate the model in two steps. In the first step I solve the model for 2,744 unique combinations of the model's three parameters for the baseline model specification under both default option (3% and 6%). In the second step, I use the Hooke-Jeeves optimization method to estimate the preference parameters in a region close to the optimum values from the first step. For each combination of preference parameters, I solve for the value function by iterating the problem from the last period of life (period 272 corresponding to age 90). I then simulate 5,000 individuals in the opt-in group and 5,000 in the auto-enrollment group with identical realization of the stochastic variables. Estimation is computationally intensive. The program was compiled with Intel Fortran, and estimation was is done across 16 simultaneous jobs each parallelized on 42 computer processors using OpenMP on the MIT High Power Computing facility.

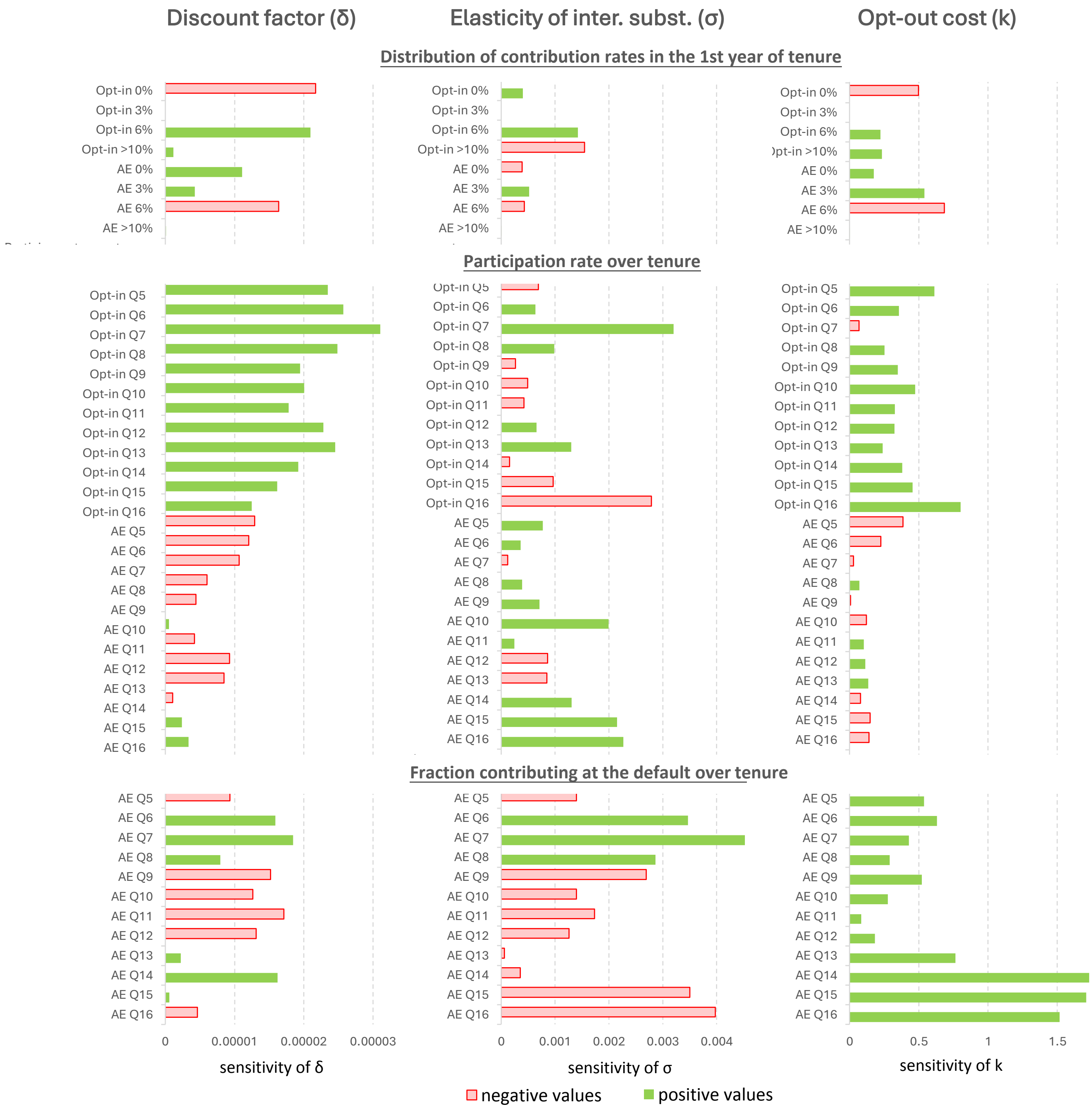
J Sensitivity

I plot in Figure A.23 the elements of the sensitivity matrix as defined in Andrews et al. (2017). These values capture how a 1-percentage-point increase in each empirical moment changes the estimated parameters.

Time preferences. According to the sensitivity matrix plotted in Figure A.23, more contributions at the employer match threshold (6% of salary), and fewer contributions above (≥10%) in the opt-in cohort, would imply to a higher estimate of the elasticity of intertemporal substitution. This result is consistent with the finding in Best et al. (2020) that bunching at—with missing mass above—an interest rate notch can identify the elasticity of intertemporal substitution separately from the discount factor.

Switching cost. The sensitivity measure implies that more bunching at the auto-enrollment default (especially later in employees' tenure) would increase the estimated switching cost. The share of 0% contributions under opt-in is jointly determined by (i) the discount factor (the lower the intertemporal discount factor, the higher is the share contributing 0%) and (ii) the switching cost (0% is the default contribution rate for the opt-in group, and the higher the switching cost, the higher is the share staying at the 0% default). The sensitivity matrix indicates that a higher share at 0% leads to a lower estimate of the discount factor (both in the first year of tenure and later up to four years of tenure). When agents are estimated to be more impatient, a smaller switching cost is required to match the observed bunching at the default. This indirect effect (i.e., a lower discount factor leading to a lower switching cost) dominates the direct effect (i.e., a higher switching cost leading to more mass at the 0% opt-in default), and the sensitivity matrix implies that a higher share at 0% under opt-in leads to a smaller switching cost. Identification is simpler in the case of contributions at 3% under the auto-enrollment regime. The intertemporal discount factor is not as sensitive to the share of contributions exactly at 3%, and thus, in the model, the size of bunching at the 3% auto-enrollment default primarily reflects the size of the switching cost. Both in the first year of tenure and for every quarter 5 to 16 of tenure, a higher share of contributions at 3% under auto-enrollment leads to a higher estimate of the switching cost. A 1 p.p. increase in the share contributing 3% in the first year of tenure leads to a higher switching cost by around 50cts, and a 1 p.p. increase in the share contributing exactly 3% after 4 years (16th quarter of tenure) increases the estimated switching cost by $1.5.

Figure A.23: Sensitivity of preference parameters to estimation moments



Notes: This figure shows the sensitivity matrix as defined in Andrews et al. (2017) under the baseline preference estimates from column 1 of Table 4. Sensitivity values are rescaled to correspond to a 1-percentage-point increase in each moment.

References

Altmann, S., F. Armin, P. Heidhues, and R. Jayaraman (2019). Defaults and donations: Evidence from a field experiment. *Review of Economics and Statistics 101*(5), 808–826.

Andrews, I., M. Gentzkow, and J. M. Shapiro (2017). Measuring the sensitivity of parameter estimates to estimation moments. *The Quarterly Journal of Economics 132*(4), 1553–1592.

Arnoud, A., T. Choukhmane, J. Colmenares, C. O'Dea, and A. Parvathaneni (2021). The evolution of u.s. firms retirement plan offerings: Evidence from a new panel data set. *Working Paper*.

Bernheim, B. D., A. Fradkin, and I. Popov (2015). The welfare economics of default options in 401 (k) plans. *American Economic Review 105*(9), 2798–2837.

Best, M., J. Cloyne, and E. Ilzetzki (2020). Estimating the elasticity of intertemporal substitution using mortgage notches. *Review of Economic Studies 87*(2), 656–690.

Blumenstock, J., M. Callen, and T. Ghani (2018). Why do defaults affect behavior? experimental evidence from afghanistan. *American Economic Review 108*(10), 2868–2901.

Borella, M., M. De Nardi, and F. Yang (2018). The aggregate implications of gender and marriage. *The Journal of the Economics of Ageing 11*, 6–26.

Brown, J. R., A. M. Farrell, and S. J. Weisbenner (2016). Decision-making approaches and the propensity to default: Evidence and implications. *Journal of Financial Economics 121*(3), 477–495.

Brown, J. R. and A. Previtero (2020). Saving for retirement, annuities and procrastination. *Working Paper*.

Bureau of Labor Statistics (1947-present). Consumer price index for all urban consumers (cpi-u): All items in u.s. city average. https://fred.stlouisfed.org/series/CPIAUCSL. Retrieved from Federal Reserve Bank of St. Louis, FRED.

Caplin, A. and D. Martin (2017). Defaults and attention: the drop out effect. *Revue économique 5*(5), 747–755.

Carroll, C. D. (2022). Solution methods for microeconomic dynamic stochastic optimization problems. *Working Paper*.

Carroll, G. D., J. J. Choi, D. Laibson, B. C. Madrian, and A. Metrick (2009). Optimal defaults and active decisions. *The quarterly journal of economics 124*(4), 1639–1674.

Choukhmane, T. and T. de Silva (2023). What drives investors portfolio choices? separating risk preferences from frictions. Technical report, Working paper.

Cribb, J. and C. Emmerson (2016). What happens when employers are obliged to nudge? automatic enrolment and pension saving in the uk. *IFS Working Paper*.

Dahlquist, M., O. Setty, and R. Vestman (2018). On the asset allocation of a default pension fund. *The Journal of Finance 73*(4), 1893–1936.

DellaVigna, S. (2009). Psychology and economics: Evidence from the field. *Journal of Economic literature 47*(2), 315–372.

DellaVigna, S. (2018). Structural behavioral economics. In *Handbook of Behavioral Economics: Foundations and Applications*, Volume 1, pp. 613–723.

DellaVigna, S., A. Lindner, B. Reizer, and J. F. Schmieder (2017). Reference-dependent job search: Evidence from hungary. *The Quarterly Journal of Economics 132*(4), 1969–2018.

Federal Reserve Board (2016). Survey of consumer finances (scf): Public use microdata. https://www.federalreserve.gov/econres/scfindex.htm.

Franco, C. (2004). Unemployment benefits reduced by pensions and social security: A fact sheet.

Goda, G. S., M. R. Levy, C. F. Manchester, A. Sojourner, and J. Tasoff (2020). Who is a passive saver under opt-in and auto-enrollment? *Journal of Economic Behavior & Organization 173*, 301–321.

Guvenen, F. (2009). An empirical investigation of labor income processes. *Review of Economic dynamics 12*(1), 58–79.

Haggag, K. and G. Paci (2014). Default tips. *American Economic Journal: Applied Economics 6*(3), 1–19.

Kaplan, G. and G. L. Violante (2014). A model of the consumption response to fiscal stimulus payments. *Econometrica 82*(4), 1199–1239.

Laibson, D. (1997). Golden eggs and hyperbolic discounting. *The Quarterly Journal of Economics 112*(2), 443–478.

Laibson, D., P. Maxted, S. Chanwook Lee, A. Repetto, and J. Tobacman (2024). Estimating discount functions with consumption choices over the lifecycle. *The Review of Financial Studies*.

Low, H., C. Meghir, and L. Pistaferri (2010). Wage risk and employment risk over the life cycle. *American Economic Review 100*(4), 1432–1467.

Lusardi, A., P.-C. Michaud, and O. S. Mitchell (2017a). Data and code for "optimal financial knowledge and wealth inequality". https://doi.org/10.1086/690950. Distributed by the University of Michigan, Panel Study of Income Dynamics Data Archive.

Lusardi, A., P.-C. Michaud, and O. S. Mitchell (2017b). Optimal financial knowledge and wealth inequality. *Journal of Political Economy 125*(2), 431–477.

Madrian, B. C. and D. F. Shea (2001). The power of suggestion: Inertia in 401 (k) participation and savings behavior. *The Quarterly journal of economics 116*(4), 1149–1187.

Menzio, G., I. A. Telyukova, and L. Visschers (2016a). Data and code for "directed search over the life cycle". https://doi.org/10.1016/j.red.2015.03.002.

Menzio, G., I. A. Telyukova, and L. Visschers (2016b). Directed search over the life cycle. *Review of Economic Dynamics 19*, 38–62.

O'Dea, C. (2018). Insurance, efficiency and the design of public pensions. *Working Paper*.

O'Donoghue, T. and M. Rabin (1998). Procrastination in preparing for retirement. In *Behavioral Dimensions of Retirement Economics*.

Samuelson, W. and R. Zeckhauser (1988). Status quo bias in decision making. *Journal of risk and uncertainty 1*, 7–59.

Social Security Administration, Office of the Chief Actuary (2014). Death probabilities and life expectancy by age and sex, 2014. https://www.ssa.gov/oact/STATS/table4c6_2014.html.

Sun, L. and S. Abraham (2021). Estimating dynamic treatment effects in event studies with heterogeneous treatment effects. *Journal of Econometrics 225*(2), 175–199.

Tauchen, G. (1986). Finite state markov-chain approximations to univariate and vector autoregressions. *Economics letters 20*(2), 177–181.

UK Office for National Statistics (ONS) (1997-2017). Annual survey of hours and earnings panel (nes/ashe). Data accessed via the ONS Secure Research Service.

UK Office for National Statistics (ONS) (2012). Annual business survey (abs). Data accessed via the ONS Secure Research Service.