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Extrapolative income expectations and retirement savings

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Abstract

This article examines how biased income expectations affect annual contributions to retirement accounts, highlighting variations across income levels. Empirical findings show that low-income workers are generally pessimistic about future earnings, whereas high-income workers tend to be overly optimistic. I develop a lifecycle model that merges these expectation biases with US 401(k) plan features. The model reveals that biased expectations can account for observed delays in retirement contributions, which increase gradually with tenure. Contributions rise at different rates, with low-income workers starting later than high-income workers. Policy simulations indicate that automatic enrollment boosts initial contributions but results in a relative decline compared to active enrollment. Nonetheless, cumulative savings increase by 4.8 percent on average, with gains surpassing 10 percent for the lowest income quartile. These results highlight the significance of addressing income expectations in retirement policies and show that automatic enrollment can enhance welfare, particularly for lower-income individuals.

Keywords: extrapolative expectations; income forecast errors; illiquid savings; 401(k) accounts; retirement contribution.
JEL classifications: D15, E21, J26, J32.

1. Introduction

Income expectation biases—whether pessimistic or optimistic—distort saving behavior and often result in lower savings rates than those predicted by standard rational wealth accumulation models. In the context of retirement saving, these biases accumulate over an individual's lifecycle, contributing to retirement inequality. This article makes a novel contribution by developing a lifecycle model with extrapolative expectations that quantifies the impact of these biases on retirement savings behavior. Specifically, it highlights how income expectation dynamics, shaped by empirical evidence, drive savings disparities across income levels. I show that low-income workers tend to be more pessimistic about future earnings, leading them to favor liquid savings over illiquid retirement accounts. In contrast, high-income workers are often overly optimistic, delaying retirement contributions in anticipation of sustained high income. These biases in expectations drive contribution dynamics, resulting in significant disparities in retirement savings outcomes due to compounding effects.

To motivate the expectations model, I analyze data from the Michigan Survey of Consumers (MSC; University of Michigan 1986–2012), revealing that workers' income expectations follow an extrapolative pattern. Workers who earn less than expected adjust their future income expectations downward, while those earning more revise expectations

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upward. This dynamic is shaped by both individual income histories and broader patterns in forecast errors. Although pessimism is widespread across income groups, cross-sectional differences play a crucial role in how expectations evolve over time. In particular, low-income workers exhibit greater variability in forecast adjustments, highlighting the role of cumulative income experiences in shaping consumption and saving behavior.

This interplay between expectations and behavior extends to the precautionary motive for saving. Empirical data show that workers systematically overestimate the likelihood of job loss, a bias that strengthens precautionary savings behavior, especially among those with pessimistic expectations. Building on the expectation model in (Rozsypal and Schlafmann 2023), I demonstrate within a finite-horizon framework that these patterns align with observed data and help explain the strong preference for liquidity among low-income workers.

By including expectation dynamics in the lifecycle model, this article advances our understanding of savings behavior and retirement contributions, offering insights into policy interventions that address retirement inequality. The empirical analysis suggests that expectation biases play a crucial role in shaping retirement savings behavior across income groups, highlighting the need to account for these biases when designing policies aimed at improving financial security. In particular, understanding how low-income and high-income workers' expectations about future income differ sheds light on the observed disparities in savings contributions and liquidity preferences.

Although no dataset directly links expectation patterns to retirement savings, I leverage data from the Survey of Consumer Finances (SCF; Board of Governors of the Federal Reserve Board 1989–2019) to show that low-income workers increase their retirement savings share more slowly than their higher-income counterparts. The observed age-related changes in savings accumulation, combined with income-based differences, align with the theoretical insights about how shifts in individual expectations influence contribution dynamics. These findings underscore the importance of income expectations in retirement policy adjustments aimed at reducing retirement inequality.

To explore the broader implications of expectation and saving dynamics, I include the expectation model within a novel, comprehensive lifecycle framework with micro-founded retirement contribution incentives, similar to those in US 401(k) plans. This model shows that workers gradually increase contributions over time, but low-income workers tend to delay these increases until later in their careers. The gradual adjustment pattern aligns with worker-firm level data from (Parker et al. 2022), providing a new explanation for delays in savings rates within defined contribution (DC) plans with substantial tax incentives. By linking income expectations to saving behavior, the model offers a unique foundation for evaluating policy interventions aimed at strengthening retirement security.

Despite the increase in retirement saving incentives through employer matching schedules, participation rates, and subsequent contributions have remained relatively stable over time (Parker et al. 2022). This lack of responsiveness to saving incentives has led to the development of models incorporating opt-in and adjustment costs (Dahlquist, Setty, and Vestman 2018; Choukhmane 2021), which are often considerable relative to household budgets (DellaVigna 2018). Behavioral biases, such as self-control problems (Ameriks et al. 2007) or present bias (Benartzi and Thaler 2007), also influence retirement savings decisions, but estimating their effects directly from the data is challenging. I contribute to this literature by incorporating income expectation dynamics, derived from expectation surveys, and linking them to variations in savings decisions within the context of contribution incentives.

While studies by De Nardi, French, and Jones (2009), De Nardi, French, and Jones (2010), and Grevenbrock et al. (2021) explore the impact of longevity expectations on retirement savings and consumption, my model draws on empirical findings about changes in contribution rates following income shocks (Ghilarducci, Saad-Lessler, and Reznik 2018; Goda et al. 2020). It quantifies the impact of income expectations on retirement contributions, showing that the expectation bias produces different effects for low- and high-income workers. In particular, high-income workers tend to start their contributions earlier, which aligns with the well-documented responsiveness of high earners to incentive schemes (Blanchett, Finke, and Liu 2022; Goda et al. 2020; Devlin-Foltz, Henriques, and Sabelhaus 2015).

Following US government guidelines and the Pension Protection Act (PPA) of 2006, US employers began automatically enrolling employees in DC plans at a default rate (*auto-enrollment*), rather than requiring active participation (*active enrollment*). Research shows that auto-enrollment initially boosts contribution rates in the first two to four years (Beshears et al. 2009, 2022; Choi et al. 2003). However, Choukhmane (2021) finds that this effect diminishes after about three years, likely due to low opt-out costs. Given limited contribution data and the recent enactment of the PPA, the long-term effects remain uncertain and depend on model assumptions. While Choukhmane (2021) simulates a substantial 25 percent wealth increase for lower-income workers under auto-enrollment with opt-out costs, I introduce a counterfactual model based on expectation bias that decreases with age, generating plausible lifecycle contribution rates.

Beyond default contribution rates, recent literature has also explored default retirement savings funds that generate returns over the lifecycle. For instance, Parker et al. (2022) find that the PPA increased age-dependent equity shares in DC accounts by default, although it did not significantly affect contribution rates. Given the number of passive contributors who stick to their default options, Dahlquist, Setty, and Vestman (2018) propose an optimal default fund strategy that substantially improves retirement welfare compared to age-dependent benchmarks. I examine the effect of default by mandating savings through automatic enrollment while holding the return to savings fixed. My findings show that automatic enrollment alone generates considerable welfare gains through mandatory contributions in the early stages of a worker's career.

The counterfactual model aligns with empirical results from Choukhmane (2021), showing that contribution rates initially rise over a two-year period before falling relative to the active enrollment benchmark as workers' tenure progresses. However, the returns on these higher early contributions accumulate over time, leading to a 5.4 percent average increase in retirement savings, with the bottom 25 percent of earners experiencing an increase of 10 percent. These findings support the idea that auto-enrollment does not interfere with other financial decisions, as workers maintain stable levels of liquid savings (Beshears et al. 2022).

I further examine the effectiveness of the automatic enrollment policy by calculating the welfare gains, focusing solely on retirement welfare, as suggested by (Dahlquist, Setty, and Vestman 2018). These calculations show a 5.83 percent increase in aggregate retirement welfare, with gains reaching 10.52 percent for the lowest 25 percent of earners. This highlights the potential of automated policies in contribution schemes that provide substantial benefits for workers at higher risk of financial insecurity in retirement, who are more often pessimistic and prefer maintaining liquid savings as buffers.

This article also contributes to the growing literature on the role of expectations in shaping consumption and saving choices (Cocco, Gomes, and Lopes 2022; Blundell, Pistaferri, and Preston 2008), and in explaining borrowing choices and marginal propensities to consume (Rozsypal and Schlafmann 2023). Changes in expectations influence the trade-off between savings and consumption, with effects varying over time. In this way, expectations are shaped by the entire path of income realizations, effectively modeling a proxy for individual experience and incorporating variation based on differences in complete income history.

In addition to the delay in contribution rates, I show that expectations play an important role in shaping the aggregate saving rate. The increase in precautionary savings, driven by these expectations, results in relatively flat liquid saving rates across the income distribution. This suggests that even higher-income individuals prioritize liquidity, especially early in their careers. This finding is consistent with research by Fagereng et al. (2019) and De Nardi and Fella (2017). In contrast, retirement savings rates increase with income, emphasizing the need for policies that address retirement inequality. These policies should focus on reducing income disparities and incentivizing earlier contributions, particularly among lower-income workers, whose expectations often lead to delayed savings and underpreparedness for retirement.

Automatic enrollment is often considered a straightforward policy solution to improve retirement savings. My analysis shows that the welfare gains from automatic enrollment may be more substantial than typically acknowledged, particularly for workers in the lowest income brackets. While workers may adjust their mandatory savings later in their careers, the welfare benefits persist toward retirement, driven by the cumulative effects of early incentives. By highlighting the role of income expectations in shaping retirement behavior, this article demonstrates that automatic enrollment, based on a micro-founded model of expectations, is a powerful tool for enhancing financial security and reducing retirement inequality.

2. Data

2.1 Income forecast biases in the MSC

The extrapolative expectations model builds on income expectation patterns derived from the 1986–2012 subsample of the MSC.[1] I extend the analysis of Rozsypal and Schlafmann (2023) and Das and Van Soest (1999) by leveraging several survey questions related to income, job loss, and retirement expectations. This enables me to examine the influence of subjective expectations on retirement savings behavior, focusing on expected changes in future income levels (Questions 1 and 2), as well as perceived future uncertainty (Questions 3 and 4):

1) *During the next 12 months, do you expect your income to be higher or lower than the previous year?*
   1.a) *By approximately what percentage do you expect your income to (increase/decrease) in the next 12 months?*
2) *What do you think is the likelihood that your income in the next 12 months will be higher than it was in the past 12 months?*
3) *What do you think is the likelihood that you will lose a job that you wanted to keep in the next 5 years?*
4) *What do you think the chances are that your income from Social Security and job pensions will be sufficient to maintain your living standards when you retire?*

Individual responses to Question 1 define the income expectation error as the difference between expected and realized income:

$$e_t = \frac{\widehat{y}_{t+1} - y_{t+1}}{y_t},$$

where optimists are those with a positive error (i.e., they expected an increase but earned more than expected), while pessimists have negative forecast errors (i.e., they expected their income to be lower than realized).

Using forecast errors and perceived probabilities from Questions 2 and 3, I identify three key empirical patterns supporting the extrapolative expectations framework. First, I find

[1] Between 1986 and 2012, households were asked to estimate the percentage change in their income. In later survey waves, responses were grouped into percentage brackets.

that income forecast errors systematically vary by income level and age, with errors generally decreasing as workers age. These errors differ not only in sign—high-income workers are typically over-optimistic, while low-income workers tend to be more pessimistic, as shown in (Rozsypal and Schlafmann 2023)—but also in precision. Specifically, low-income workers exhibit more volatile expectations about future income, while high-income workers tend to show more consistent but overly optimistic forecasts. In particular:

1) Income forecast errors vary systematically by income level, including in sign, precision (i.e., standard deviation), and skewness.
2) Workers extrapolate from recent income realizations, adjusting their expectations accordingly.
3) All workers overestimate the uncertainty of future income.

Building on the work of Rozsypal and Schlafmann (2023), I further investigate the distributional variations and age-dependent dynamics of income forecast errors, and explore differences in skewness and precision across income groups. The increase in precision over time and with income level highlights the importance of individual income history in shaping future expectations.

2.2 Forecast error distribution estimates

Figure 1 shows the distribution of forecast errors across income quantiles. The mean forecast error increases with income, distinguishing low-income pessimists from high-income optimists. Beyond the mean, the distribution of forecast errors varies across income levels, with differences in skewness and overall variance, as shown in Table 1. Variance estimates

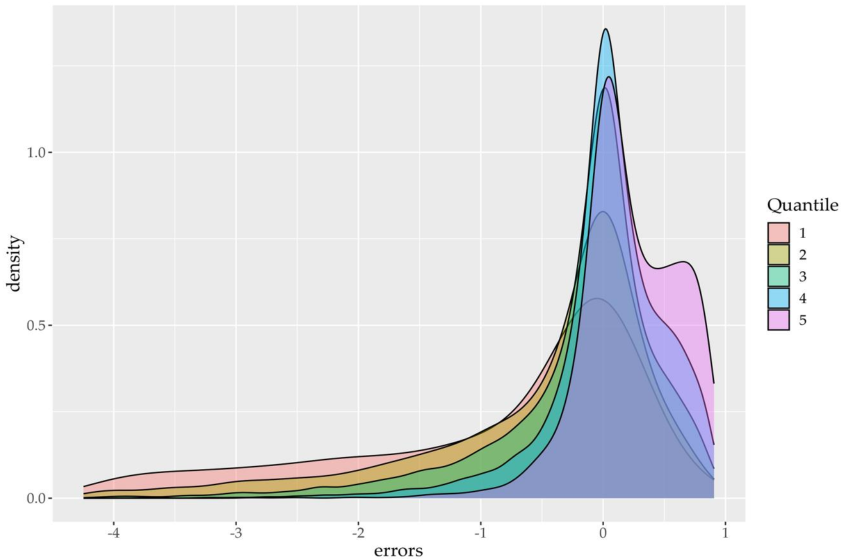


Figure 1. Income forecast error density by income quantile.

Source: MSC data. Forecast errors are winsorized at the 2.5th and 97.5th percentiles to mitigate the influence of outliers. The density is estimated using a non-parametric kernel density approach, based on 46,387 observations of income forecast errors across quantiles identified through dummy variables. Bandwidth selection follows Silverman's method with an adjustment, yielding $h = 0.107$.

Table 1. Mean, variance, and skewness of income forecast errors, by income quantile.
Source: MSC data. Forecast errors are winsorized at the 2.5th and 97.5th percentiles. All moments are computed using 45,455 survey-weighted observations. A one-way ANOVA confirms significant differences in means across quantiles ($F(4, 45450) = 2446$, $p < 0.0001$), while Levene's test indicates significant differences in variances ($F(4, 45450) = 1225.4$, $p < 0.001$). Bootstrap confidence intervals show that skewness does not differ for 4th and 3rd quantiles.

Statistic	q_1	q_2	q_3	q_4	q_5
Mean	−0.868	−0.513	−0.195	0.0382	0.222
Variance	1.51	0.974	0.503	0.256	0.163
Skewness	−1.09	−1.54	−1.86	−1.70	−0.834

show that low-income workers make larger mistakes on average, whereas all workers, regardless of income, tend to be pessimistic, which is reflected in the skewness estimates.[2]

2.3 Extrapolation and overstating income volatility

The second empirical pattern highlights the role of recent income changes, supporting the idea of extrapolation in expectation formation. Building on this, the third pattern emphasizes workers' perceptions of income volatility, proxied by job loss expectations. Together, these findings inform the model of expectations by uncovering two key properties: the level effect and the volatility effect. The level effect, captured by the influence of recent income changes on future income forecasts, evolves over time and with income dynamics. In contrast, the volatility effect persists across income levels and introduces an additional precautionary motive for savings.

While forecast errors exhibit systematic variation across income levels (as shown in fig. 1), it remains unclear whether households adjust their expectations based on recent income experiences. To investigate this, I analyze responses to Question 2, which asks about the perceived likelihood of income growth in the year after agents have observed their forecast errors. As shown in Appendix Table A2, recent forecast errors have a "corrective" effect on expectations, with those who overestimated income growth revising their expectations downward. This aligns with evidence from the Netherlands and the USA (Ghilarducci, Saad-Lessler, and Reznik 2018; Massenot and Pettinicchi 2019) and suggests that such dynamic adjustments may influence savings behavior over the lifecycle.

The third empirical pattern reveals a general tendency for workers to overstate their perceived risk of job loss, as shown by subjective probabilities derived from Question 3. These estimates, averaged across age and education groups, are compared with annual worker displacement rates reported by Love (2006), determined using data from the Displaced Worker Survey (Farber 2005). Since these external benchmarks do not include standard error estimates, the comparisons are intended to be illustrative rather than definitive. For further detail, the underlying regression model is presented in Appendix Table A7.

Individual-level probability estimates denoted as $\widehat{p}_i$ are derived from survey responses to measure perceived job loss risk. To reflect a constant annual probability of job loss, I convert worker's estimates into one-year-ahead predictions using the formula:

$$\widehat{\mathbb{P}}_i = 1 - (1 - \widehat{p}_i)^{\frac{1}{5}}.$$

The transformed probabilities are averaged across demographic groups defined by age and education, and then compared to observed worker displacement rates. The results

2 Age-dependent error distributions exhibit a reduction in forecast errors with age, as shown in Appendix Figure A2.

Table 2. Subjective job loss predictions across age and education levels, compared to the displaced worker data.
Left table: Presents average subjective job loss probabilities from a subsample of 20,421 working-age respondents in the MSC data, excluding NBER recession years. Group-based probability averages are weighted using survey weights, and standard errors are reported in parentheses. Right table: Displays yearly worker displacement rates from Love (2006), based on data from the Current Population Survey, with a sample size of 412,000 workers (Farber 2005).

Subjective Job Loss Probabilities (MSC data)				**Displaced Worker Frequencies (Love 2006)**			
$\widehat{\mathbb{P}}$	$ed < 12$	$12 \le ed \le 15$	$ed > 15$	$\widehat{\mathbb{P}}$freq.	$ed < 12$	$12 \le ed \le 15$	$ed > 15$
Age 25–34	0.079 (0.013)	0.072 (0.004)	0.068 (0.003)	25–34	0.068	0.052	0.035
Age 35–44	0.093 (0.011)	0.081 (0.003)	0.065 (0.002)	25–34	0.058	0.043	0.030
Age 45–54	0.098 (0.015)	0.092 (0.004)	0.065 (0.003)	25–34	0.053	0.039	0.028
Age 55–66	0.065 (0.011)	0.072 (0.004)	0.055 (0.003)	25–34	0.057	0.039	0.027

(Table 2) reveal a consistent pattern: workers tend to perceive a greater likelihood of job loss than what observed rates suggest. While higher education and income levels are associated with lower subjective probabilities (Appendix Table A7), the tendency to overstate risk persists across all groups.

This systematic overestimation indicates the presence of precautionary motives for savings. By overestimating job loss probabilities, workers may prioritize savings in liquid accounts as a buffer.

2.4 Retirement confidence

Retirement savings strategies often include a mix of pension accounts and homeownership, with the latter serving as an implicit form of savings for many households. Using responses from Question 4 on future retirement well-being, I examine the relationship between homeownership, home value, and retirement confidence. As shown in Appendix Table A5, home value exhibits a weak correlation with retirement confidence, which, along with the low adoption rates of reverse mortgages in the USA (Mayer and Moulton 2022), points to the central role of income in shaping both retirement confidence and saving behavior.

Next, I introduce a model of extrapolative expectations, adapting the framework of Rozsypal and Schlafmann (2023), to a finite-horizon setting. This approach enables the model to capture key features of the data, including heterogeneity in income dynamics and forecast errors. I then revisit the three primary empirical findings from the MSC data—variations in forecast errors across income levels, the corrective role of recent income changes, and the overestimation of income uncertainty. By aligning the model with these observed patterns, I highlight the relevance of extrapolative expectations for understanding workers' consumption and savings decisions.

2.5 Relating forecast errors to the model

The extrapolative expectations model assumes that workers misperceive the persistence of their income. Before turning to individual savings decisions, I revisit key expectation patterns and focus on the dynamics of expectations and the implied perceived income uncertainty.

A standard lifecycle income process is modeled as follows:

$$Y_{it} = A_i G(t) \Gamma_{it} P_{it}, \quad \log A_i \sim \mathcal{N}(\mu_\alpha, \sigma_\alpha^2), \ \log \Gamma_{it} \sim \mathcal{N}\left(-\frac{\sigma_\Gamma^2}{2}, \sigma_\Gamma^2\right), \tag{1}$$

$$\log P_{it} = \lambda \log P_{it-1} + \xi_{it}, \quad \xi_{it} \sim \mathcal{N}(\mu_\xi, \sigma_\xi^2), \tag{2}$$

where A_i represents the individual-specific component, $G(t)$ captures the age-dependent deterministic growth, and $\Gamma_{i,t}$ is a transitory component. The persistent component P_{it} is characterized by the persistence parameter λ.

Building on (Rozsypal and Schlafmann 2023), I analyze how workers form expectations about their future income under a systematic misperception of the persistence of their income process. Specifically, I assume that workers overestimate the persistence parameter, such that $\widehat{\lambda} > \lambda$, where $\widehat{\lambda}$ represents the perceived persistence and λ is the true parameter. This misperception influences the way that workers perceive their income process:

$$\widehat{Y}_{it} = A_i G(t) \Gamma_{it} \widehat{P}_{it} \quad \text{and} \log \widehat{P}_{it} = \widehat{\lambda} \log \widehat{P}_{it-1} + \xi_{it} \Rightarrow \mathbb{E}_t^* Y_{i,t+1} = A_i G(t) P_{i,t-1}^{\widehat{\lambda}}, \tag{3}$$

which defines extrapolative expectations $\mathbb{E}_t^*$. Using logs, for $y_{it} = \log Y_{it}$, $p_{it} = \log P_{it}$, and $\widehat{p}_{it} = \log \widehat{P}_{it}$, I show that the difference between subjective and rational expectations

$$\begin{aligned} \mathbb{E}_t^*[y_{i,t+T}] - \mathbb{E}[y_{i,t+T}] &= \mathbb{E}^*[p_{i,t+T}] - \mathbb{E}[p_{i,t+T}] \\ &= (\widehat{\lambda}^T - \lambda^T)(p_{i,t} - \mu_\xi), \quad \forall T, \end{aligned}$$

depends on the difference between λ and $\widehat{\lambda}$, and the level of current income level p_{it}. This separates optimists with a positive error from pessimists with a negative one.

Using the properties of the persistent component, for $\widehat{\lambda} = \lambda + \varepsilon$, the difference

$$\mathbb{E}_t^*[p_{i,t+1}] - \mathbb{E}_t[p_{i,t+1}] = \varepsilon \left(\sum_{s=0}^{t-1} \widehat{\lambda}^{t-s} \xi_{i,s} + \widehat{\lambda}^t p_{i,0} \right) \tag{4}$$

shows that the entire income history defines the worker as an optimist or a pessimist, which is consistent with the extrapolation evidence from the MSC data. More importantly, recent income realizations have a significant effect.

Similarly, perceived income volatility is always higher than the true one

$$\mathbb{V}_t[p_{t+T}] = \sigma_\xi^2 \frac{1-\lambda^{2T}}{1-\lambda} < \widehat{\mathbb{V}}_t[p_{t+T}] = \sigma_\xi^2 \frac{1-\widehat{\lambda}^{2T}}{1-\widehat{\lambda}}, \forall t = 1, \ldots, T, \tag{5}$$

owing to the difference in the persistent component. In particular, all workers overstate their income volatility, regardless of their income level. In the same way, workers' predictions about job loss from the MSC data overestimate the actual income volatility, as measured by worker displacement data.

To quantify the degree of extrapolation, I estimate the misperceived persistence parameter $\widehat{\lambda}$. Specifically, I simulate the income process under the correctly perceived values of λ and the potential values of $\widehat{\lambda}$. I treat these simulations as income forecast errors and optimally choose $\widehat{\lambda}$ that minimizes the difference in MSC forecast errors across different income quantiles and simulations counterparts. The expectation calibration is outlined in detail in the Appendix Section A.3.1.

2.6 Retirement savings data in the SCF

While the MSC captures workers' expectations, it does not provide data on savings behavior. To address this, I turn to the SCF to explore how the allocation between liquid and retirement savings varies across income levels. I find that low-income workers maintain higher levels of liquid savings throughout their lifecycle, which is consistent with a more pessimistic outlook on future income. In contrast, high-income workers tend to reduce their liquid savings over time, shifting more wealth into illiquid retirement accounts. These patterns, linked to pessimism among low-income workers and optimism among high-income workers, form the foundation for the expectation-driven mechanism in the model.

To quantify these patterns, I analyze liquid-to-illiquid savings ratios using SCF data from 1989 to 2019. The sample comprises of workers under 75 years of age who report being employed or self-employed, with their wage income exceeding the combined total of Social Security benefits and other transfers received in a given year. Liquid savings are defined as the sum of checking and savings accounts, along with directly held stocks, bonds, and mutual funds.[3] Illiquid savings correspond to retirement accounts, including IRA/Keogh plans, current and future pension benefits, thrift accounts, and other private retirement plans.

I regress the share of liquid savings in total savings (denoted as ϕ_i) on a set of observables, including wage percentiles and age group indicators, to examine how the allocation between liquid and illiquid savings varies across income levels and age groups. Due to the variability at the wage percentile level, I apply a smoothing function to better capture the general patterns in the data. Additionally, I include smoothed lines for different age groups to observe how the pattern evolves over the lifecycle.

I estimate the following regression model:

$$\phi_i = \beta + \beta_1 \text{year}_i + \beta_2 \text{wage}_i + \beta_3 \text{age}_i + \beta_4 \text{educ}_i + \beta_5 \text{non-fin. assets}_i + \delta \mathbb{X}_i + \varepsilon_i,$$

where "year," "family characteristics," and "education" are represented by dummy variables, while wage and non-financial assets are continuous variables. $\mathbb{X}_i$ denotes the remaining controls.[4] The regression results are presented in Appendix Table A8. Using this model, I predict the share ϕ_i at the individual level, and then sort the predictions across wage percentiles. I then apply a smoothing function to capture the general patterns in the data. The results are plotted for separate age groups in figure 2, with predictions displayed across wage percentiles and age groups.

Figure 2 shows that the share of liquid savings falls as workers approach retirement, with a more pronounced decrease among higher-income workers. While the share of liquid savings decreases consistently with income, it remains relatively stable for the top 25 percent of earners until mid-career. Lower-income workers maintain a higher proportion of their savings in liquid accounts throughout their working lives, with this share decreasing from around 60 percent for the lowest income groups to approximately 40 percent for higher-income groups just before retirement. After retirement, the share of liquid savings increases for all groups, stabilizing around 65 percent.[5]

I later revisit predicted shares to calibrate the risk aversion parameter of the lifecycle model. To further support my model choice of fully illiquid retirement accounts, I examine the extent to which workers access their private retirement accounts and find that fewer than 2 percent of SCF respondents report withdrawing funds and incurring penalties.

[3] This definition includes money market deposit accounts, stock and bond mutual funds, tax-free mutual funds, and government bond mutual funds.

[4] Age is represented through bins with separate dummy variables, and $\mathbb{X}$ includes a dummy characterizing family characteristics (marital status, children, and combinations therein), gender, race, and dummy-coded housing and non-financial wealth and non-wage income quantiles.

[5] For robustness, I estimate the savings share distribution for workers already participating in defined contribution retirement plans.

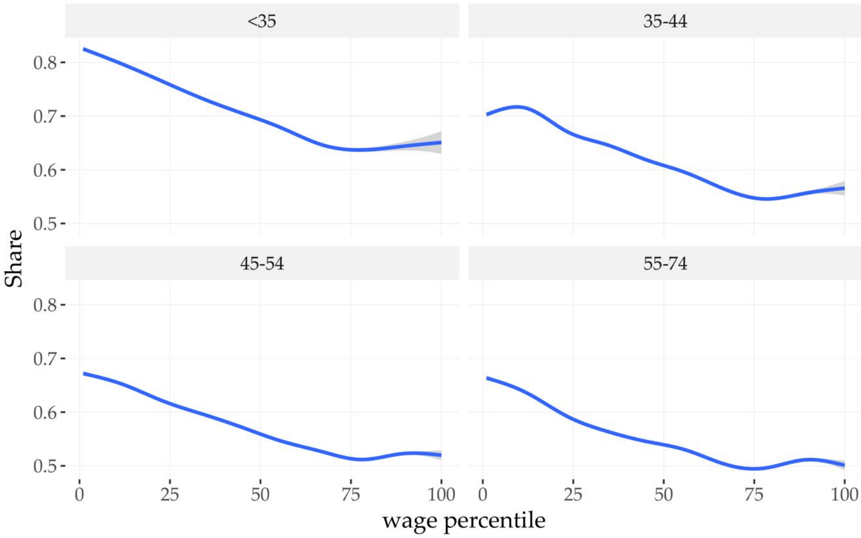


Figure 2. Predicted share of liquid savings by age group and wage percentile. *Source*: SCF subsample of workers, 1989–2019. This figure shows smoothed lines of predicted shares of liquid savings ϕ based on the regression model presented in Appendix Table A8. The model controls for factors including year, wage, age (using dummy variables), education, non-financial assets, family characteristics (e.g., marital status, children), gender, race, housing wealth, and non-wage income quantiles.

3. Full lifecycle model

Building on expectations patterns identified in the MSC data and the liquid-to-retirement savings ratios documented in the SCF, I develop a structural lifecycle model with extrapolative expectations and retirement savings. This model captures key elements of subjective workers' saving behavior and explains observed patterns in retirement contributions. It also serves as a benchmark for assessing potential retirement policy adjustments.

The model considers both transitory and permanent income shocks, which drive the trade-off between liquid and illiquid savings. Combined with subjective income expectations, these shocks shape the evolution of expected income and savings allocation decisions over the lifecycle. This section details the model's foundational assumptions and the critical trade-offs that workers face in balancing precautionary liquid savings with long-term retirement objectives. The computational procedure uses the two-dimensional endogenous grid method outlined in Druedahl (2021), which nests the two savings choices problem and enables faster computation.

3.1 Worker's problem

Workers receive labor income y_t at the beginning of each year and decide how much to save in a liquid savings account a_t and how much to contribute to their retirement savings account d_t. The remainder is allocated to consumption c_t, which yields:

$$u(c_t) = \frac{c_t^{1-\gamma}}{1-\gamma}.$$

Each period, workers face both persistent and transitory income shocks, modeled through a log-transformation of the income process defined in the expectation model motivation (equations (1) and (2) in Section 2). Specifically, the income process follows:

$$y_{i,t} = \alpha_i + g(t) + p_{i,t} + \zeta_{i,t}, \quad \alpha_i \sim \mathcal{N}(\mu_\alpha, \sigma_\alpha^2), \ \zeta_{i,t} \sim \mathcal{N}\left(-\frac{\sigma_\Gamma^2}{2}, \sigma_\Gamma^2\right), \tag{6}$$

$$p_{i,t} = \lambda p_{i,t} + \xi_{i,t}, \quad \xi_{i,t} \sim \mathcal{N}(\mu_\xi, \sigma_\xi^2). \tag{7}$$

In contrast to rational workers, subjective workers do not fully understand their income process and instead extrapolate from prior income realizations. I denote subjective expectations as $\mathbb{E}_t^*$ and outline all model equations using the rational expectations notation ($\mathbb{E}_t$). All equations hold for extrapolative expectations by replacing $\mathbb{E}_t$ with $\mathbb{E}_t^*$.

3.1.1 Retirement savings account

The retirement savings account in the model is a private DC account, modeled after US 401(k) and 403(b) plans. Workers are subject to an employer-employee matching schedule and can choose their annual contribution rate, denoted as d_t. Setting up the account incurs no setup costs and can be deferred to a later time. Participation is voluntary and workers can adjust their contribution rates at no cost. Once the account is created, however, workers cannot withdraw funds. While US 401(k) accounts allow withdrawals, they incur a 10 percent penalty on all illiquid savings. SCF data suggest that such withdrawals are infrequent and negligible, which justifies the assumption in this model that retirement savings are fully illiquid.

There is no minimum contribution requirement; however, the maximum contribution, denoted as $\max_t$, is age-dependent and governed by US regulations, imposing the constraint $d_t y_t \leq \max_t$. The matching schedule in the model reflects a smooth approximation of the typical employer-employee matching structure, incentivizing contributions up to 6 percent of income:

$$h(d_t y_t) = \chi \log(b + a d_t y_t), \ \forall t \leq T_{ret}.$$

Following Choukhmane (2021), savings in the DC account yield returns R_b, which include tax deferrals and are higher than the returns in standard liquid savings accounts with returns R_a. At the end of each year, the retirement savings b_t consist of accumulated savings n_t, and matched contribution $d_t y_t$:

$$b_t = n_t + d_t y_t + h(y_t d_t), \ \text{where } n_t = R_b b_{t-1}, \ \forall t = 1, \ldots, T_{ret} - 1.$$

3.1.2 Liquid savings account

The liquid savings account yields a return R_a, where $R_a < R_b$ reflects its lower yield compared to retirement savings. Workers primarily use this account to meet current consumption needs and to maintain a buffer against income shocks.

Given their participation in the DC account, denoted by $z_t = 1$ for contributors and $z_t = 0$ for non-contributors, workers allocate the remaining portion of their budget m_t between consumption c_t and liquid savings a_t. The worker's budget constraint, alongside the accumulation of both liquid savings a_t and retirement savings b_t, is given by the following equations:

$$c_t + y_t d_t \mathbf{1}_{\{z_t=1\}} + y_t \mathbf{1}_{\{z_t=0\}} \leq m_t - a_t \tag{8}$$

$$b_t = R_b b_{t-1} + y_t d_t + h(y_t d_t) \tag{9}$$

$$m_{t+1} = R_a a_t + y_{t+1}. \tag{10}$$

Workers decide between liquid savings, accessible during their career, and higher-return retirement savings, which include employer matching but are inaccessible until retirement.

Despite the incentives to invest in retirement accounts, pessimistic income expectations may lead workers to maintain higher liquid savings for consumption security.[6]

3.2 Retiree's problem

At retirement, which is deterministic and occurs at age T_{ret}, accumulated savings in the DC account are converted into annuity payments y_{an}. These annuity payouts represent the primary source of retirement income, as the remainder of the DC account does not yield additional returns. Workers who did not participate in the DC account rely instead on a baseline retirement benefit $\bar{b}$. The retiree's problem is modeled as a standard consumption-saving framework, where optimal consumption and savings depend on the retiree's savings decisions during their working life:

$$\max_{\{c_t, a_t \geq 0\}} u(c_t) \text{ s.t. } c_t \leq m_t - a_t$$
$$m_{t+1} = R_a a_t + \mathbf{1}_{\{DC\}} y_{\text{an}} + (1 - \mathbf{1}_{\{DC\}})\bar{b}.$$

3.3 The value function

Given the income process in equations (6) and (7), the budget constraint (8), and asset accumulation equations (9) and (10), workers maximize their stream of future consumption. State variables of the lifecycle model are the persistent income component $p_{i,t}$, a persistent and transitory shock $\xi_{i,t}$ and $\zeta_{i,t}$, cash-on-hand $m_{i,t}$, and retirement savings $n_{i,t}$ [7]. Cash-on-hand m_t consists of accumulated liquid savings a_{t-1} and current labor income y_t. Throughout the rest of the article, subscript i is omitted.

The problem workers face involves making decisions about whether to participate in a DC retirement savings plan and how to allocate resources between current consumption and liquid savings. Starting a DC account is an irreversible decision, defined with z_t, where $z_{t-1} = 1$ indicates participation. Once a worker opts in ($z_t = 1$), she remains a contributor for the remainder of her career ($z_s = 1$ for $s = t, \ldots, T_{\text{ret}}$). At each period, the worker maximizes her value function, which depends on her current participation status. If she has not yet opted in ($z_{t-1} = 0$), she decides whether or not to opt in.

$$V(0, p_t, \zeta_t, \xi_t, m_t, n_t) = \{v_t(z_t = 1, p_t, \zeta_t, \xi_t, m_t, n_t), v_t(z_t = 0, p_t, \zeta_t, \xi_t, m_t, 0)\}.$$

For workers who choose not to participate ($z_t = 0$), the problem boils down to choosing how much to save in readily available liquid assets

$$v_t(0, p_t, \zeta_t, \xi_t, m_t, n_t) = \max_{c_t \geq 0} u(c_t) + \beta \mathbb{E}_t[V_t(0, p_{t+1}, \zeta_{t+1}, \xi_{t+1}, m_{t+1}, n_{t+1})],$$

subject to constraints (8), (9), and (10). For workers who are participating ($z_t = 1$), the decision involves determining the optimal amounts to contribute to their retirement savings, consume, and save in liquid assets:

$$v_t(1, p_t, \zeta_t, \xi_t, m_t, n_t) = \max_{0 < d_t \leq 1, c_t \geq 0} u(c_t, d_t) + \beta \mathbb{E}_t[V_t(1, p_{t+1}, \zeta_{t+1}, \xi_{t+1}, m_{t+1}, n_{t+1})],$$

under constraints (8), (9), and (10).

[6] In the online supplementary material, I develop a stylized three-period model and show that pessimists allocate their savings to liquid accounts due to their fear of being constrained.

[7] Following Druedahl (2021), I separate the end-of-period savings level $b_{i,t}$ form the beginning-of-period savings level that $n_{i,t} = R_b b_{i,t-1}$, which defines n_t as a state.

The worker's problem yields the following first-order conditions for the interior solution:

$$\begin{aligned} u'(c_t) &= \beta \mathbb{E}_t[v_{m,t+1}] \\ d_t y_t &= \frac{1}{a} \frac{\chi}{R_a \mathbb{E}_t[v_{m,t+1}] - R_b \mathbb{E}_t[v_{n,t+1}]}, \end{aligned} \tag{11}$$

These conditions describe the trade-offs workers face in each period. Contribution rates increase with the expected benefits, denoted by χ, and decrease when the marginal value of current liquidity, represented by $R_a \mathbb{E}_t[v_{m,t+1}]$, exceeds the marginal value of retirement savings, $R_b \mathbb{E}_t[v_{n,t+1}]$. Pessimistic expectations tend to overestimate the likelihood of low income in the future, and increase the perceived value of liquidity, leading workers to favor liquid savings. Over time, as income rises with age, pessimism diminishes and the incentives to prioritize retirement savings become more pronounced.

3.4 Estimation

The model estimation follows a two-step procedure. First, I incorporate a set of external estimates as parameters. Next, I estimate the internal parameters by matching simulated model outcomes to target moments derived from SCF data.

The income process parameters are set externally, using age coefficients derived from Panel Study of Income Dynamics (PSID) data estimates for high school graduates (Cocco, Gomes, and Maenhout 2005), and the persistent component from Storesletten et al. (2004). To calibrate the income forecast bias, I simulate the income process and, by varying the perceived persistence parameter $\widehat{\lambda}$, I minimize the distance between the empirical expectation errors and their simulated counterparts. Additionally, I define the maximum retirement contributions based on income quantiles from MSC data and approximate the employer matching schedule using a smooth function fitted to the average default match rate observed among US employers.

In the second step I simulate the lifecycle model and use the resulting savings paths to calibrate the risk aversion parameter. This is done by matching the liquid-to-retirement savings ratios derived from SCF data to those generated by the model simulations. The final parameter values are reported in Table 3.

3.4.1 *Contribution match schedule*

The benefit function $h(y_t, d_t)$ captures the standard matching schedule in the USA. Typically, employers match 50 percent of employees' contribution rates, up to 6 percent of their wage. Specifically, if the worker contributes less than 6 percent of their wage, the employer matches 50 percent of that contribution. However, if the contribution rate exceeds 6 percent, the employer's match is capped at 3 percent of the employee's wage. The model approximation of this benefit function is a smooth representation of this schedule:[8]

$$h(d_t, y_t) = \chi \log(b + a d_t y_t).$$

The maximum contribution limit, $\max_t$ is set based on the IRS-regulated caps for 2015. In that year, the maximum contribution was \$18,000 for workers under 50, and \$24,000 for those aged 50 and older. I adjust self-reported income levels from MSC data to 2015 equivalents to obtain the corresponding distribution quantiles. These quantiles are then used as the maximum contribution limits in the model simulations, as outlined in Table 3.

3.4.2 *Other model parameters*

The retirement savings return corresponds to the average return of a standard lifecycle fund, which is the default option widely chosen among 401(k) contributors (Mitchell et al. 2006;

8 The figure of the approximation fit is in Appendix Section A.3.2.

Table 3. Model parameters. All parameters, except for γ, are set externally. The discount factor (β), retirement age (T_{ret}), and liquid savings returns (R_a) follow standard parameterization practices. Parameters for the matching schedule (χ, a, and b) are derived based on the typical employer matching schedule in the USA. The return on retirement savings (R_b) incorporates adjustments for tax deferrals.

Parameter	source/target	Value
χ	Matching schedule, US data	1.91
a		0.67
b		1.01
$\max_{t<50}$	MSC income quantiles corresponding to max contributions	0.08
$\max_{t\geq 50}$		0.135
β	Duarte et al. (2021)	0.96
T_{ret}	Duarte et al. (2021)	65
T	Love (2006)	90
R_a	Choukhmane (2021)	1.02
R_b		1.045
γ	Calibrated to match liquid-to-illiquid ratio in the SCF	3.7

Parker et al. 2022). The return on liquid assets incorporates a tax differential, as gains on 401 (k) savings are tax-deferred (Choukhmane 2021). The remaining model parameters are set to standard values established in the literature. I calibrate the risk aversion parameter to match the age patterns in the liquid-to-illiquid asset ratios from the SCF (compared against wage percentiles in fig. 2 of data analysis).

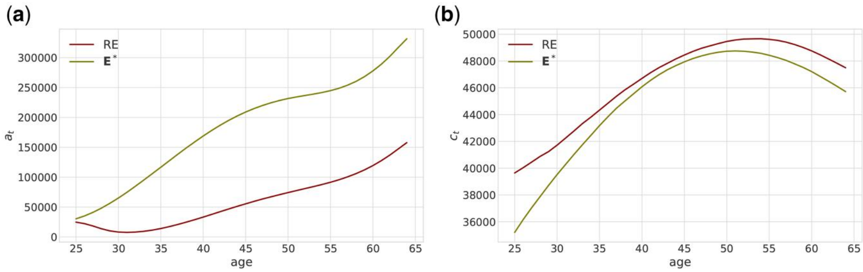
4. Results

This section examines the differences in savings behaviors between rational and subjective workers. I focus on contribution rates to DC accounts, and show that the savings patterns of subjective workers align closely with contribution averages from firm-level data (Parker et al. 2022). I also show that the liquid-to-illiquid asset shares documented in SCF data (fig. 2) match the subjective worker's savings shares more closely than when using a standard rational expectations model. These results provide strong support for incorporating subjective expectations as a benchmark for retirement policy adjustments.

4.1 Rational versus subjective workers: a comparative analysis

Lifecycle differences in consumption and savings policies between rational and subjective workers lead to substantial disparities in accumulated retirement savings. Early in the lifecycle, subjective workers prioritize liquid savings, as reflected in the elevated levels shown in figure 3a, while maintaining lower consumption. Over time, as the perceived income bias diminishes and uncertainty perceptions evolve, subjective workers adjust their consumption upward. This transition is depicted in figure 3b, highlighting the gradual shift in their lifecycle behavior.

To analyze the differences in contribution rates throughout the working lifecycle, I compare the patterns under rational and subjective expectations, aligning them with empirical data. For an average subjective worker, retirement contributions rise steadily over the mid-career period before tapering off slightly just prior to retirement. In contrast, rational workers maintain relatively flat contribution rates throughout their working lives, as illustrated in figure 4. The gradual increase in subjective workers' contributions mirrors the



Liquid savings path. Consumption path.

Figure 3. Lifecycle savings and consumption paths (2015 USD). The green curves represent subjective workers, while the red curves depict rational workers. The savings and consumption levels reflect age-dependent averages, illustrating that subjective workers allocate more to liquid savings and consume less over the lifecycle.

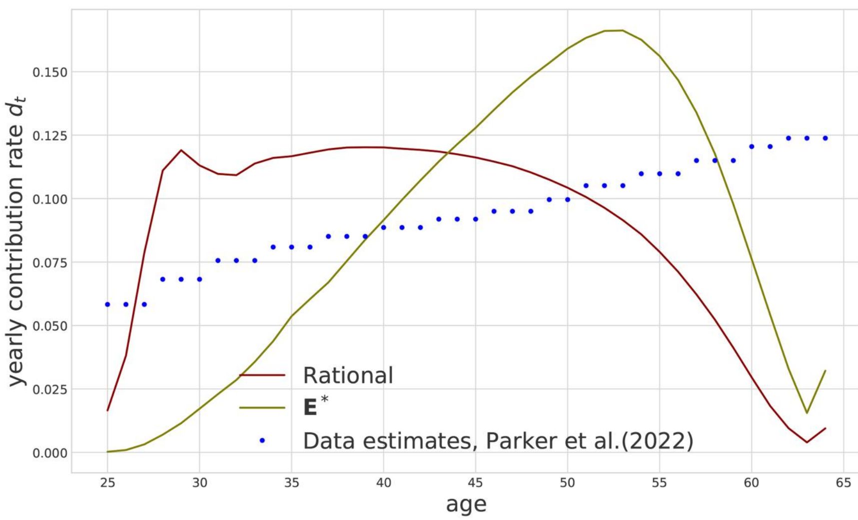


Figure 4. Contribution rates over the lifecycle for a worker earning the mean income. Rational expectations are shown in red, while subjective expectations are shown in green. Data points represent the within-person realized retirement contribution rates from Parker et al. (2022).

yearly contribution rates observed in employee-level data reported by Parker et al. (2022).[9] This pattern holds for different income levels.

4.1.1 *Liquid-to-illiquid savings ratio across the work life*

In addition to contribution rates, the subjective expectations model aligns well with liquid savings shares from the SCF data. Figure 5 shows liquid savings ratios for subjective workers (SE model), rational workers (RE model), and the SCF data counterpart across different stages of the work life.

The SE model overstates the liquid savings share, while the RE model predicts a significantly lower share throughout the work life. In the model, young workers tend to be

[9] Average contribution rates are obtained from Table A22 in Parker et al. (2022), which reports realized retirement contribution rates. Specifically, I use Column 8, which corresponds to workers allocating 0–25 percent of their contributions to a Target Date Fund.

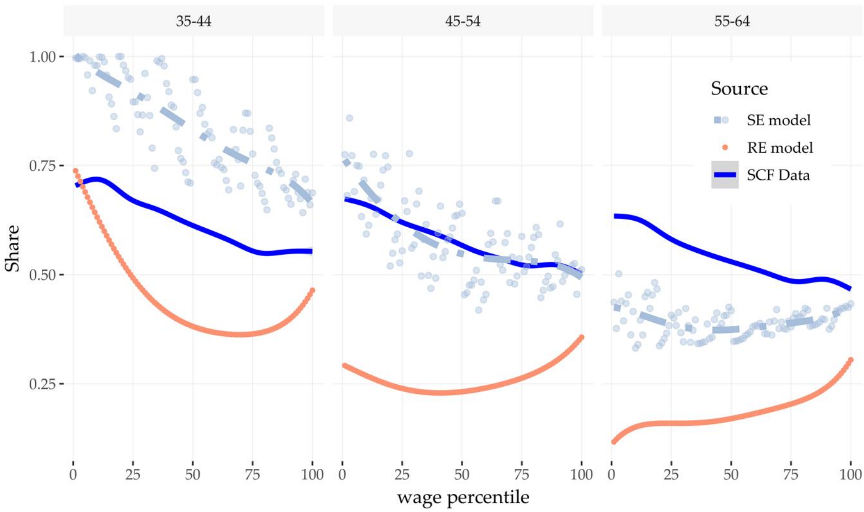


Figure 5. Liquid savings shares across wage income and age: model simulations compared to SCF data. Model simulations are based on 10,000 workers, grouped into corresponding age groups and wage percentile brackets. Points represent simulated shares, with dashed lines showing averages across age groups. The SCF data counterparts correspond to the savings share breakdown outlined in the data analysis. Rational expectations simulations are presented as averages only, for clarity.

low-income and pessimistic, leading to precautionary saving and higher liquid savings ratios. As workers progress through their careers, they consume more and allocate a larger portion of their savings to retirement accounts, especially in the upper half of the income distribution (middle panel of fig. 5). Ten years before retirement workers continue to contribute to retirement accounts but save less in liquid assets.

I also calculate the net liquid saving rate in the model and find that, consistent with the data (De Nardi and Fella 2017; Fagereng et al. 2019), savings rates are relatively similar across different income levels, as shown in figure 5. This is partially driven by a strong precautionary motive, whereby workers overestimate income uncertainty. At the same time, differences in retirement savings rates—primarily driven by pessimism—contribute to the persistence of retirement inequality. While both low- and high-income workers tend to delay saving for retirement, high-income workers typically begin contributing earlier.[10] The earlier start allows them to accumulate more savings over time, ensuring a higher level of consumption in retirement.

To address retirement inequality, many retirement policies include default savings options, encouraging workers to begin saving earlier. Since subjective contributions align well with real-world data, I now explore how policies such as automatic enrollment could influence savings rates and overall retirement savings.

5. Policy experiment: automatic enrollment

While automatic enrollment policies have become more widespread, the long-term impacts, particularly in terms of default contribution rates, remain unclear. Existing research primarily focuses on short-term effects, often measured within 5–7 years after enrollment. This article, alongside Choukhmane (2021), is among the first to explore the potential long-term effects of automatic enrollment on workers' tenure, using a structural model to assess these impacts.

[10] I disaggregate contribution paths across income levels in the Supplementary Appendix.

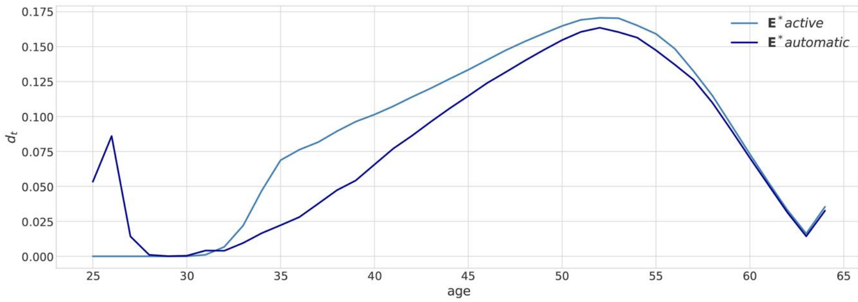


Figure 6. Subjective worker's contribution rate under active and auto-enrollment policy. The figure depicts average contribution rates for subjective workers under active and automatic enrollment policies. The effect of the default enrollment persists until around age 28, after which contributions level off.

Given that subjective expectations align with retirement contribution patterns observed in the data, I use this framework to analyze the impact of the automatic enrollment policy in two ways. First, I compare differences in contribution rates over the lifecycle. Second, building on Dahlquist, Setty, and Vestman (2018), I assess the policy's impact on welfare by calculating consumption-equivalent gains during retirement. Under automatic enrollment, workers contribute 3 percent of their wage to retirement accounts in the first year, with the option to adjust their contributions without any cost.

The first part of the analysis examines the differences in contribution rates, as shown in figure 6. Under automatic enrollment, contribution rates initially increase by default but tend to level off over time, remaining relatively lower than those under active enrollment. Interestingly, liquid savings remain elevated, which aligns with empirical research suggesting that automatic enrollment has a limited effect on other financial behaviors, such as borrowing (Beshears et al. 2022). Even when workers reduce part of their contributions under automatic enrollment, they ultimately make up for this shortfall, catching up on their savings over time.

Dahlquist, Setty, and Vestman (2018) assume that a worker consumes the CE amount $\bar{c}$ under active enrollment, and $\bar{c}(1+g)$ under automatic enrollment.[11] The worker's total welfare, evaluated at age 25 ($t=0$), combines the welfare during her working life and during retirement, denoted V_r, as in the following equation:

$$V_0 = \frac{\bar{c}^{1-\gamma}}{1-\gamma}\frac{1-\beta^{40}}{1-\beta} + \beta^{40} V_r, \quad V_r = \frac{(\bar{c})^{1-\gamma}}{1-\gamma}.$$

Similarly, $\bar{c}(1+g)$ defines the welfare gain during retirement under automatic enrollment V_r^A.

I calculate welfare gains from automatic enrollment as the difference between welfare under automatic and active enrollment, computing this for both the average worker and by income quantiles over the final 5 years of employment. The overall welfare gain is 5.83 percent, with quantile-specific gains detailed in Table 4. For the bottom 25 percent of older workers, mandatory contributions yield a 10.52 percent welfare increase, while the top 25 percent see a more modest 2.55 percent gain.

As shown in Table 4, welfare gains largely reflect increases in retirement account balances due to automatic enrollment, especially for low-income workers. The model assumes no retirement uncertainty, so low-income retirees deplete their liquid savings and rely primarily on DC payouts. Following Dahlquist, Setty, and Vestman (2018), the CE measure

[11] Following their approach, I further assume that the CE amount is equal to consumption in the last period of life, $\bar{c} = c_T$.

Table 4. Retirement savings and CE welfare gains under automatic enrollment. All estimates are based on model simulations for 10,000 workers. The table shows the percentage increases in retirement savings and welfare across income quantiles. The quantile groups are defined based on 5-year averages of income realizations in the last five working years before retirement.

	q_1	q_2	q_3	q_4
Retirement savings increase (%)	10.52	5.25	3.95	2.88
Welfare gain (CE %)	10.52	5.25	3.96	2.55

benchmarks welfare against final-period consumption, directly linking welfare gains to accumulated retirement savings. Wealthier individuals retain some liquid assets, which weakens the relationship between retirement savings and welfare gains.

Although workers partially offset the mandatory contributions in their first year under automatic enrollment, the policy significantly improves their overall retirement savings, especially for low-income workers. Savings initially rise until around age 28, after which they fall relative to active enrollment. Nevertheless, by age 65, the policy still results in improved welfare. These findings are consistent with research showing that automatic enrollment disproportionately benefits low-income workers (Choi et al. 2002; Choukhmane 2021). Overall, my results demonstrate that while contributions increase by default in the short term and diminish during the working years, the policy still leads to significant long-term welfare gains. Furthermore, the welfare gain is largest among low-income workers, highlighting the effectiveness of automatic enrollment in improving retirement well-being for groups that are more exposed to retirement savings risks.

6. Conclusion

In this article, I explore how biases in income expectations—driven by either pessimism or optimism—shaped retirement savings behavior over the course of workers' careers. Building on Rozsypal and Schlafmann (2023), I use data from the MSC and outline key patterns in income expectations. I find that workers tend to extrapolate from recent income realizations, with low-income workers displaying a more pronounced pessimism and high-income workers exhibiting optimism. Additionally, regardless of age or education, workers consistently overstate their future income volatility, compounding the effect of income expectation bias on savings behavior.

I leverage the SCF to examine retirement savings share across income and age and show that low-income workers adjust their asset allocation more slowly compared to their higher-income counterparts. Using this finding, I motivate the preference for liquidity among low-income workers and revisit this mechanism through the lens of the micro-founded lifecycle model with liquid assets and retirement accounts.

The extrapolative expectations model provides insight into how pessimistic and optimistic expectations influence savings behavior, particularly in terms of the trade-off between saving for short-term needs and long-term retirement goals. Pessimistic workers prioritize liquid savings, while optimistic workers delay retirement contributions, though both groups eventually catch up on retirement savings. The model rationalizes key patterns in the income expectations data and is consistent with retirement contributions across US workers estimated in Parker et al. (2022).

I apply these insights to analyze the effects of 401(k) automatic enrollment policies. Although automatic enrollment initially increases contribution rates, workers tend to offset these contributions, ultimately saving at lower rates compared to the active enrollment benchmark. However, I find that automatic enrollment policies lead to a 5.83 percent increase in aggregate retirement welfare. These welfare gains are especially pronounced for low-income workers, with a 10.52 percent increase in welfare for the low-income workers, and a smaller, 2.55 percent gain for the top 25 percent of earners.

My findings highlight the importance of incorporating income expectation biases into retirement savings policy evaluations. I show that automatic enrollment, grounded in microfounded expectation models, is an effective policy for enhancing financial security. The gradual increase in contribution suggests that policies like automatic enrollment, which raises contribution rates in the short term, could be enhanced with auto-escalation features to incentivize retirement saving without mandating early contributions that are large and distortive to young workers' consumption.

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Supplementary material

Supplementary material is available at *Review of Finance* online.

Data availability

The data underlying this article are available in University of Michigan repository and can be accessed at https://data.sca.isr.umich.edu/, and in the Board of Governors of the Federal Reserve Board repository and can be accessed at https://www.federalreserve.gov/econres/scf-previous-surveys.htm.

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Appendix A

A.1 Data estimates and robustness checks

A.1.1 Income forecast errors—linear estimates

Following Rozsypal and Schlafmann (2023), I use the MSC data from 1986 to 2012, where survey responses contained expected percentage increases in income. I restrict the sample to track re-interviewed households, estimate the income forecast error, and outline key empirical patterns that motivate extrapolative expectations in the lifecycle consumption-savings problem.

I take respondents who exhibit no change in household structure or education and receive income greater than unemployment benefits in a given year. I winsorsize the data by estimating the reported year-to-year income gain, to remove outliers that had experienced or misreported an implausible income shock. I remove the bottom 1 and top 1 percent of income differences. Similarly, I winsorize the data based on forecast errors and remove implausible expectations, going over 400 percent of current reported income. All together, the data comprises 45,455 re-interviewed households. Figure A1 depicts individual income forecast errors across the income distribution.

For exposition purposes I regress income forecast errors on worker’s characteristics, reinstate the income quantile effect found in Rozsypal and Schlafmann (2023), and use the regression coefficients in Table A1 to pin down the extrapolation parameter in the lifecycle model. The majority of regressors are indicator variables, whereas *age* and age^2 are rescaled, following Gelman (2008), and significant for income errors forecast, which aligns with non-parametric estimates in Figure A2.

A.1.2 Evidence of the extrapolation bias

I analyze responses to Question 2, which asks about the likelihood of income increases in the coming year, to examine the presence of extrapolation. I find that recent realized forecast errors lead to corrective adjustments in future expectations. Table A2 shows that individuals who overstated their income gains in the previous year revise their forecasts downward. This finding underscores the importance of expectation dynamics. Even if workers are initially optimistic based on their income level, they adjust their expectations downward when income growth falls short of their forecasts.

A.1.3 Income forecast variation by age

Forecast error density estimates in the main text outline quantile-based differences and the transition from pessimism to optimism. Given that the regression coefficients with age polynomial are significant, albeit of different signs, this serves as another argument that age does affect the income growth bias.

Kernel density estimates consider only the working-age population and show a decrease in forecast error dispersion across the work life. A follow-up table of estimated means and standard deviations, Table A3, shows that age-based means are negative, indicating the low effect of experience in forming expectations about future income.

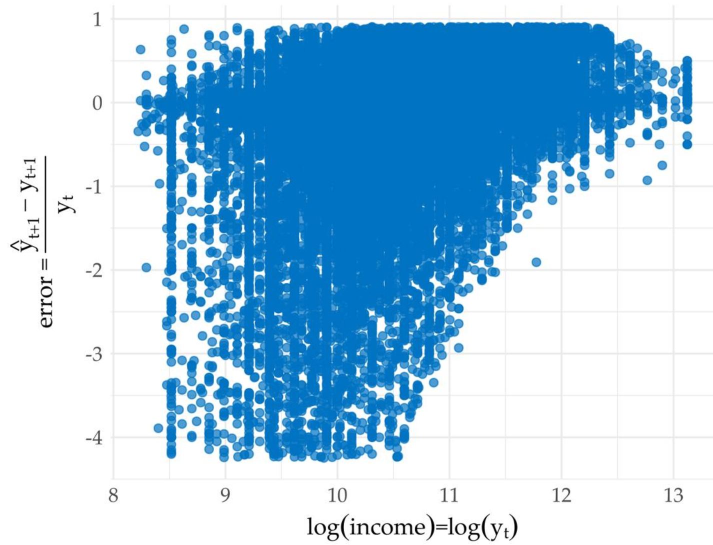

Figure A1. Income forecast errors as a function of log-transformed income.
Source: MSC data with 45,455 observations.

A.1.4 Interview timing

For robustness, I estimate the regression model using responses with initial interviews in the second half of the year, in order to avoid sensitivity to the imperfect time overlap between the period of expectations and realizations. Signs of all coefficients remain the same, while the size of the coefficient with the income quantile input increases slightly (depicted by coefficients in Table A4).

A.1.5 Housing as a means of saving for retirement

Retirement savings may not include only private retirement accounts, as workers may be saving in other illiquid savings such as housing. Added to current evidence on low usage of home equity loans and reverse mortgages in the USA (Mayer and Moulton 2022), I show that both retirement confidence and income expectations exhibit similar patterns across all workers, despite their housing status.

I binned subjective probabilities into four separate groups ($<$25percent, 25–50 percent, 50–75 percent, and 75–100 percent) that gradually separate pessimists from optimists. The estimates imply that retirement confidence rises with individual income and that owning a home has a non-significant effect on individual retirement outlook, as depicted with coefficients in Table A5.

Using a subsample of homeowners who report the value of their home, I also find that income expectations do not significantly vary with home value (depicted in Table A6). Overall, these findings suggest that homeowners and renters exhibit similar income and retirement expectations.

A.1.6 Job loss predictions

In the main text, I compare empirical job separation rates to the predicted probabilities of losing a job (shown in Table 2) and argue that households overstate the probability of losing their job, regardless of their age and education. I also show that a lifecycle model of extrapolative expectations reflects the misperceived income volatility. Looking deeper into the patterns of misperceived income volatility, I find that misperceived uncertainty

Table A1. Income forecast error regression estimates.
Source: MSC subsample of re-interviewed households. Forecast errors are winsorized at the 2.5th and 97.5th percentile to mitigate the impact of implausible expectations. Age and age^2 are rescaled following Gelman (2008), and income, household structure, education, and gender are represented as dummy variables, with the 1st quantile, two-people households, high school, and female as base categories. Estimates control for fixed effects by month, year, and region, and include survey weights. *$P < .1$; **$P < .05$; ***$P < .01$.

	Income forecast errors
Age	−0.127***
	(0.048)
age^2	0.129***
	(0.047)
Income quantile: q_2	0.364***
	(0.013)
q_3	0.690***
	(0.014)
q_4	0.926***
	(0.015)
q_5	1.115***
	(0.016)
Single	0.045***
	(0.015)
Multi-adult household	− 0.014
	(0.013)
No high-school	0.021
	(0.015)
College	− 0.002
	(0.009)
Male	0.008
	(0.008)
Constant	−0.744***
	(0.031)
Observations	45,455
R^2	0.183
Adjusted R^2	0.182
Residual Std. Error	0.780 (df = 43500)

decreases among high-income and older workers, reflected by positive coefficients in Table A7.

A.2 SCF data, liquid-to-illiquid savings ratios

In the main text, figure 2 represents predicted shares of liquid savings in overall savings accounts. Liquid accounts include checking, savings, and money market deposit accounts, directly held bonds and stocks, shares in stocks and bonds, mutual funds, tax-free mutual funds, government bonds, and combination mutual funds. About 1.6 percent of workers withdrew money out of their retirement accounts and faced penalties. For robustness, I perform a separate set of estimates for 78,369 workers who participate in DC accounts.

I model the share of liquid accounts in all savings accounts ϕ_i, and regress it on a set of worker's observables. I use the regression predictions defined by Table A8, and find similar effects across worker types. Within each age bin of all workers and I plot the predicted shares across wage percentiles smooth out the plots to get figure 2.

Table A2. Income increase likelihood, ordered logistic regression results.

Source: MSC data subsample of workers, includes survey weights. Controlled for family characteristics and year effects, clustered at the individual level. The probability of an income increase is reported in percentages, divided into brackets: "below 25%," "25-50%," "51-75%," and "76-100%." Age and age^2 are rescaled, and region, income quantiles, gender, and education levels are represented as dummy variables, with the central region, 1st quantile, male, and high school as base categories. Controls include family structure and year fixed effects. *$P<.1$; **$P<.05$; ***$P<.01$.

	P(future income increase)
Region: North Central	−0.063***
	(0.002)
Northeast	−0.027***
	(0.002)
South	−0.046***
	(0.002)
Age	−0.562***
	(0.036)
Agesq	−0.109***
	(0.036)
Inc. growth errors	−0.286***
	(0.0003)
Income quantile: q_2	0.301***
	(0.003)
q_3	0.622***
	(0.003)
q_4	0.699***
	(0.004)
q_5	0.868***
	(0.004)
Female	−0.152***
	(0.001)
No high school	−0.172***
	(0.005)
College	0.213***
	(0.001)
Pseudo R^2	0.04
Observations	17,659

A.3 Model equations and numerical implementation

A.3.1 *Calibrating the income growth bias* $(\widehat{\lambda})$

I calibrate the $\widehat{\lambda}$ parameter using a Method of Simulated moments. I simulate the income process for 50,000 individuals and calibrate $\widehat{\lambda}$ using expectation error as target moments. I parametrize the income process

$$y_{i,t} = \alpha_i + \text{const.} + g_1 t + g_2 t^2 + g_3 t^3 + p_{i,t} + \gamma_{i,t}, \text{ and } p_{i,t} = \lambda p_{it} + \xi_{i,t}, \tag{A.1}$$

and use stand-in parameter estimates from the literature. Specifically, I combine the age coefficients estimates for high-school graduates from the PSID given in (Cocco, Gomes, and Maenhout 2005)[12] with transitory and persistent components estimates in Storesletten et al. (2004). The true persistence parameter is set to 0.972. In this way, true $\lambda = 0.972$ becomes the lower bound for misperceived $\widehat{\lambda}$.[13]

12 Rozsypal and Schlafmann (2023) show that objective income growth rates from the PSID align with patterns in the MSC.

13 Different estimates in the literature reproduce contribution patterns fairly well. That is, the model solution does not depend on the change in the parameter values.

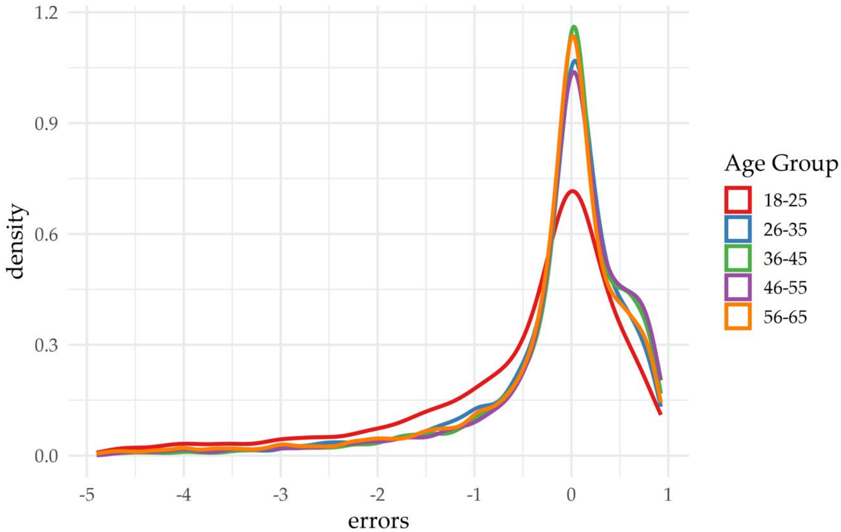

Figure A2. Density of income forecast errors across age groups.

Source: MSC data with 37,547 workers under the age of 65. Errors are winsorized at the 2.5th and 97.5th percentiles to exclude extreme values. Kernel density estimation includes survey weights and uses Silverman's method for optimal bandwidth selection, with adjustment, $h = 0.107$.

Table A3. Mean and dispersion of forecast errors across age groups.

Source: MSC data with 37,547 workers under the age of 65. Errors are winsorized at the 2.5th and 97.5th percentiles to exclude extreme values. All moments are calculated using survey weights. Pairwise mean difference test shows the significant difference in means across all groups but "36-45" and "46-55."

Age	Mean	Standard deviation
18–25	−0.506	1.259
26–35	−0.198	0.780
36–45	−0.127	0.688
46–55	−0.128	0.762
56–65	−0.223	0.886

Each grid element $\widehat{\lambda}$ defines the objective function for income persistence bias calibration. The Method of Simulated Moments minimizes the difference between simulated income forecast errors implied by the current $\widehat{\lambda}$ and the true model λ, and the empirical income growth forecasts obtained in the MSC data.

That is, for each income quantile, the perceived persistence parameter minimizes the mean forecast error. Each grid member represents the sample's income error forecast. After taking out age effects, the residuals are used as the dependent variable in a linear regression that makes predictions for income growth forecast errors, at a given income quantile. In this way, simulated residuals correspond to the income forecast error in the data and define a loss function.

The calibration includes 50,000 households with separate income processes. The loss function is

Table A4. Regression estimates of forecast errors among households with first interview in June.
Source: MSC data with forecast errors derived from interviews conducted in the second half of the year. Age and age2 are standardized following Gelman (2008), and income, education, and gender are represented as dummy variables, with the 1st quantile, high school, and female as base categories. Estimates control for fixed effects by month, year, and region, and include survey weights. *$P<.1$; **$P<.05$; ***$P<.01$.

	Income forecast errors
Age	−0.140**
	(0.060)
Age^2	0.150**
	(0.060)
Income quantile: q_2	0.397***
	(0.017)
q_3	0.717***
	(0.018)
q_4	0.959***
	(0.019)
q_5	1.146***
	(0.020)
Single	0.039**
	(0.019)
Multi-adult household	−0.018
	(0.016)
No high-school	0.021
	(0.019)
College	−0.008
	(0.011)
Male	0.005
	(0.010)
Constant	−0.717***
	(0.034)
Observations	27,849
R^2	0.185
Adjusted R^2	0.184
Residual Std. Error	0.778 (df = 26553)

$$L(\widehat{\lambda}) = \sqrt{\sum_{i=1}^{5} w_i (\mathrm{err}(\widehat{\lambda})_{q_i} - \mathrm{err}(\lambda)_{q_i})^2}, \tag{A.2}$$

where w_i is the weight of a given quantile, and is inversely proportional to the lifecycle variance of each income quantile.

The optimal $\widehat{\lambda} = 0.99$ minimizes the loss function L. Calibration results do not depend on the outlier criteria for empirical forecast error data. Moreover, results do not depend on the choice of the grid for $\widehat{\lambda}$ and yield $\widehat{\lambda} > \lambda$. Most importantly, quantile-based forecast error means change sign from low-income (pessimistic) to high-income (optimistic) quantiles (Table A9).

A.3.2 *Contribution match schedule*

To approximate the standard matching schedule in the USA, I use the simulated income process and exploit the variation in potential contribution rates to fit the benefit function

$$h(y_t, d_t) = \chi \log(a d_t y_t + b), \forall y_t \quad \text{and} \quad d_t \in [0, 0.7]. \tag{A.3}$$

Table A5. Retirement confidence, ordered logistic regression.

Source: MSC data subsample with working-age respondents and corresponding survey weights. Probabilities are binned into four categories: "below 25%," "25-50%," "51-75%," and "76-100%". Gender, education, income, and homeownership are defined as dummy variables, with female, high school education, the first income quantile, and renter serving as the base categories. Estimates control for year and age effects, and standard errors are heteroskedasticity-robust. **P*< .1; ***P*< .05; ****P*< .01.

	P(comfortable retirement)
Male	0.218***
	(0.019)
No high school	0.206***
	(0.033)
College	0.053
	(0.020)
Married	−0.058***
	(0.016)
Income quantile: q_2	0.179***
	(0.011)
q_3	0.325***
	(0.016)
q_4	0.515***
	(0.043)
q_5	0.619***
	(0.083)
Homeowner	0.022
	(0.017)
Pseudo R^2	0.017
Observations	19,867

I minimize the distance between contribution realizations of the standard matching plan and the smooth benefit function. The resulting parameters are $\chi = 1.91$, $a = 0.67$, and $b = 1.01$, and the fit is depicted in Figure A3.

The solution method uses the *Nested Endogeneous Grid Method*, following (Druedahl and Jørgensen 2020). All details regarding the numerical solution, resulting consumption and saving policy functions, and lifecycle paths differences across expectations forms are explained in detail in the supplementary material.

A.4 Subjective expectations and savings rates across the wealth distribution

Subjective expectations simulations also produce realistic liquid savings rates. I define the net saving rate as the rate excluding unrealized capital gains, consistent with the definition in Fagereng et al. (2019). Due to my model setup, this equates to the net liquid saving rate, which I compare across the wealth distribution. In contrast, the gross saving rate includes unrealized capital gains, which reflect the accumulation of gains in retirement accounts due to their illiquidity.

Specifically, Fagereng et al. (2019) find that the net saving rate (i.e., liquid savings from income) remains flat starting from the 20th wealth percentile. The subjective expectations model reflects this flat savings rate across the wealth distribution (shown in the right graph of Figure A4), while the rational expectations model predicts a steeper increase in the savings rate at the upper end of the wealth distribution (depicted in the left graph of Figure A4).

The gross savings rate, which includes accumulated capital gains in retirement accounts, increases with wealth, reinforcing retirement inequality, even though all workers in the

Table A6. Income forecast error and housing status.

Source: MSC subsample of 12,024 homeowners, survey weights applied. Age is standardized following Gelman (2008), and income quantile, household type, education, gender, and home value are represented as dummy variables, with 1st quantile, two-people household, high-school, female, and 1st home value quantile as base categories. Estimates control for region and year effects, and standard errors are heteroskedasticity-robust. *$P<.1$; **$P<.05$; ***$P<.01$.

	Income forecast errors
Age	-0.306^{***}
	(0.094)
Age^2	0.306^{***}
	(0.089)
Income quantile: q_2	0.330^{***}
	(0.027)
q_3	0.664^{***}
	(0.029)
q_4	0.905^{***}
	(0.030)
q_5	1.086^{***}
	(0.033)
Single	0.105^{***}
	(0.029)
Multi-adult household	0.012
	(0.023)
No high-school	−0.054
	(0.035)
College	−0.013
	(0.015)
Male	−0.011
	(0.013)
Home value quantile: h_2	0.004
	(0.022)
h_3	0.043^{*}
	(0.023)
h_4	0.006
	(0.024)
h_5	0.001
	(0.026)
Constant	-1.079^{***}
	(0.093)
Observations	12,024
R^2	0.184
Adjusted R^2	0.181
Residual Std. Error	0.693 (df = 11636)

model are eligible to contribute. Contribution rates, which are delayed primarily due to pessimism, follow this increasing pattern across the wealth distribution. The resulting differences in savings rates contribute to retirement consumption inequality.

A.5 Automatic enrollment policy evaluation

In the main text, I evaluate the welfare gains from automatic enrollment policies, which have been promoted by US legislation over the past decade. Following the approach of Dahlquist, Setty, and Vestman (2018), I quantify ex-ante welfare gains by comparing welfare through certainty-equivalent (CE) consumption during retirement. Since retirement

Table A7. Job loss predictions, ordered logistic regression.

Source: MSC data, uses 19,927 observations of working-age respondents with survey weights. Probabilities are binned in groups: "below 25%," "25-50%," "51-75%," "76-100%," with gender, education, age, and income defined as dummy variables, and female, high-school, age 18–25 and 1st quantile as base categories. Estimates control for year effects and family characteristics, standard errors are heteroskedasticity robust. $^{*}P<.1$; $^{**}P<.05$; $^{***}P<.01$.

	P(job loss within 5 years)
Male	0.131^{***}
	(0.018)
No high school	0.137^{***}
	(0.039)
Ed3	-0.094^{**}
	(0.046)
Age 25–34	-0.030
	(0.033)
Age 35–44	0.117^{***}
	(0.043)
Age 45–54	0.103^{**}
	(0.063)
Age 55–66	-0.437^{***}
	(0.100)
Income quantile: q_2	0.058^{***}
	(0.011)
q_3	-0.131^{***}
	(0.010)
q_4	-0.218^{***}
	(0.021)
q_5	-0.283^{***}
	(0.024)
Pseudo R^2	0.012
Observations	19,927

policies are designed to enhance long-term financial well-being, I abstract from any potential gains or losses experienced during the working period, focusing solely on the welfare effects realized in retirement.

The model of consumption and saving with active enrollment and arbitrary expectations $\mathbb{E}$ denotes lifetime utility as

$$V_0 = \mathbb{E}_0\left[\sum_{t=0}^{T-1} \beta^t \frac{c_t^{1-\gamma}}{1-\gamma}\right],$$

with $t=0$ denoting the worker's age of 25, and $t=T$ denoting the last period in the lifecycle at age 90.

As in Dahlquist, Setty, and Vestman (2018), I denote $\bar{c}$ as the CE consumption under the benchmark, the active enrollment. I also load the welfare gain onto the retirement period and therefore assume that consumption in retirement under automatic enrollment differs by the gain/loss g, and equals $\bar{c}(1+g)$.

Assuming that $\bar{c} = c_T$ and iterating back to period $t=0$ yields the lifecycle value function under CE

Table A8. Liquid savings share regression results.
Estimates are based on SCF worker data (1989–2019) with survey weights applied. Savings amounts and wages are adjusted using the CPI deflator. The liquid savings share is defined as the ratio of liquid accounts to overall savings. Age, gender, and education level are included as dummy variables, with "below 35," "male," "white," and "high school" as baseline categories. Additional controls include family structure, race, residential and non-residential property values, year effects, non-labor income (categorical), and labor income (continuous). Column 1 reports estimates for workers with DC account participation, while Column 2 includes all workers. *$P<.1$; **$P<.05$; ***$P<.01$.

	Share of liquid savings in all savings accounts	
	(DC participants)	**(All workers)**
age: 35–44	-0.094^{***}	-0.080^{***}
	(0.003)	(0.002)
45–54	-0.145^{***}	-0.120^{***}
	(0.003)	(0.003)
55–64	-0.177^{***}	-0.157^{***}
	(0.004)	(0.003)
65–74	-0.112^{***}	-0.044^{***}
	(0.007)	(0.006)
Female	-0.018^{***}	-0.012^{***}
	(0.004)	(0.003)
Education: high-school/GED	-0.015^{***}	-0.112^{***}
	(0.005)	(0.004)
Some college	0.0001	-0.140^{***}
	(0.005)	(0.004)
College	0.022^{***}	-0.170^{***}
	(0.005)	(0.004)
Renter	0.047^{***}	0.049^{***}
	(0.006)	(0.005)
Constant	0.626^{***}	1.011^{***}
	(0.010)	(0.007)
Observations	78,369	150,562
R^2	0.099	0.110
Adjusted R^2	0.099	0.110
Residual Std. Error	18.976 (df = 78337)	22.784 (df = 150530)

Table A9. Mean income growth forecast error by income quantile, $\widehat{\lambda}$ calibration. This table compares average income forecast errors across income quantiles for the true (λ) and perceived ($\widehat{\lambda}$) income persistence parameters. Errors are obtained by simulating income paths for 10,000 workers and comparing expected versus realized income. The $\widehat{\lambda}$ parameter is calibrated by minimizing the loss function A2.

Mean error quantile	q_1	q_2	q_3	q_4	q_5
$\lambda = 0.972$	−0.6172	−0.2909	0.0012	0.2149	0.4078
$\widehat{\lambda} = 0.99$	−0.0787	−0.0322	0.0019	0.0331	0.0759

$$V_0 = \frac{\bar{c}^{1-\gamma}}{1-\gamma}\frac{1-\beta^T}{1-\beta}. \tag{A.4}$$

During retirement the worker's value under active enrollment is

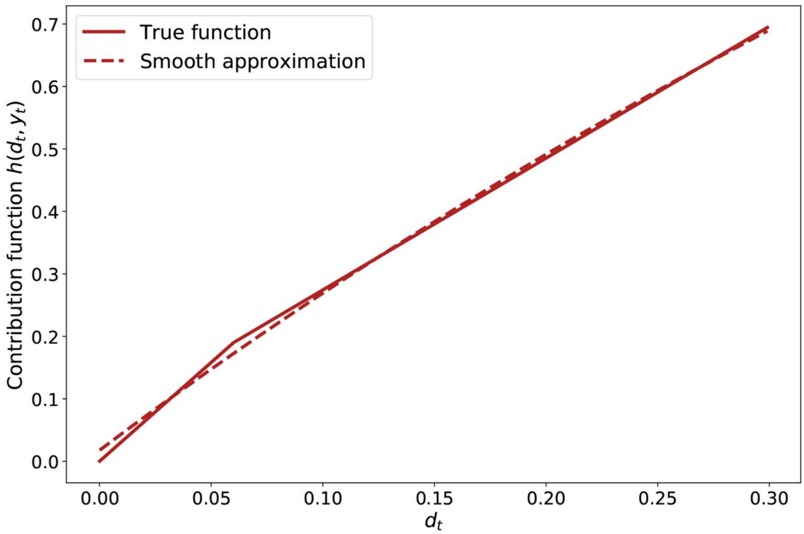

Figure A3. Benefit function—smooth approximation. Smooth approximation (dashed line) is obtained by minimizing the distance between employer-employee matches and the log curve A3.

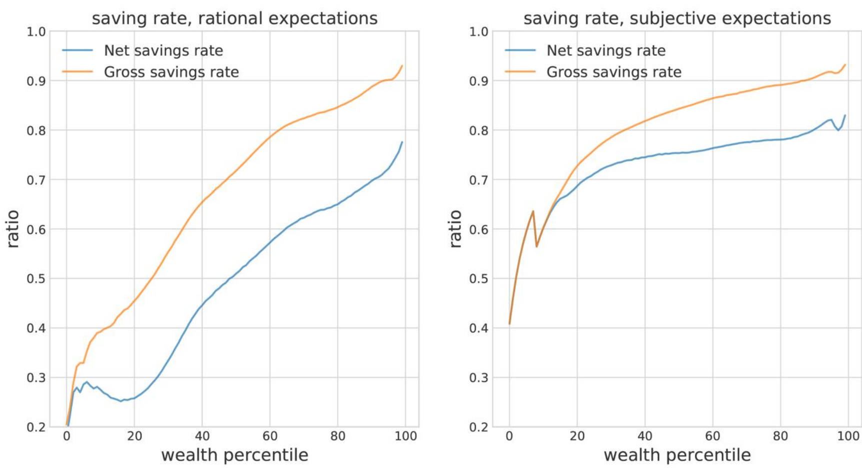

Figure A4. Net and gross savings rates, rational expectations (left), subjective expectations (right). The net savings rate represents liquid savings from income, while the gross savings rate includes both savings in retirement accounts and unrealized capital gains. Simulated savings rates are sorted across the wealth distribution to align with the empirical counterpart in Fagereng et al. (2019).

$$V_r = \frac{\bar{c}^{1-\gamma}}{1-\gamma}\frac{1-\beta^{25}}{1-\beta},$$

and, under the assumption that $\bar{c}(1+g)$ denotes consumption in retirement under automatic enrollment, the worker's value under automatic enrollment is:

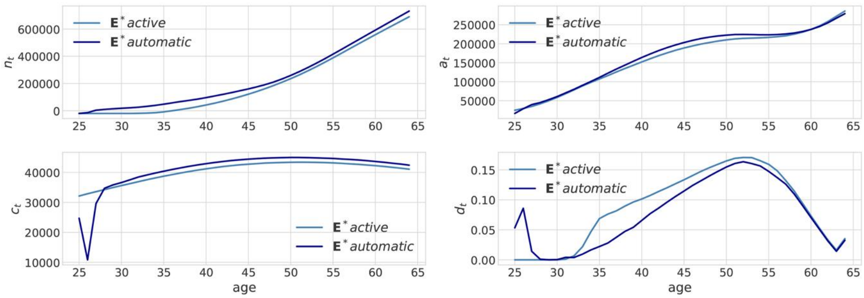

Figure A5. Lifecycle paths under active and automatic enrollment policies, model simulations. Based on simulations under active and automatic enrollment across 10,000 workers. The top left figure compares the retirement savings level, the top right compares liquid savings levels, the bottom left outlines consumption, and the bottom right shows contribution rate differences.

$$V_{r^A} = \frac{(\bar{c}(1+g))^{1-\gamma}}{1-\gamma}\frac{1-\beta^{25}}{1-\beta}. \tag{A.5}$$

All together, the worker's value over the lifecycle under automatic enrollment is

$$V_{0^A} = \frac{\bar{c}^{1-\gamma}}{1-\gamma}\frac{1-\beta^{40}}{1-\beta} + \beta^{40} V_{r^A}. \tag{A.6}$$

Combining equations (A.4), (A.5), and (A.6) yields

$$\underbrace{\frac{V_0 - \frac{\bar{c}^{1-\gamma}}{1-\gamma}\frac{1-\beta^{40}}{1-\beta}}{\beta^{40}\frac{\bar{c}^{1-\gamma}}{1-\gamma}\frac{1-\beta^{25}}{1-\beta}}}_{M} = (1+g)^{1-\gamma} \Rightarrow g = M^{\frac{1}{1-\gamma}} - 1.$$

I use this formula to obtain welfare gains in the main text.

Model simulations depicted in Figure A5 show that, despite mandated contributions in the first year of tenure and the offset in contribution rates, automatic enrollment does increase retirement savings, without distorting liquid savings policies, which supports findings in Beshears et al. (2022).

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