Retirement Savings Adequacy in U.S. Defined Contribution Plans*

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Abstract

We evaluate retirement savings adequacy in the U.S. using a large panel dataset comprising the contribution rates, salary, tenure, account value, plan features and asset allocations of more than 300 thousand US workers with a 401(k) account. Our simulations account for medical expenditure, longevity, and investment risks, and realistically model the likelihood of withdrawals due to hardship, job separation, and reaching age 59 1/2. We find that, based on their current account balances, income, saving, and investment behavior, close to three quarters of the workers in our sample are not saving enough for retirement. The dispersion is related to the generosity of employer contributions, account balances, but also worker saving behavior, which can potentially be changed going forward. The shortfall worsens if we introduce a bequest motive, decrease the fraction of housing equity available, or consider lower expected returns going forward. Only if we assume that individuals have both low risk aversion and very high discount rates do we conclude that the median agent is saving optimally. Given the magnitude of the problem, only major policy changes would fully addressed it, but a reasonable age-dependent minimum contribution rate could have a sizable impact, particularly for younger generations which have many years ahead of them to benefit from such a policy.

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1 Introduction

Defined contribution schemes are gradually replacing traditional defined benefit pension in several countries and, given the structural funding problems associated with the latter, this phenomenon is likely to accelerate and expand to many more countries in the near future. Defined contribution pension plans address the potential under-funding problem of their counterparts. Furthermore, they allow individuals to choose their life-cycle retirement savings plan and how to invest those savings. However, in a world where most individuals might have limited financial literacy (e.g. Lusardi and Mitchell (2014), and Clark, Lusardi and Mitchell (2015)), time-inconsistent preferences (e.g. Laibson (1997), and Harris and Laibson (2001)) or suffer from behavioral biases, these choices might leave them financially vulnerable at retirement.[1]

The National Retirement Risk Index computed by the Center for Retirement Research at Boston College (Munnell, Webb and Delorme (2006)) suggest that a large fraction of the U.S. population is not saving enough for retirement. Yet, perhaps surprisingly, most other previous studies conclude that the vast majority of U.S. workers is actually saving adequately for retirement (e.g. Engen, Gale, and Uccello (2005), Scholz, Seshadri, and Khitatrakun (2006) and Hurd and Rohwedder (2012)).[2]

In this paper we use data on more than 300 thousand U.S. workers enrolled in a defined contribution pension plan and evaluate whether, given their actual savings and investment decisions, they are likely to have enough wealth to finance an optimal retirement consumption path. Our data include information on age, current account balance, contribution rate, salary, portfolio allocation and tenure at the company, among others. Using this information as the starting point, we simulate forward each individual's income and wealth accumulation over time, and compute the distribution of her implied wealth accumulation at age 65. It is important to mention that we do not assume that investment and savings decisions remain the same at each age and simulation. Rather, in the first year of each simulation we set the

[1]Choi, Laibson and Madrian (2011) document the prevalence of highly suboptimal contribution rates in 401(k) plans. Ahmed, Barber and Odean (2016) show that the current suboptimal asset allocation decisions of many individuals is likely to generate largely suboptimal retirement wealth accumulation.

[2]Poterba (2015) provides a comprehensive discussion of the difficulties in evaluating optimal retirement savings, and the different approaches to address them.

portfolio allocations and the contribution rates at the value that we observe for each agent and, over time, we let them evolve according to the patterns that we observe in our sample. Using our panel, we estimate portfolio shares and contribution rates as functions of worker's observable characteristics, and we use those estimated profiles in our simulations.

Our measure of the total resources available at retirement combines DC wealth accumulation, pension income, non-DC wealth, and net housing equity.[3] We estimate the distribution of social security income based on the simulated income profiles and the social security administration formulas. We obtain measures of wealth accumulation in non-retirement accounts and of net housing wealth from estimates based on the Health and Retirement (HRS). More precisely, we use HRS data to express non-retirement and housing wealth as a function of wealth accumulation in the retirement account and use the estimates to construct these variables in our simulations. As a result, instead of assigning average values to all individuals in our sample and in all simulations, we assign a different value of non-DC wealth and net housing equity to each individual in each simulation. Combining these four, DC wealth accumulation, pension income, non-DC wealth and net housing equity we have a measure of the total resources available at retirement.

For each simulated path, we compute the level of retirement consumption that the individual can finance using a model of retirement consumption and savings decisions that incorporates medical expenditure, longevity, and investment risks. We then evaluate the optimal of retirement consumption using two measures. The first, which we label certainty equivalent ratio (henceforth CEQR), compares the certainty equivalent of future consumption across all simulations with current consumption. The second, which we label consumption retirement replacement ratios (henceforth CRRR) consists of the ratio of current and retirement consumption. Both measures take into account that several expenditures take place early in life (e.g. children-related expenses, and housing purchases), and scale current consumption by a factor less than 1. Thus, if our measure is less than 1, the worker will not be able to

[3]Net housing equity is potentially available to finance consumption at retirement to the extent that individuals choose to downsize or use a reverse mortgage. Since neither of these options are commonly observed in the data (e.g. see Caplin (2002), Venti and Wise (2004) or Davidoff (2015)), we consider different scenarios regarding the fraction of housing wealth available/used to finance expenditures during retirement.

finance her optimal consumption at retirement, either along that particular simulation path (for the CRRR) or in a risk-adjusted sense (for the CEQR).

Our simulations also take leakages into account. In the U.S., workers are allowed to withdraw funds from their retirement accounts, prior to retirement, in the event of hardship, a job separation, due either to an unemployment spell or a job switch, or after reaching age 59 1/2. As documented by Munnell and Webb (2015), these "leakages" can be substantial and have a non-trivial impact on the amount of wealth available to finance retirement. Based on data from our own sample, Vanguard How America Saves tables, and Munnell and Webb (2015), we estimate both the probability of each of these withdrawals, and the fraction of funds withdrawn, as functions of worker income and age. Based on these estimates, we then compute individual-specific withdrawal probabilities and withdrawal fractions, for each of those four separate contingencies, and include them in our simulations.

In our baseline results, we find that close to three quarters of the workers in our sample is not saving enough for retirement. The median individual has more than 40% probability of having to decrease her consumption after age 65.[4] For those at the 25th and 10th percentiles of the distribution face a 50% probability of having to cut their standard of living by about half and by almost 9% and 22%, respectively. Even those in the top 25th percentile of the distribution face approximately a 25% probability of having to scale down their consumption at retirement.

To assess the robustness of the results, we conduct a series of comparative static exercises. We find that the magnitude of the retirement under-saving problem is significantly worse if we include a bequest motive, decrease the fraction of home equity available to finance consumption from age 65 onwards, or make more conservative assumptions about future average asset returns. We also consider different values of the preference parameters used in the computation of optimal consumption at retirement.[5] Although the optimal retirement savings of agents with lower discount rate are lower, even with for a discount rate of 0.9, the median CRRR across both simulations and individuals is still low, at 0.72. As we decrease risk aversion individuals care less about medical expenditure risk and longevity risk and as

[4]These figures refer to actual consumption (hence standard-of-living/utility), not just expenditure.

[5]Our baseline scenario assumes a relative risk aversion of 5, and a discount factor of 0.95.

such they optimally save less. However, only for combinations of risk aversion of 2 and values of the discount factor close to 0.9, we find that the median worker would be saving optimally for retirement, although a substantial fraction of the population would still fall short.

To better understand the determinants of the cross-sectional heterogeneity in accumulated retirement wealth and CRRRs, we regress the median wealth and consumption retirement replacement ratio (i.e. the 50th percentile of the distribution of the CRRR) on multiple individual characteristics from our original data. We find that retirement wealth is a convex function of age, and a concave function of salary at the starting point of the simulations. We also find that account features matter: one percentage point increase in contribution rate increases retirement wealth at age 65 by $30,580, while a 10 percentage point higher equity allocation increases it by $7,120 on average. Finally, a $1,000 higher balance on the last observation date in the sample corresponds on average to $1,294 higher median wealth at retirement. The generosity of the employer contributions is also extremely important, highlighting the relevance of these plan features in determining retirement outcomes. Finally, all else equal, workers employed at companies that are older, are more likely to be private, invest more and have higher net income are likely to have accumulated more wealth by the time they reach retirement age.

Our results also indicate that workers sort into companies that exacerbate the cross-sectional dispersion in retirement wealth, and that this is especially the case for younger workers. Once we take company features into account, the median wealth at age 65 for a worker who is 26 in our sample and earns the median salary for his age is 2.44 times the wealth he would have if he earned the 10th percentile salary for his age group and 47% of the wealth he would have if he earned the 90th percentile salary. This spread is significantly larger than the ones we have calculated based on just age and salary (1.56 times vs. 58%) or age, salary and account-level variables (1.61 times vs. 53%). We find that once we take company characteristics into account, this spread also increases for workers of median and 90th percentile age, albeit to a lesser extent.

We also find that the median consumption retirement replacement ratio is a convex function of age and are heavily influenced by contribution rates. A one percentage point increase in contribution rates generates a 2.67 ppts increase in CRRR, corresponding to a consumption level 2.67 ppts higher in all retirement years. The size of the account and the equity share have the expected positive and statistically significant coefficients, but smaller economic magnitudes: a $10,000 increase in account value corresponds to a 69 basis points increase in CRRR, while a 10 ppts increase in the equity share corresponds, all else equal, to a 58 bps increase in CRRR. A more generous employer match is also associated to a large increase in retirement consumption: a 10 ppts higher employer match generates a 2.95 ppts higher annual retirement consumption. Further, workers employed at firms that are private, older, and have higher capital expenditures and net income tend to have higher CRRRs on average. On the contrary, workers at firms with more assets and employees have on average lower CRRRs. Finally, workers living in areas with higher financial literacy and with a higher fraction of college educated people are more likely to have higher CRRRs.

We also observe a striking difference between the younger cohort and the others. Half of those aged 35 or less have median CRRRs of 1.25 or higher, while the other age groups have median CRRRs around 1. This result is partially explained by younger individuals being enrolled in plans with more generous employer contributions. Moreover. the dispersion of outcomes increases quite noticeably with age, primarily due to an increase in the left tail of the distribution. This finding is particularly concerning as those close to retirement have much fewer years left to benefit from possible changes in behavior due to additional financial education, or specific policy measures.

In the final section of the paper, we consider some counterfactual experiments to quantify the impact of different policies to improve retirement wealth accumulation. One limitation of our approach is that it is subject to the Lucas critique. When evaluating different policy interventions, we are not computing workers' optimal responses to them, as we are not using a structural model with optimizing agents for the pre-retirement period. Rather, we assume that the stochastic processes for contributions and portfolio allocations will remain unchanged. While estimating a structural model would potentially avoid this issue, capturing the full cross-sectional heterogeneity in the sample, i.e. matching, both at the individual and aggregate levels, the contribution rates and portfolio allocations that we observe in the data would be a very tall order for any model. Given that individuals in our sample do not seem to behave optimally along several dimensions (e.g. contribution rate and asset allocation), such a model would be extremely difficult to develop, and might be of limited value in capturing real life retirement savings. Indeed, the empirical evidence on this issue suggest that individuals often respond very passively to changes in the features of their 401(k) plans (e.g. Choi, Laibson and Madrian (2009), Choi, Laibson, Madrian and Metrick (2004), Choi, Laibson, Madrian and Metrick (2003) and Madrian and Shea (2001)).

The first counterfactual experiment we run is about limiting pre-retirement withdrawals. While there are good reasons for allowing withdrawals due to hardship or a job separation event, the case for allowing withdrawals from age 59 1/2 onwards without a justification is less clear. Eliminating this option increases retirement consumption by 5% or more and wealth at age 65 by 15% to 20% for those at the bottom of the distribution.

On the contrary, setting a minimal contribution rate of 2% or 5% has negligible effects, and increases consumption retirement replacement ratios by 0.01 or less. Higher contribution rates would be more effective. However, imposing minimum contribution rates in excess of 5% for all workers could be problematic, particularly for younger workers who are also saving to buy a house, cover child-related expenses, and for precautionary motives. Forcing them to contribute 7% or 8% to their 401(k) might lead many to opt-out of the pension plan altogether. Therefore, we explore the effect of a minimum contribution that increases with age, such that it averages to 10% (between ages 21 to 65) but starts from a low level of 4.5% and increases gradually to 15.5% before retirement, when the individuals can presumably afford to save more. This policy generates sizeable increases in retirement consumption for all age groups, and particularly for the workers at lower end of the distribution.

In our final experiment we study the impact of an increase in the actual contributions. Given that it would be hard to implement a policy that forces each worker to increase his/her current contribution by a specific amount/percentage, the goal of this experiment is to understand what increase in savings would be required for workers to be able to improve their age-65 financial situation significantly. We find that a 2 (5) ppts increase in contributions would improve retirement consumption by 2% (4%) to 9% (20%). Nevertheless, even a 5% increase in contributions would still leave about 2/3 of the population with a median CEQR below 1, highlighting the magnitude of the current under-saving problem. In sum, our experiments suggest that modest increases in saving rates, and/or certain policy measures, could improve retirement outcomes by sizable amounts for a large fraction of the population. At the same time, a significant fraction of workers is so behind in its savings that only drastic measures will avoid large reductions in their retirement consumption.

Our paper is closely related to others who have also evaluated retirement preparedness. Engen, Gale, and Uccello (2005) and Scholz, Seshadri, and Khitatrakun (2006) solve an optimal life-cycle model of consumption and savings decisions and compare the wealth accumulation implied by the model with that of individuals in the HRS, conditioning on age and other characteristics. Scholz, Seshadri, and Khitatrakun (2006) assume that households make full use of their net housing equity during retirement and conclude that 84% of them are saving enough for retirement. Engen, Gale, and Uccello (2005) estimate that number at 65% when housing equity is fully used, and at 56% when only half of the individual's housing wealth is considered, which is the baseline assumption in our paper. In addition to our more comprehensive data, our study differs from the papers above along several important dimensions. First, we do not assume that individuals necessarily behave optimally going forward. Instead, we estimate future behavior by projecting forward the estimates from the current data. This is an important distinction. In their analysis, an individual who currently saves sub-optimally is assumed to automatically revert to the correct saving rate going forward. To the extent that current lower savings rates reflect limited financial literacy, behavioral biases (e.g. inertia), or time-inconsistent preferences, such reversion is unlikely and assuming it will over-estimate the individual's resources at retirement. In addition, our analysis also takes "leakages" into account, and assumes that only half of housing equity is available to finance consumption at retirement, in line with the observed behavior of retirees. Nevertheless, even if make all housing equity available to the individuals in our sample, we still find that about half of the workers are not saving enough for retirement. Finally, it is important to mention two other potential sources for the differences in our results relative to these papers. First, our analysis focuses exclusively on individuals with DC accounts, while theirs focuses mostly on individuals with defined benefit (DB) pensions. If individuals with DB plans are better prepared for retirement, then that could help to explain the differences. Of course, even if that is the case, studying individuals with DC plans is extremely important since they constitute a large, and more importantly growing, fraction of the population. Second, the economic situation might have changed from the time those studies were conducted, and several factors might have altered the financial situation of households since then.[6]

More recently, Hurd and Rohwedder (2012) estimate consumption trajectories from HRS data, use them to input a desired consumption path, and, based on simulations, estimate the probability that each worker has enough resources to finance that particular consumption stream. They assume that housing equity is fully available to finance retirement, and conclude that 71% of the individuals in their sample are adequately preparing for retirement.

Another strand of the literature measures retirement adequacy by estimating income retirement replacement ratios. Using data from the Survey of Consumer Finances, Munell, Webb and Delorme (2006) conclude that, even if households took full advantage of their home equity through reverse mortgages, 43% of them are not be saving enough for retirement. Purcell (2012) estimates the median income retirement replacement ratio in the Health and Retirement Study at around 0.62 which he views as not being too far below the recommended level. Finally, Poterba, Venti, and Wise (2012) take a novel approach and study the evolution of wealth of older retirees. They find that almost half of them died with no financial assets, living fully out of their social security income, and that therefore they were not prepared to face any unusual or unexpected expenses if they had lived longer.

The remainder of the paper is organized as follows. Section 2 presents the data and summarizes our methodological approach. In sections 3 and 4, we discuss the simulations of the pre-retirement period in more detail, while in section 5 we estimate optimal retirement consumption. In section 6, we discuss our baseline results and comparative static exercises, and in section 7 we relate those results to our original data to identify the drivers of cross-sectional heterogeneity. In section 8 we consider a series of counter-factual experiments, and in section 9 we conclude.

[6]For example, Lusardi, Mitchell and Oggero (2017) document that the late-in-life financial vulnerability of recent cohorts appears to be higher because they have taken on more debt early in life.

2 Data and overview of the methodological approach

2.1 Data

Our primary data is a proprietary dataset provided by Edelman Financial Engines, the largest independent registered investment advisor in the U.S., which provides advice and investment management to participants in 401(k) plans. The data includes information on worker 401(k) balances and contributions, salary, tenure at the firm, asset allocation split up over five aggregated asset classes and company stock, zip code, and demographic characteristics. It also comprises information on the returns, balance sheet and income statement of the firms the individuals work at, through CRSP, Capital IQ and Compustat, detailed information on plan characteristics, investment options, and employer contributions, from DOL Form 5500, and fees for a more recent sub-period.

The original data includes approximately 3.8 million individuals working at 296 different firms. Bekaert, Hoyem, Hu and Ravina (2017) show that these firms are on average larger than those in Compustat, with a median number of employees of 4,600, compared to only 475 in the Compustat sample, have higher ROA, have an average age of 65 years, and are approximately half publicly listed and half privately held. They also show that the average worker in the sample has a higher salary and longer tenure than the ones in the Current Population Survey. In this paper, we restrict the sample to 1.6 million workers aged 20 to 64, who have valid tenure data, and make more than the minimum wage. The sample also exclude individuals who have "managed accounts", whereby Edelman Financial Engines manages the portfolio on behalf of the client, charging a fee on assets under management. Panels A and B of Table 1 show that this sample is very similar to the full sample in terms of observable characteristics, with the possible exception of worker age which is 45.4 in the full sample, and only 42.4 in ours. The average salary is $56,739 in our sample, compared with $57,183 in the full sample, the average tenure at the firm is 9.9 vs. 10.48 years, the average contribution rate is 6.9% compared to 6.5%, and the average account value is $56,588, compared to $62,652. This similarity is comforting, given the further constraints we have imposed on the sample.

As a baseline, we start by studying the subsample of workers employed at firms that offer only defined contributions plans, and no defined benefit ones. This sample is more straightforward to analyze and reflects the increasingly common situation of workers having access only to DC plans and being responsible for saving enough for retirement. We plan to extend the analysis to workers with access to both DC and DB plans in the next version of the paper. Panel C of Table 1 contains the summary statistics for this subsample and shows that the average worker in this group has slightly lower age (41.3 years), has worked at the firm two years less than the average worker in the sample (7.8 vs. 9.9 years), and has a correspondingly slightly lower salary ($54,521 vs. $56,739). Such worker also contributes less to the plan (6.3% of salary vs. 6.9% for the full sample), invests more conservatively, with a risky share of 61.9% compared to the 67% for whole sample, and pays slightly lower fees.[7] These results run counter to the intuition that companies offering only DC plans would provide more generous terms, and that workers in such companies, lacking the buffer of a defined benefit plan, would save at a higher rate. Panel D of Table 1 presents a comparison of the characteristics of the firm these workers are employed at with those in the larger sample, and shows that the DC-only firms tend to be significantly younger and smaller, have less employees, are more likely to be private and to have a foreign parent, have higher profitability, lower capital expenditures, but have similar leverage and investment intensity. Finally, if we consider house values in the zip code where the worker lives as a proxy of her wealth and socioeconomic status, we find that DC-only workers live in more affluent areas than the average worker in the sample.

Our dataset also contains information about asset allocations, categorized in five broad asset classes and company stock, in addition to fee information and other plan characteristics. For the purposes of this paper, we aggregate the investments in small and mid-cap funds, large cap funds, international equity funds and company stock into a general equity asset class, investments in bonds into a bond asset class, and short-term treasury bills and cash-like investments in a cash asset class. The returns of these asset classes are estimated from the returns on the CRSP value-weighted] index, the weighted average of the returns

[7] In section 3.1.3. we show that the workers in this sample also have access to less generous employer contributions.

of several bond market indices, weighted by their US market capitalization at the time of the estimation, and the 30-day T-Bill, respectively. Specifically, the bond indices we use are the Barclays Capital Intermediate Government Bond Index, the Barclays Capital Long Term Government Bond Index, the Salomon Brothers Non-US Government Bond Index, the Barclays Capital Corporate Bond Index, and the Barclays Capital Mortgage Backed Securities Index., and the weights are derived from the average monthly holdings of each asset class by Americans, based on the ICI Factbook.

We also calculate plan-specific fees for each worker, based on their individual exposure to equity, bonds, and cash, either directly or through target date funds, and the fees charged by the mutual funds available through her plan.[8]

2.2 Methodology overview

The analysis will consist of three steps. Here we provide a brief outline of each of them, and in Sections 3 to 5 we describe them in detail.

The first step involves using simulations to compute, for each worker, the joint expected distribution of total wealth accumulation at retirement (W_{i65}^{T}) and pension income (Y_{i65}), assuming a retirement age of 65. We decompose total wealth at retirement into four components. Letting a denote the age of each worker on the latest date she appears in the sample, we have

- Wealth in both the retirement account active at age a and in all future potential retirement accounts (W_{i65})

- Wealth in retirement accounts associated with jobs held prior to age a (W_{i65}^{other})

- Wealth in non-retirement accounts that is available at retirement age (W_{i65}^{FW})

- Net housing wealth at retirement age (W_{i65}^{HW})[9]

We obtain a a distribution of W_{i65} by starting from each worker's current retirement account balance and simulating forward until retirement. The simulations are based on the savings and investment behavior observed in the data. Specifically, we estimate the evolution

[8]Investments in company stocks are assigned a fee of zero.

[9]We consider different scenarios regarding how much of this wealth is available for consumption at retirement.

of employee contribution rates as a flexible function of the employee's own lag contribution rate, age, salary, tenure at the firm, and their interactions. We estimate the evolution of employer contributions based on the plan rules reported in the Form 5500 and the worker's characteristics. Our simulations take into account IRS limits on employee and employer contributions, and the fact that upon turning 55 workers can elect to contribute more. We also estimate the evolution of the allocations to equity, bonds, and cash, based on regressions including the worker allocation's own lag, age, salary, tenure, and their interactions. Consistent with Madrian and Shea (2001) and the subsequent literature on 401(k) accounts, both employee contribution rates and asset allocations show significant sluggishness and inertia.

We follow a similar procedure to estimate the potential wealth accumulated in retirement accounts at previous jobs (W_{i65}^{other}). Using worker's tenure at the current firm, and assuming she started working at 20, we calculate how long she has worked for previous employers and compute W_{i65}^{other} by applying the same simulation approach that we used to compute W_{i65}. Finally, we obtain measures of wealth accumulation in non-retirement accounts (W_{i65}^{FW}) and of net housing wealth (W_{i65}^{HW}) from estimates based on the Health and Retirement Study . Instead of assigning average values of non-retirement wealth to all individuals in our sample, we assign a different value of W_{i65}^{FW} and W_{i65}^{HW} to each individual in each simulation, based on those estimates.

The second step of the analysis consists of computing the optimal level consumption at retirement for a given combination of retirement wealth accumulation (W_R) and pension income (Y_R). We use a consumption and savings model with investment, longevity, and medical expenditures risk.

This part of our analysis is similar to Hurd and Rohwedder (2012). In addition to the differences in the available data, our study differs from theirs in that they study whether current retirees have saved enough or not. On the contrary, we focus on whether, given their current savings patterns and accumulated wealth, current workers are saving enough to be on track for retirement.

Finally, in the third step we compare the retirement consumption computed in the second step with a measure of required consumption based on imputed pre-retirement consumption for each individual. This imputation is based on the estimation of consumption functions from the Consumer Expenditure Survey (CEX), and takes taxes into account. The details of the retirement model and the measurement of required consumption are discussed in Section 5.

3 Wealth accumulation in the current DC account

We start the simulations at the oldest age for which we observe each agent ($t = a$), taking her current job's retirement account balance as the starting point, and simulating forward until retirement age.

3.1 Wealth evolution without leakages

To facilitate the exposition, we first explain the evolution of wealth in the absence of pre-retirement withdrawals (”leakages”).

3.1.1 Assets, returns and fees

In our baseline analysis, retirement wealth can be invested in three assets, stocks, bonds, and cash, with gross returns R_t^S, R_t^B and R^f, respectively. The real return on cash (R_f) is assumed to be constant and calibrated to 0.5% based on the historical mean real return of 30-day T-Bills from 1926 to 2016. The returns on bonds and stocks are assumed to be normally distributed and i.i.d. over time:

$$R_t^S \sim \qquad N(\mu^S, \sigma^S) \tag{1}$$

$$R_t^B \sim \qquad N(\mu^B, \sigma^B) \tag{2}$$

The equity return is set equal to the historical real return on the CRSP value-weighted index, with an annual standard deviation is 20%, and an equity premium of 6%, which is slightly lower than the historical value of 8.3%. As discussed in Section 2, in our data the bond portfolio is a combination of five different bonds types, each matched to a specific index. We set $\mu^B = 3.85\%$, the historical return on the indices weighted by their relative market capitalization, and since the the weighted average standard deviation is 8.5%, and the average correlation between the different indices is very close to 1 (0.85), we set $\sigma^B = 0.08$.

Finally, we explicitly include in the simulations the individual-specific fees that each worker pays on her stock and bond portfolios, τ_i^S and τ_i^B, respectively. Such fees vary significantly across plans and investment vehicles.

3.1.2 The wealth accumulation equation

In the absence of any pre-retirement withdrawals, retirement wealth evolves as a result of the (net-of-fee) returns on previous account balances and the additional inflows from the worker and, if applicable, the employer contributions. These inflows are represented as fractions, k_{it} and k_{it}^e respectively, of current income (Y_{it}). More precisely, retirement wealth at time t (W_{it}) is given by:

$$W_{it} = \left[\alpha_{i,t-1}^S R_t^S (1-\tau_i^S) + \alpha_{i,t-1}^B R_t^B (1-\tau_i^B) - (1-\alpha_{i,t-1}^S - \alpha_{i,t-1}^B) R^f\right] W_{i,t-1} + (k_{it} + k_{it}^e) Y_{it} \tag{3}$$

where:

α_{it}^S :	share of wealth invested in stocks at time$t$
α_{it}^B :	share of wealth invested in bonds at time$t$
W_{ia} :	account balance on the last sample date

In the first year of the simulation we set the portfolio shares (α_{it}^S and α_{it}^B) and the contribution rates (k_{it}) at the value that we observe for each individual. Over time we let these evolve according to the patterns that we observe in our sample. Consistent with our goal of using the actual observed behavior of the individuals as an input in our simulations, we use our panel to them as functions of worker's observables. The preferred empirical specifications were

$$\alpha_{it}^S = \quad 0.081880053 + 0.91617255\alpha_{i,t-1}^S \tag{4}$$

$$\alpha_{it}^B = \quad 0.91410212\alpha_{i,t-1}^B + (3.467069E-4)a - (4.088E-8)Y_{it} + (1.199E-11)a^2 Y_{it} \tag{5}$$

The estimated equations reveal significant persistence in portfolio shares, consistent with our prior that individuals don't change their asset allocations drastically from one year to another. Finally, if the implied values of α_{it}^S and α_{it}^B are such that $\alpha_{it}^S + \alpha_{it}^B > 1$, we scale them down proportionally.

The equation we have estimated for the contribution rate is

$$k_{it} = -0.0096 + 0.851 * k_{i,t-1} + 0.000692 * a - 0.00000628 * a^2 \tag{6}$$

Contribution rates are also very persistent over time, and they are a concave and increasing function of age.[10]

3.1.3 Employer contributions

Motivated by the heterogeneity we observe in our data, we capture the features of the employer contribution schemes with the following flexible representation

$$k_{it}^e Y_{it} = Min\{Min\{k_i^{e0} Y_{it}, \overline{K}_i^0\} + K_i^{match}, \overline{K}_i^{Tot}\} \tag{7}$$

where k_i^{e0} captures the portion of the employer contribution independent from the employee's own contribution, expressed as a percentage of current salary. The total dollar value of this payment ($k_i^{e0} Y_{it}$) might be subject to a maximum of $\overline{K}_i^0$. This contribution is then combined with the employer matching contribution (K_i^{match}) which is capped at $\overline{K}_i^{Tot}$.

The matching contribution scheme might have multiple tiers. For example, the company might match 100% of the employee's contributions up to 3% of her salary, and 50% of the contributions up to an additional 2% of her salary. Therefore, we specify a fairly general

[10]In the simulations, the contribution rates are constrained to be non-negative and below 30%, which is higher than the 99th percentile in our sample.

formulation for the employer matching:

$$K_i^{match} = \begin{cases} \kappa_i^{e1} * k_{it} & \text{if } k_{it} \leq \overline{k}_i^{e1} \\ \kappa_i^{e1} * \overline{k}_i^{e1} + \kappa_i^{e2} * (k_{it} - \overline{k}_i^{e1}) & \text{if } \overline{k}_i^{e1} < k_{it} \leq \overline{k}_i^{e2} + \overline{k}_i^{e1} \\ \kappa_i^{e1} * \overline{k}_i^{e1} + \kappa_i^{e2} * \overline{k}_i^{e2} + \kappa_i^{e3} * Min\{k_{it} - (\overline{k}_i^{e2} + \overline{k}_i^{e1}), \overline{k}_i^{e3}\} & \text{if } k_{it} > \overline{k}_i^{e2} + \overline{k}_i^{e1} \end{cases} \tag{8}$$

In the previous example, we would have

$$\kappa_i^{e1} = 100\%, \overline{k}_i^{e1} = 3\%, \kappa_i^{e2} = 50\%, \overline{k}_i^{e2} = 2\%, \kappa_i^{e3} = 0\%$$

The features of each pension plan are represented in our simulations by the following vector of parameters:

$$\{k_i^{e0}, \overline{K}_i^0, \kappa_i^{e1}, \overline{k}_i^{e1}, \kappa_i^{e2}, \overline{k}_i^{e2}, \kappa_i^{e3}, \overline{k}_i^{e3}, \overline{K}_i^{Tot}\}$$

-

Table 2 provides descriptive statistics for these parameters. For comparison we report values for both the full selected sample mentioned in the data section, and the DC-only sample used in the current analysis. The average non-matching employer contribution (k_i^{e0}) is 1.83% of salary for the full sample, but only 1.58% for the DC-only sample. The median is 0% in both samples, as two thirds of firms only provide matching contributions. For the full sample the median (average) firm matching contribution is 60% (72%) of the employee's contributions up to a median (average) limit of 4% (3.82%). For the DC-only sample, the median (average) firm matching contribution is 100% (63%) of the employee's contributions up to a median (average) limit of 4.5% (3.13%). These numbers show that the employee contributions for the DC-only sample tend to less generous than for the full sample. Finally, more than two thirds of the firms don't make further contributions (i.e. $\kappa_i^{e2} = \kappa_i^{e3} = 0$), and only 1% of the workers have a third tier ($\kappa_i^{e3} > 0$). For this reason, we do not consider additional tiers in our simulations.

3.2 Wealth evolution with leakages

Individuals are allowed to withdraw funds from their retirement accounts in case of hardship, a job separation (an unemployment spell or a job switch), and upon reaching age 59 1/2. Munnell and Webb (2015) document that (on average) individuals withdraw significant sums from their retirement accounts in response to all of the above. They conclude that these "leakages" reduce "aggregate 401(k)/IRA retirement wealth by about 25 percent". Therefore, we explicitly consider these potential withdrawals in our simulations. Next, we describe how we model these withdrawals in our simulations, and at the end of the section we discuss the estimation of the different withdrawal probabilities and withdrawal amounts.

3.2.1 Withdrawal due to job switch

Individuals face a probability $\pi^s(.)$ of switching to another job, in which case retirement wealth accumulation is given by

$$W_{it} = \begin{cases} R^W_{it} W_{i,t-1} + (k_{it} + k^e_{it}) Y_{it} & \text{with probability } 1 - \pi^s_W(.) \\ R^W_{it} W_{i,t-1} + (k_{it} + k^e_{it}) Y_{it} - l^s(.) W_{i,t-1} & \text{with probability } \pi^s_W(.) \end{cases} \tag{9}$$

where

$$R^W_{it} = \alpha_{i,t-1} R^S_t (1 - \tau^S_i) - (1 - \alpha_{i,t-1}) R^B_t (1 - \tau^B_i)$$

and

$\pi^s_W(.)$: probability of withdrawal due to job switch

$l^s(.)$: withdrawal amount due to job switch (as a percentage)

We assume that the new job has a 401(k) plan that is equivalent to the one the worker was previously enrolled in.

3.2.2 Withdrawal due to job loss

Likewise, each worker faces a probability $\pi^u(.)$ of suffering an unemployment spell, under which the evolution of retirement wealth is given by

$$W_{it} = \begin{cases} R_{it}^W W_{i,t-1} + (1-u(.))(k_{it}+k_{it}^e)Y_{it} & \text{with probability } 1-\pi_W^u(.) \\ R_{it}^W W_{i,t-1} + (1-u(.))(k_{it}+k_{it}^e)Y_{it} - l^u(.)W_{i,t-1} & \text{with probability } \pi_W^u(.) \end{cases} \tag{10}$$

where

$u(.)$:	duration of unemployment spell (in a fraction of a year)
$\pi_W^u(.)$:	probability of withdrawal due to unemployment
$l^u(.)$:	withdrawal amount due to unemployment (as a percentage)

In this case the contributions only take place while the individual is employed, for a fraction $(1-u(.))$ of the year. Finally, we assume that, if an agent becomes unemployed, once she finds a new job she will have access to a 401(k) plan similar to the one in her previous job.

3.2.3 Withdrawal due to hardship

A hardship event occurs with probability π^h and, for our purposes, it is defined as one in which funds are withdrawn from the retirement account, so that $\pi_W^h = 1$ by definition. In such an event, no contribution is made to the retirement account, and therefore wealth accumulation is given by

$$W_{it} = R_{it}^W W_{i,t-1} - l^h(.)W_{i,t-1} \tag{11}$$

where $l^h(.)$ captures the withdrawal amount due to hardship as a percentage of account balances.

3.2.4 Withdrawal upon reaching age 59 1/2

Starting at age 59 and a half, workers can withdraw funds from their retirement account without penalty. In our simulations this occurs with probability π_W^{60}. Thus, the evolution of retirement wealth becomes

$$W_{it} = R_{it}^{W} W_{i,t-1} - l^{60}(.) W_{i,t-1} \tag{12}$$

where $l^{60}(.)$ captures the withdrawal fraction. As before, the worker does not contribute funds to the account if she makes a withdrawal.

3.2.5 Estimations

Leakages can be classified into two categories:

1. Cash out at job separation, either involuntary and followed by unemployment or voluntary/involuntary when the worker joins another firm.

2. In-service withdrawals – either for hardship or upon reaching age 59 1/2.

Unemployment rates and duration are estimated as a function of industry, age, salary, and education from the Current Population Survey Merged Outgoing Rotation Groups (MORG), a monthly household survey conducted by the Bureau of Labor Statistics to measure labor force participation and employment. We assume that workers enter the labor force at 20, don't get any more education once they start working, and, when changing jobs, they stay in the same industry. Our preferred specifications for the probability of unemployment (π^u) and its expected duration (u) are reported below

$$\pi^u = constant_prob_u - 0.0248848 * a + 0.00024636 * a^2 \tag{13}$$

$$u = constant_dur_u + 1.0450717 * a - 0.0078187 * a^2 \tag{14}$$

where the constant term is individual-specific and includes the constant in the regression, industry fixed effects and education effects, estimated for each individual based on her industry, age, salary. Applying the estimates above to our sample results in an average unemployment duration of 28 weeks, which is in line with the aggregate statistics.[11]

We obtain industry-level separation ratios due to unemployment and job switches from the Job Openings and Labor Turnover Survey (JOLTS), conducted monthly by the Bureau of Labor Statistics.[12]

The first two columns of Panel A of Table 3 reports data from Munnell and Webb (2015) and Vanguard's *How America Saves* (2013) on the percent of plan participants cashing out upon job separation, and the average percent of funds they withdraw of the total funds

[11] Average unemployment duration figures can be found at: https://www.statista.com/statistics/217837/average-duration-of-unemployment-in-the-in-the-us/, and are very similar to those obtained by applying the coefficients estimated from MORG to our sample.

[12] This information allows us to estimate the probability of switching jobs based on the following formula: probability of changing firms instead of being laid off = (unemployment rate/separation ratio)-unemployment rate.

available for each age bracket. The Panel also reports our computations of the probability of unemployment and job switching described above, the total amount of funds available to each age group, calculated from our data, the average account value, and the average fraction of the account being withdrawn, by age and cause for the separation. For example, columns (3) and (4) show that a worker in her 20s who leaves her firm has a 43.84% probability, if unemployed, or a 30.03% probability, if switching jobs, of cashing out. These probabilities are calculated so to make the overall probability of cashing out equal to 35%, like reported by Munnell and Webb (2015), and to take into account that the probability of leaving the firm because of unemployment is lower than for switching (see Columns (9) and (11), which report the estimates from the equations above), and that, based on Englehardt (2003), the probability of cashing out if unemployed is 46.7% higher than if switching jobs. Column (7) reports the average account value in our dataset, column (8) calculates the total assets in our panel that are withdrawn by those who left their firm, based on the fraction from Munnell and Webb (2015) reported in column (2), while column (16) reports the fraction of the individual account withdrawn, conditional on leaving the firm and making a withdrawal. Based on these estimates, the probability of cashing out due to unemployment and job switches, and the fraction of the worker's own account that is withdrawn are given by

$$\pi^u_W = 0.4384 I_{a\in[20,29]} + 0.3997 I_{a\in[30,39]} + 0.3983 I_{a\in[40,49]} + 0.2982 I_{a\in[50,59]} + 02361 I_{a\in[60,69]} \tag{15}$$

$$\pi^s_W = 0.3003 I_{a\in[20,29]} + 0.2738 I_{a\in[30,39]} + 0.2728 I_{a\in[40,49]} + 0.2042 I_{a\in[50,59]} + 0.1617 I_{a\in[60,69]} \tag{16}$$

$$l^s = 0.4286 I_{a\in[20,29]} + 0.3438 I_{a\in[30,39]} + 0.3125 I_{a\in[40,49]} + 0.2917 I_{a\in[50,59]} + 0.2105 I_{a\in[60,69]} \tag{17}$$

As a consistency check, we calculate the weighted average of the fraction of the account that is withdrawn based on our estimates and find that it is 30.3%, compared to 28.8% reported by Munnell and Webb (2015). We also calculate the percentage of the total assets being withdrawn and find that it is about 7% both in our sample and in Munnell and Webb's.

In addition, Munnell and Webb (2015) use data from the Survey of Consumer Finances and from Vanguard's *How America Saves* to estimate that people who take hardship withdrawals are 1.2% of the total (see Fig. 3 in their paper) and they withdraw 0.3% of total assets. Based on this information, the fraction of workers in our sample who are aged 59 or less, the fraction of the total assets they own, and their average account value, we estimate that, conditional on making a hardship withdrawal, they withdraw 0.28% of the total assets belonging to their age group, and on average 27.6% of the funds in their individual account. As a consistency check, we find that Vanguard estimates that on average people who make hardship withdrawals withdraw 0.37% of the funds available to those younger than 60 and 25% of the funds in their individual accounts.

Finally, upon reaching age 59 1/2, workers can start withdrawing from their accounts without incurring a penalty. Based on the computations in Munnell and Webb (2015), 2.8% of the population makes such withdrawals and cashes out 0.2% of the total assets in the system. Since in our sample people aged 59 and higher are 9.83% of the workers and own 18.33% of the assets, we estimate an average probability of making a withdrawal upon reaching 60 of 9.49%, and an average fraction withdrawn of 11.49%. Both the probability of withdrawing and the fraction withdrawn are estimated as a (negative) function of the worker's salary decile. The estimates are reported in Panel B of Table 3.

3.2.6 Labor income process

Following the life-cycle consumption and savings literature, we model labor income as

$$Ln(Y_{it}) = \begin{cases} f^Y(t, Z_{it}) + P_{it} + U_{it} & \text{with probability } 1 - \pi^u(.) \\ (1-\theta)(f(t, Z_{it}) + P_{it} + U_{it}) & \text{with probability } \pi^u(.) \end{cases} \tag{18}$$

where $f^Y(t, Z_{it})$ is a deterministic polynomial of age and household characteristics and θ is the fraction of income lost during an unemployment spell. $\pi^u(.)$ is the probability of unemployment, defined above, and

$$U_{it} \sim \quad N(0, \sigma_U^2) \tag{19}$$

$$P_{it} = \quad P_{it-1} + N_{it}, N_{it} \sim N(0, \sigma_N^2) \tag{20}$$

We set both σ_N and σ_U to 0.1, as it is standard in the life-cycle consumption and savings literature (e.g. Gourinchas and Parker (2002), Carroll (1997) or Cocco, Gomes and Maenhout (2005)). As discussed above, the probability of unemployment is worker-specific, while the fraction of income lost in a year with an unemployment spell is taken from Brown, Fang and Gomes (2012). We initialize our simulations with the actual observed wage income for each individual, and use this stochastic process to simulate income changes going forward.

3.2.7 Social security income

As previously discussed, in order to determine the total resources available to finance consumption during retirement, we need an estimate of the individual's pension income. Therefore, in addition to simulating income growth forward, we also use the stochastic process given by (18) to simulate income growth backwards. This procedure provides us with a full simulated life-cycle income path $\{Y_{it}\}_{t=20}^{65}$, which we use to compute the implied pension income for each simulation. To obtain the implied pension (Y_{iR}), we apply the actual current social security formula to the simulated income profile. Specifically, for each path, pension income is a non-linear function of the different income realizations:

$$Y_{iR} \equiv Y_{iR}(\{Y_{it}\}_{t=20}^{65})$$

4 Other sources of wealth

Most individuals in our sample have worked in at least one previous company before joining their current employer. It is therefore important to estimate the pension wealth accumulated during these previous employment spells (W_{i65}^{other}). In addition, they might have also accumulated financial wealth outside of pension accounts (W_{i65}^{FW}). Finally, households can also release some or all of their home equity (W_{i65}^{HW}) during retirement by either downsizing to a smaller house or by entering into a reverse mortgage. Since both of these options are rarely observed in the data (see Caplin (2002), Venti and Wise (2004) and Davidoff (2015)), we consider different scenarios regarding the fraction of housing wealth available to finance expenditures during retirement (θ). Combining all these sources, total wealth accumulation at retirement, is given by

$$W_{i65}^{T} = W_{i65} + W_{i65}^{other} + W_{i65}^{FW} + \theta W_{i65}^{HW} \tag{21}$$

Except for the scenarios that would allow for a large fraction of housing wealth to be spent during retirement (very high θ), W_{i65}^{T} is largely determined by the DC account balances ($W_{i65} + W_{i65}^{other}$), which constitute the primary output of our simulations. In our baseline case, where $\theta = 0.5$, the median value of $(W_{i65} + W_{i65}^{other})/W_{i65}^{T}$ is 0.66, i.e. two thirds of the total wealth available to finance retirement is coming from the DC accounts. Moreover, even at the 25th percentile of the wealth distribution this ratio is still larger than 0.50 (0.53).

4.1 DC wealth from previous employers

In order to estimate potential DC wealth accumulation at previous employment spells, we first estimate the total length of those spells by combining information on the current age (a) and tenure at the current job ($\bar{t}$). In our baseline analysis, we assume that everybody started working at age 20 (t_0). We then make the same assumptions as above, namely that during any previous employment spell(s) the individual had access to a pension scheme identical to the current one, and that she had followed the previously described decision rules for contribution rates and portfolio allocation.[13] Under these assumptions, the evolution of other DC wealth is given by

$$W_{it}^{other} = \begin{cases} R_{i,t-1}^{P} W_{i,t-1}^{other} + (k_{it} + k_{it}^{e}) Y_{it} & t \in [t_0, a - \bar{t}] \\ R_{i,t-1}^{P} W_{i,t-1}^{other} & t \geq a - \bar{t} \end{cases} \tag{22}$$

where

$$R_{i,t-1}^{P} \equiv \alpha_{i,t-1}^{S} R_{t}^{S} (1 - \tau_{i}^{S}) + \alpha_{i,t-1}^{B} R_{t}^{B} (1 - \tau_{i}^{B}) - (1 - \alpha_{i,t-1}^{S} - \alpha_{i,t-1}^{B}) R^{f} \tag{23}$$

The first branch of the formula captures the wealth evolution while the individual was enrolled in the plan, and therefore includes annual contributions. Like we did to compute

[13] Thisa assumption will not create a bias unless we think that the individuals are on average likely to be in companies with either better or worse pension plans early in their careers.

social security income, we use the stochastic process (18) to simulate labor income backwards for these years. The second branch captures the evolution of the account balance from the time the individual started working in his/her current job, at which point no additional contributions were made to the previous plan. As mentioned, $\alpha_{i,t}^S$, $\alpha_{i,t}^B$, and k_{it} are given by the formulas described above. Likewise, τ_i^S and τ_i^B are assumed to be the same as in the current plan.

4.2 Financial wealth outside of retirement accounts

Throughout their lives individuals also save outside of their retirement accounts, and these savings can be used to finance either retirement or pre-retirement expenditures. In order to capture only the former, and measure how much wealth households save for retirement outside of their pension accounts, we construct non-retirement financial wealth at age 65 (W_{i65}^{FW}) and estimate its relationship to retirement wealth at age 65 in the Health and Retirement Study. More precisely, we use the HRS data to fit the following regression and use the resulting mapping from retirement to non-retirement wealth in our simulations.

$$W_{i65}^{FW} = \alpha^{FW} + \beta^{FW} * W_{i65} + \varepsilon_i^{FW} \tag{24}$$

-

Workers' outside financial wealth at retirement is estimated at the household level based on the 2010 Wave of the Health and Retirement Study (HRS). We narrow our focus to those who are married and between age 62 and 67, and estimate the relationship between their total household net wealth, excluding retirement and housing wealth, and the balance in their defined contribution plans, controlling for the salary in their current job or in their last job before retirement. Total household net wealth, excluding retirement and housing wealth, is computed as the sum of (value of stocks, mutual funds, and investment trusts; checking, savings, or money market accounts; CD, government savings bonds, and T-bills; bonds and bond funds, all other savings) less debt (excluding real estate-related debt). We restrict the estimation to married people to avoid underestimating households' outside wealth by including both single individuals and couples in the same regression. We confirm that the wealth of single individuals between the age of 62 and 67 in the 2010 wave of the HRS is about half of the total household wealth of married ones. Married people constitute 67% of the respondents in the 62-67 age bracket.

As a further consistency check, Panel A of Table 4 reports a comparison of the account balance, both total and from the last job, of the people between 62 and 67 in the HRS, with the account balance for the people between 62 and 67 in our sample. The table shows that they are very similar, not only in terms of their mean and median, but also in terms of their overall distribution. The exception is the unconditional total retirement wealth, which is zero for the bottom quartile of the HRS sample, possibly due to issues with this survey question (see Gustam et al. (2014) for a detailed analysis of the pension wealth data files in the HRS). For this reason, we estimate outside financial wealth as a function of total DC account balance, rather than total retirement wealth. Panel A also shows that the balance from the main account or the account connected to last job is very similar to the total balance, suggesting that most people close to retirement/already retired have consolidated all their balances into one account.

Panel B of Table 4 reports the coefficients of the regression of outside financial wealth on account balance, both including and excluding salary. The coefficients on account balance are stable across specifications, and we picked the specification (4) because of the higher R^2.

4.3 Housing Wealth

During retirement, households can release part or all of their home equity by either downsizing to a smaller house or by entering into a reverse mortgage. Since both of these options are rarely observed in the data (see Caplin (2002), Venti and Wise (2004) or Davidoff (2015)), we consider different scenarios as to what fraction of housing equity we include in our measure of total wealth available to finance retirement.

We compute housing equity using a three-step procedure. First, for each individual we estimate the probability of being a homeowner at age 65 (p^h_{i65}). Then, we estimate her house value at age 65 (H_i) by projecting forward her current house value estimated using Zillow median house values in the zip code where she lives. Housing wealth is projected forward to age 65 using an expected housing price appreciation (r^H) of 1%, taken from Cocco (2005).[14] In the final step, we combine these values with an estimate of the loan-to-value ratio at age 65 obtained from the HRS. Thus, our estimate of housing wealth is given by

$$W_{i65}^{HW} = p_{i65}^{h} * (1 + r^H)^{65-a} H_i * (1 - LTV_{i65})$$

The probability of being a homeowner is estimated using a probit model. Similar to the outside financial wealth estimation, we focus on married individuals between the age of 62 and 67. HRS data indicate that single individuals in this age bracket are more likely to be renters, and, if they are homeowners, they tend to have cheaper houses, and about half the housing wealth of married couples. Panel A of Table 5 shows that on average the loan to value on the first residence for our target group is 27.4%, while the median is 5.7%, indicating that most people have paid down their mortgages almost completely by the time they have reached retirement age (Column (2)). The table also shows that most people in this group don't own additional real estate (Columns (3) and (4)) , and that the house values from the HRS and those from Zillow are quite similar over our sample period (Columns (5) and (6)).

Panel B of Table 5 reports the estimates we use in the simulations. Columns (1) and (2) show the probability of being a homeowner as a function of retirement wealth and salary, while Columns (3) and (4) show the LTV as a function of the same variables.

5 Retirement period and retirement wealth optimality

5.1 Preferences and budget constraint

We compute the optimal consumption at retirement as the solution to an intertemporal optimization problem starting at age 65. Our model includes longevity risk and medical expenditure shocks, and captures the individual's preferences with a time-separable power utility function

$$U = E \sum_{t=R}^{100} \beta^{t-R} \left(\prod_{j=0}^{t-2} p_j \right) \left\{ p_{t-1} \frac{(C_{it})^{1-\gamma}}{1-\gamma} \right\} \qquad (25)$$

[14]The value used in Yao and Zhang (2005) is even lower: 0%.

where p_t denotes the probability that the individual survives to age $t+1$, conditional on being alive at age t. As we explain in more detail below, these probabilities are stochastic, allowing us to account for longevity risk. Finally, to avoid carrying around another preference parameter, we do not include an explicit bequest motive in the model, but rather we consider the bequest motive in the final comparison.[15]

We assume the retiree has access to a risky asset, stocks, and a riskless asset, T-bills.[16] Instead of solving for an optimal portfolio allocation, we assume fixed portfolio shares throughout retirement, based on the evidence that individuals rebalance their portfolios only very infrequently. Contrary to the evidence, for most combinations of the preference parameters, our model would imply that the optimal portfolio changes significantly with age. We therefore prefer to present results for different hypothetical portfolio shares which we keep constant over the retirement period. Further, as shown in Section 6.2.2, the main conclusions about retirement preparedness are unchanged under different assumptions about the worker's asset allocation.[17]

The dynamic budget constraint is

$$W_{i,t+1}^{T} = R_{t+1} W_{it}^{T} - C_{it} - M_{it} + \overline{Y} \tag{26}$$

where M_{it} denotes the medical expenditure shocks, R_{t+1} is the return on the fixed portfolio, and $\overline{Y}$ is pension income.

[15]Love, Palumbo and Smith (2008) and DeNardi, French and Jones (2010), among others, nicely illustrate the importance of longevity risk, mortality risk, medical expenditure risk, and bequests for explaining wealth evolution during retirement.

[16]Interestingly, the set of available assets turns out not to be important for our analysis. A reason why is that, as discussed next, we assume an exogenous portfolio rule which we vary to illustrate the sensitivity of the results to the particular risk/return combination that an individual takes in her retirement investments. Moreover, as shown below, the main conclusions about retirement preparedness are unchanged under different assumptions about the worker's asset allocation.

[17]Similarly, annuity products have been shown to potentially generate non-trivial welfare gains at retirement if individuals were to invest (more) in such assets (e.g. Horneff, Maurer, Mitchell and Stamos (2010)). We do not include them in our model, as we aim at capturing observed, as opposed to optimal, behavior.

5.2 Longevity risk and medical expenditures

We capture longevity risk following Lee and Carter (1992), who model death rates for age t and calendar time x ($d_{t,x} = 1 - p_{t,x}$) as

$$ln(d_{t,x}) = a_t + b_t \times \phi_x \tag{27}$$

The a_t coefficients capture the average shape of $ln(d_{t,x})$ over the life-cycle, while the b_t coefficients reflect how mortality rates at different ages respond to mortality shocks over time, ϕ_x.[18] Finally, the random variable ϕ_x is given by

$$\phi_x = \mu^{\phi} + \phi_{x-1} + \varepsilon_x^{\phi} \tag{28}$$

where μ^{ϕ} is the drift parameter and ε_x^{ϕ} is normally distributed with mean zero and standard deviation σ^{ϕ}. We take the values for a_t, b_t, μ^{ϕ} and σ^{ϕ} from Cocco and Gomes (2012).

We estimate the process for medical expenditures using data from the Health and Retirement Study. We consider the sub-sample of retirees older than 65. Since in the data medical expenditures are highly correlated with the level of income, we model them as a ratio to disposable income at age 65

$$\frac{M_{it}}{Y_R} = f^M(t) + V_{it} \tag{29}$$

where t denotes age and

$$V_{it} = \rho V_{it} + \varepsilon_{it}, V_{it} \sim N(0, \sigma_V^2) \tag{30}$$

We have experimented with estimating equation (29) both in logs and in levels and found that the latter better fits the data.[19] We fit $f^M(t)$ as a third order polynomial and estimate $\rho = 0.4377$ and $\sigma = 0.2842$.[20]

[18]The b_t coefficients are a relative measure, normalized to sum to one.

[19]Both in the model and in the simulations we restrict M_{it} to be positive, and we cap M_{it}/Y_R at 2.0. Since there are no observations in the HRS for which this ratio exceeded 200%, this constraint does not affect the validity of the estimation and is strongly motivated by the data.

[20]The coefficients of the age polynomial are 0.1463164, 0.0025844, -0.0001708, and 0.0000174, for the constant, linear, quadratic, and cubic terms, respectively.

5.3 Optimization Problem

The full maximization problem is given by

$$\underset{\{C_t\}_R^{100}}{Max}\, E \sum_{t=R}^{100} \beta^{t-R} \left(\prod_{j=0}^{t-2} p_j \right) \left\{ p_{t-1} \frac{(C_{it})^{1-\gamma}}{1-\gamma} \right\} \tag{31}$$

subject to the budget constraint in equation (26), the stochastic process for the survival probabilities in equations (27) and (28), and the process for medical expenditures in equations (29) and (30). We normalize $\overline{Y}$ to 1, so that we are left with four state variables: wealth ($W_{i,t}^T$), age (t), the persistent medical expenditure shock ($V_{i,t}$), and the current survival probability (p_t). The model is initialized at the wealth level available at the start of retirement, W_{iR}^T. Thus, the optimal consumption path for a value of $W_{iR}^T/\overline{Y}$ is

$$\{C_{iR}(W_{iR}^T/\overline{Y}), C_{i,R+1}(W_{iR}^T/\overline{Y}), \ldots\}$$

We solve the model for a grid of potential values of $W_{iR}^T/\overline{Y}$, and, using interpolation, we obtain the implied optimal consumption sequence for each of the thousands of paths we simulate.

5.4 Evaluating the optimality of retirement wealth

In the final step of our analysis, we combine the results from the pre-retirement simulations with those of the post-retirement model to evaluate whether wealth accumulation at age 65 is sufficient to finance the optimal level of consumption at retirement. Below we discuss the methodology used to perform this evaluation.[21]

5.4.1 Certainty equivalent ratio

From a utility maximization perspective, an agent is saving optimally for retirement if the discounted marginal utility of saving one more dollar of income is equal to marginal utility

[21] Poterba (2015) provides a comprehensive discussion of the trade-offs involved in different approaches used to perform this evaluation in the literature.

of consuming that dollar today. Thus, the optimal consumption path should satisfy

$$U'(C_{ia}) = \beta^{(R-a)} E[U'(C_{iR})(R^p_{i,a,R})^{(R-a)}] \tag{32}$$

where C_{ia} denotes current consumption, C_{iR} denotes consumption at retirement age, and $R^p_{i,a,R}$ is the return on an feasible investment portfolio from age a to age R.[22] The left and right-hand sides of (32) can then be computed by assuming a specific utility function and a distribution of returns.

For ease of exposition, we take a conservative baseline case where we assume that β and the moments of the return process, including its covariance with the marginal utility of consumption growth, are such that equation (32) becomes

$$U'(C_{ia}) = E[U'(C_{iR})] \tag{33}$$

The reason why this is a conservative assumption is that, in the context of a standard life-cycle model with risky assets, consumption at retirement age is typically higher than the average consumption over the working years, and in fact significantly higher than consumption in the early years, due to the presence of liquidity constraints and background risk (see, for example Cocco, Gomes and Maenhout (2005)).[23] In the data we do observe a significant fraction of households saving little for retirement and for whom consumption will fall quite rapidly right at retirement age. The implicit view in our analysis is that this drop is the largely result of individuals having time-inconsistent preferences (e.g. Laibson (1997) and Laibson, Repetto and Tobacman (1998)), other behavioral biases, or poor financial literacy, rather than being optimal.

Indeed, if we assumed everybody behaved optimally, then exercises such as ours would be irrelevant. Note, however, that optimal consumption at retirement will typically still be

[22] This equality should hold for all pre-retirement ages. We focus on age a since it is the one we observe in our data. Likewise, this equality should also hold for all retirement years, but we can focus on C_{iR}, since the total consumption level at retirement is optimal for all ages and if the agent can't finance the optimal C_{iR}, she can't finance the optimal path going forward either.

[23] Later in life consumption will fall quite rapidly, mostly because of a decrease in conditional survival probabilities.

lower than its average pre-retirement levels because of important factors omitted in several of those models. More specifically, housing purchases and children-related expenditures tend to take place before retirement, and, once retired, households partially substitute marketplace goods for home production, which have lower financial costs (Aguiar and Hurst (2013)). For this reason, it is common practice among both financial advisors and academics to account for these differences when comparing pre and post retirement required expenditure levels (e.g. Munnell, Webb and Delorme (2006), VanDerhei (2006), Brady (2010) or Pang and Schieber (2014)), by replacing equation (33) with,[24]

$$U'(\varphi C_{ia}) = E[U'(C_{iR})] \tag{34}$$

where φ is a number smaller than 1. The limitations of evaluating retirement adequacy solely based on these measures is discussed in detail in Poterba (2015) and Biggs (2016), and acknowledged by most of the studies that use them. While our approach doesn't suffer from these drawbaks, we nevertheless want to take these differences into account, and therefore set $\varphi = 0.8$. The values of φ proposed in the literature vary with household characteristics, ranging from as low as 0.7 to close to 1.[25]

Imposing a particular utility function, power utility in our case, we obtain a measure of retirement preparedness by computing the certainty equivalent of consumption from the right-hand-side of (34). We define the certainty equivalent ratio (hereafter CEQR) as

$$CEQR = \frac{\overline{C}_{iR}}{\varphi C_{ia}} \tag{35}$$

where $\overline{C}_{iR}$ is computed from

$$E[U'(C_{iR})] = U'(\overline{C}_{iR})$$

[24] Those comparisons are often phrased with regards to income levels, and not consumption levels, but the same logic applies.

[25] One advantage of the measures we report below, is that results for different values of φ can be easily computed by just multiplying by the ratio of the two. For example, the CRRRs for $\varphi = 0.9$ (instead of 0.8) can be computed by multiplying by 0.8/0.9 the ones we report for the $\varphi = 0.8$ case.

5.4.2 Consumption replacement ratios

To be as agnostic as possible about agents' preferences, in addition to the CEQR, we also compute the distribution of $(C_{iR}/\varphi C_{ia})$ across all simulation paths. We label this measure the consumption retirement replacement ratio $\lambda(\omega)$ (hereafter CRRR)

$$\lambda(\omega) = \frac{C_{iR}(\omega)}{\varphi C_{ia}}, \omega = 1, \dots, \Omega \tag{36}$$

where Ω is the total number of simulations. We then report the percentiles of the distribution of $\lambda(\omega)$.[26] Given our previous assumptions, a risk-neutral individual would aim for a mean/median $C_{iR}/\varphi C_{ia}$ of 1, while a risk averse individual would aim for a ratio greater than 1. A value of λ less than 1 represents a clear shortfall in retirement savings, with the actual value of λ measuring the exact percentage shortfall expressed in consumption units.[27]

5.4.3 Estimating Consumption

Computing equations (35) and (36) requires both $C_{iR}(\omega)$ and current consumption, C_{ia}. Our simulated paths provide the distributions of both wealth and pension income at retirement (W_{iR}^T and Y_{iR}, respectively) which, combined with our model of retirement, yield C_{iR} as a function of W_{iR}^T/Y_{iR}

$$C_{iR} \equiv C_{iR}(W_{iR}^T/Y_{iR}, Z)$$

where $Z \equiv \{\alpha^R, \gamma, \beta\}$ denotes the parameters of the retirement model.

Since we don't observe C_{ia} in our data, we use the Consumer Expenditure Survey to estimate consumption as function of our observables, like we have used the HRS to estimate other forms of wealth. Table 6 reports the coefficients of the regression of total annual expenditures on age and salary for the CEX sample of respondents between age 20 and 65 who were interviewed between 2006 and 2011. Total expenditure is defined as the sum

[26] While solving the retirement problem requires assuming a specific utility function, we try to minimize the effect of this specific assumption by reporting the sensitivity of the results to different parameter values.

[27] Agents with a preference for earlier (later) consumption relative to the return process will aim for a ratio lower (higher) than 1. To the extent that such preferences for early consumption result from time-inconsistent preferences (e.g. Laibson (1997) and Laibson, Repetto and Tobacman (1998)), the interpretation of our results will depend on whether we take a paternalistic view or not.

of food and alcohol, tobacco, apparel and services, entertainment, personal care, housing and shelter, health, reading and education, transportation, cash and pension contributions, and miscellaneous. Since the CEX measures expenditures at the household level, we use the methodology proposed by Deaton and Zaidi (2002) to calculate adult equivalents for each household and convert household-level into individual-level expenditures. To avoid the effect of outliers and unusual circumstances, we limit the regressions to the interquartile range of the ratio of total expenditure over salary, and we explore various specifications in which age enters the regressions both linearly and as a set of 10-year range dummy variables, alone and interacted with salary and salary squared.[28] Column (1) of Table 6 estimates total expenditure as 50.4% of salary, plus a term dependent on the respondent's age. For example, a 42 year old individual with the median salary of $50,000 in 2010, would have annual total expenditures of $30,045, equal to 60% of his income. The more flexible specifications in Columns (2) to (5) yield similar results. We pick the specification in Column (4) as our favorite and calculate total expenditure in our 401(k) dataset as a function of worker age and salary.[29] As a further check, in Panel B of Figure 1, we plot the distribution of the ratio of expenditures to salary in our 401(k) sample and confirm that it closely mirrors the CEX one in the fourth quadrant of Panel A.

5.4.4 Adjusting for taxes

While our measure of C_{ia} is already net of taxes, since it is estimated using actual consumption in the CEX, we need to convert the value of retirement consumption obtained in each simulation ($C_{iR}^{notax}(\omega)$) into an after-tax number ($C_{iR}(\omega)$) that reflects both federal and local taxes.

$$C_{iR}(\omega) = C_{iR}^{notax}(\omega) - FederalTax - LocalTax$$

Our procedure automatically takes into account the potentially sizable differences in tax rates during working life and retirement. Based on equation (26), and assuming for simplicity

[28]These restrictions correspond to realistic expenditure to salary ratios between 0.4 and 1. Panel A of Figure 1 reports the distribution of the expenditure to salary ratios for different sample restrictions.

[29]According to this specification, the 42 year old worker with $50,000 salary in our example would have an expenditure to salary ratio of 61%.

that after retirement both social security payments ($\overline{Y}$) and dis-saving from existing financial wealth ($R_{t+1}W_{it}^{T} - W_{i,t+1}^{T}$) are taxed at the same rate, we can apply the appropriate tax rates directly to each simulated value of $C_{iR}^{notax}(\omega)$.[30]

$$C_{it} = R_{t+1}W_{it}^{T} - W_{i,t+1}^{T} - M_{it} + \overline{Y}$$

Our calculations take into account the progressivity in federal tax rates. In addition, state-specific taxes are calculated for each individual based on the zip code where she currently lives, and, to economize on computations, on her median simulated income.[31]

6 Baseline Results and Sensitivity Analysis

6.1 Baseline results

Table 7 shows the results for a baseline case where we assume risk aversion of 5, a discount factor of 0.95 and a 50% equity allocation at retirement, i.e.

$$Z \equiv \{\alpha^{R}, \gamma, \beta\} = \{50\%, 5, 0.95\}$$

The first six columns report the consumption retirement replacement ratio (λ), and the certainty equivalent replacement ratio ($CEQR$) for various scenarios. Columns (2) through (6) present the results for different percentiles of the distribution of λ across realizations for the same individual, from the 10th lowest percentile to the median, while the rows represent different percentiles of the distribution of λ across individuals. For example, the row labelled "50%" refers to the worker with the median value of λ. We find that she has a 50% probability of obtaining a CRRR of 1.11, a 30% probability that this ratio will only be 0.90, and a 10% probability that it will be as low as 0.69. For the worker in the 25th percentile of the distribution, those numbers drop to 0.91, 0.76 and 0.60, respectively. The

[30] This will slightly under-state the tax burden since it assumes $M_{it} = 0$. Note however, that the expected value of medical expenditures at age 65 is very low.

[31] This approach assumes, for the lack of a better alternative, that the individual remains in the same state until retirement. If individuals move to states with lower (higher) taxes, they will be better (worse) off.

next five columns report total wealth accumulation ($W_{65}^{T} = W_{65} + W_{65}^{other} + W_{65}^{FW} + \theta W_{65}^{HW}$) in thousands of dollars, and follow the same structure.

Column (7) reports the certainty equivalent ratio ($CEQR$), which integrates over the full distribution of outcomes using the baseline utility function. For example, the median worker has a median consumption replacement ratio of 1.11. If she was risk-neutral this would imply that she is saving enough to finance retirement, having a more than 50% probability of matching her consumption needs. However, Column (4) shows that she has a 40% probability of not reaching her target retirement savings. For a modest degree of risk aversion, this outlook will be sub-optimal. In fact, for the baseline risk aversion coefficient of 5, the certainty equivalent ratio is only 0.86 indicating that, in risk-adjusted terms, her wealth accumulation falls short by 14%. From the point of view of the CEQRs, about 75% of the population is not saving enough for retirement, with the CEQR at the 75th percentile falling just below 1 (0.99).

The workers at the 25th percentile of the distribution face, in risk-adjusted terms, an almost 25% short-fall (CEQR of 0.76), and are not saving enough even under risk neutrality (with a median CRRR below 1). The picture is much worse at the 10th percentile of the distribution, with a median CRRR of only 0.78 and a CEQR of 0.68. In fact, even at the $90th$ percentile of the distribution there is still an approximately 15% probability of not having accumulated enough wealth by age 65.

6.2 Sensitivity analysis

6.2.1 Bequest motive and housing wealth availability

The results in the previous section assume no bequest motive, apart from the remaining housing equity.[32] If the workers in our sample wished to leave an additional bequest then their retirement savings would be even more inadequate. Panel A of Table 8 reports the results obtained by assuming a target bequest of $\$100K$ (in age-65 present value terms), and that only savings in excess of this amount can be used to finance consumption after

[32]Since the baseline results only allow for 50% of home equity to be used to finance retirement consumption, the remaining 50% is available to leave as a bequest.

retirement, while Panel B report the results obtained by assuming that all housing equity is left unused.[33]

The results from these two experiments are quite striking. The median CRRRs are now below 1 already at the 50th percentile of the distribution, implying that even under risk-neutrality the median worker is not saving enough for retirement. Furthermore, the CEQRs fall below 1 already at the 90th percentile of the distribution.

The introduction of a bequest motive (Panel A) affects the left tail of the distribution more strongly, as we are assuming an identical dollar bequest motive for all. On the other hand, the restriction on the availability of housing wealth (Panel B) hits the right tail of the distribution more strongly, since those individuals tend to have more housing wealth. Nevertheless, compared to the baseline results in Table 7, those in the 25th and 10th percentiles also suffer extremely large decreases in their certainty equivalent ratios, 13 and 10 percentage points, respectively. The latter is quite concerning since less wealthy individuals will likely find it harder to access products that allow for home equity release, or might be deterred by their costs.[34]

6.2.2 Alternative preference parameters and asset allocations during retirement

As discussed in section 5.4 the measure of the level of consumption that can be financed at retirement is based on a structural model of optimal consumption and saving decisions. Therefore, this measure is dependent on the choice of preference parameters,risk aversion γ and subjective discount factor β, and on the portfolio allocation assumed for the post-retirement period (α^R). Table 9 shows how our baseline results change for different values of these parameters. To minimize the size of the table in Panels A and B, for each choice of $Z \equiv \{\alpha^R, \gamma, \beta\}$, we only report the median CRRRs for the median individual.[35] Panel A reports the results for alternative asset allocations during retirement, 0% , 50%, and 100%

[33]This could happen because of bequest motives, but could also be the result of lack of access to, or lack of information about, financial products that allow for home equity release.

[34]These costs include both the direct financial costs and the indirect ones, e.g. obtaining and processing the necessary information.

[35]Relative to the CEQRs, the comparison of CRRRs is more intuitive since they imply comparisons across agents with different utility functions. The full set of results, including other CRRRs percentiles, is available upon request.

equity shares, and for the baseline risk aversion coefficient of 5. Panel B reports the results for different values of risk aversion, 2, 5 or 8, and for the baseline risky asset allocation of 50%. In both Panels, the rows refer to different values of the discount factor parameter, from 0.9 to 0.99.

Panel A shows that for different assumptions about the investment decision, the CRRRs vary at most 0.15, even as we consider moving from the zero to 100% investment in stocks. A 0.15 difference in average consumption every year during retirement is economically quite large. However, given the low values of the CRRRs in the baseline results, the main conclusion of the paper remains unchanged: the vast majority of the workers in our sample do not appear to be saving enough for retirement, regardless of the amount of stock market risk they are willing to take.

Turning to Panel B, we find that CRRRs increase as risk aversion falls, as investors with lower risk aversion need to save less both for retirement and during retirement, since they care less about medical expenditure risk and longevity risk. The panel shows that an individual with risk aversion of 2 (8) and a discount factor of 0.95 will have a median CRRR of 1.54 (0.85), and that workers with risk aversion higher than our baseline number will face an even more severe retirement under-savings problem, while workers with low risk aversion are likely to be saving enough for retirement.

Panel C reports the CRRRs for other percentiles of the worker distribution, assuming risk aversion equal to 2. Except for low values of the discount factor, workers in the 30th percentile have CRRRs close to 1, which is suboptimal for even a limited degree of risk-aversion. Workers at the 10th percentile of the distribution are faring worse and have a CRRR dangerously close to 1 (1.18) even with a discount factor of 0.9.

In summary, only for individuals with low risk aversion and/or low discount factor would we conclude that the median worker is saving enough for retirement. However, even in this case, we would still find that more than one third of the population currently under-saving. If we postulate that the full population consists of individuals with preferences distributed across the different ranges that we have reported in this table, then our previous conclusion holds: more than half of the workers in the sample will face a short-fall of wealth after retirement.

6.2.3 Lower average returns

One concern about the retirement wealth projections reported above is that future returns on risky assets might be lower than past ones. We explore the sensitivity of our results to other assumptions about future expected returns by repeating our simulations under a more conservative scenario in which the expected returns on both stocks and bonds are 1 percentage point lower going forward. Table 10 reports the results, including below each entry the differences relative to the baseline case.[36]

The results show that those most affected by lower future returns are the well-off. The CRRRs of those at the 10th and 25th percentiles are only modestly affected, and their CEQRs fall by only 2 percentage points. On the contrary, the consumption retirement replacement ratio of the median worker is 8% lower for the median simulation, and these losses increase as we move up along the distribution. Workers at the 75th percentile of the distribution have a 30% probability of ending up with a CRRR lower than 1, and having to lower their standard-of-living at retirement.

7 Cross-Sectional Heterogeneity

To better understand the determinants of the cross-sectional heterogeneity in our results, we regress the output of the simulations on multiple individual characteristics from our original data. Table 11 reports the coefficients from cross-sectional regressions for both the median wealth accumulation at age 65 (i.e. the 50th percentile of the distribution of W_{65}^{T}), and the median consumption retirement replacement ratio (i.e. the 50th percentile of the distribution of λ). In interpreting these results, it is important to keep in mind that these are cross-sectional regressions of the median simulated output. A particular variable X being significant and/or having a high explanatory power only means that it helps explain the degree of heterogeneity in outcomes across individuals. It does not imply that the variable X is important for explaining why the CRRRs or the wealth accumulation levels are high

[36] Note that in the case of consumption replacement ratios and the certainty equivalent ratios the differences are expressed in percentage points (e.g. $\lambda^{benchmark} - \lambda^{alternativescenario}$), while for the wealth levels the differences are reported as percentage changes ($W^{benchmark}/W^{alternativescenario} - 1$).

or low on average. Such conclusions can only be drawn by repeating the simulation exercise for different values of X, like we did in the sensitivity analysis section above.

7.1 Wealth accumulation

Panel A of Table 11 reports the wealth accumulation regressions. Column (1) shows that median wealth at age 65 is a convex function of age, and a concave function of salary. All else equal, a worker who is 41 years old today and earns the median salary in our sample, \$54,522, can expect to have accumulated \$584,270 at retirement, 3.2 times the wealth of a worker of the same age who earns the 10th percentile of salary, \$21,925, and slightly more than half the wealth of a worker with the same age, but who earns the 90th percentile of salary, \$96,794. The first five rows of Panel B of Table 11 report the covariates and median wealth calculations for a few selected cases, based on the coefficients in Column (1) of Panel A. The first three columns of Panel B show that if we consider the median, 10th, and 90th percentile salary for a worker of approximately 41 years of age, instead of the salary percentiles of the general population, we find that such worker would have accumulated \$508,770 at retirement age if, on the last day we observe her in the sample, she had the median income in her age group (40-42 years old), \$48,323. This amount is 2.5 times the wealth she would accumulate if she earned a salary at the 10th percentile of the distribution for her age group, \$23,492, and 44% of the wealth she had if she earned the 90th percentile of the salary distribution for her age, \$103,316. Column (7) to (9) show that the variance in median wealth levels upon reaching age 65 is similar for workers at the 90th percentile of the age distribution, 57 years of age. A worker of that age earning the median income for her age group, 56 to 58 years of age, would accumulate \$570,680 if she earned the median salary, 2.7 times more than if she earned the 10th percentile salary, and 47% of the wealth she had if she earned the 90th percentile salary in her age group. Column (4) to (6) show that the variance in wealth i s smaller for younger workers. A 26 years old worker, the 10th percentile of the age distribution in our sample, is predicted to have a median wealth at retirement equal to \$524,520 if she earns the median salary in her age group, \$34,292, today. This is only 1.56 times the wealth she would accumulate if she earned the 10th percentile salary for those between 25 and 27, i.e. \$19,195, and 58% of the wealth she had if she earned the 90th percentile salary, \$65,625.

These effects are qualitatively robust when we control for account balance, contribution rates, tenure at the firm, and the percent invested in equity. Column (4) of Panel A shows the importance of contribution rates and the fraction invested in equity. A one percentage point increase in contribution rates increases retirement wealth at age 65 by \$30,580, while a ten percentage point higher equity allocation increases it by \$7,120, on average. Finally, a \$1,000 higher balance on the last sample date corresponds on average to \$1,294 higher median wealth at retirement. Adding account features to the regressions increases the R^2 substantially, from 58.6% to 78.1%. The second section of Panel B shows that, compared to the results in Column (1), controlling for these additional account features accentuates the variance across salary levels for the younger cohorts, and decreases it for the older ones. When we calculate the median wealth at retirement for a 41 year old worker with the median, 10th percentile, and 90th percentile of salary for her age, and we do the same for a 26 and a 57 year old, based on the coefficients in Column (4) of Panel A, we find that the median wealth for a 41 years old with the median salary is \$509,600, remarkably close to the case with no account-level controls (\$508,770). However, adding these controls reduces the variability across salary levels: the median wealth is 2.1 times the wealth of a worker earning the 10th percentile salary, and 44% of the wealth of a worker earning the 90th percentile. The same is true for the 57 years old worker, for whom these proportions are 2.34 times and 39%. On the contrary, controlling for account-level characteristics increases the variance for the 26 years old workers, whose median wealth at retirement is now 1.61 times the wealth he would have if his salary went from the median to the 10th percentile of salaries for people his age, and 53% of the wealth he would have if he earned the 90th percentile salary.

The scenarios for the 57 and the 26 years old workers also illustrate how those in the 10th and 90th percentiles in these groups have experienced, or are on, different trajectories in the labor market. A 57 years old worker at the 10th percentile of salary has typically been at his current firm for only 3.4 years, has a very small account balance, \$3,057, low contribution rates for his age, 4.3%, and has only 60% of his portfolio invested in equities. On the contrary, a 57 years old worker at the 90th percentile of the salary distribution for her age, has typically been at her current firm for more than 16 years, has a very large account balance, \$171,567 on average, takes advantage of the additional contributions allowed after age 55 and contributes a large fraction of her salary, 16.1%, and invests 64% of her retirement portfolio in stocks. On the contrary, relative to his counterpart at the 90th percentile, a 26 years old earning the 10th percentile salary for his age has been at his current company longer (2.33 vs. 1.94 years), contributes a smaller fraction of his salary (2.29% vs. 6.68%), and allocates a significant lower fraction of his account to equities (59% vs. 78%). These profiles exemplify the interplay of labor market trajectories, and saving and investment choices in determining variation in wealth levels at retirement.

Column (5) of Panel A shows the coefficients from including plan and firm characteristics in the regressions, and the third section of Panel B performs the wealth calculations for this case, under the various scenarios outlined above. All else equal, workers employed at companies with more generous employer contributions, companies that are older, are more likely to be private, invest more, and have higher net income tend to have more wealth by the time they reach retirement age. On the contrary, workers employed at companies that all else equal are larger in terms of assets and number of employees tend to have lower wealth on average. Adding firm and plan characteristics increases the R^2 from 78.1% to 83.4%. Further, Column (6) of Panel A shows that the coefficients are robust to including company fixed effects instead of controlling explicitly for firm-level characteristics. The results in the third section of Panel B indicate that workers sort into companies that exacerbate the cross sectional variance in retirement wealth highlighted in the second and first sections, and that this is especially the case for younger workers. Once we take company features into account, the median wealth at age 65 for a worker who is 26 in our sample and earns the median salary for his age is 2.44 times the wealth he would have if he earned the 10th percentile salary and 47% of the wealth he would have if he earned the 90th percentile salary. This spread is significantly larger than the ones we have calculated based on just age and salary (1.56 times vs. 58%) or age, salary and account-level variables (1.61 times vs. 53%). Panel B shows that this spread also increase for workers of median and 90th percentile age, albeit to a lesser extent.

Column (7) of Panel A shows that the coefficients on financial literacy and the education dummies have the expected sign, and are statistically significant at the 5% or 10% level.[37]

Finally, as one might expect, wealth heterogeneity is even larger if we considered other percentiles of the account-level and firm-level variables, instead than the median for the specific age and corresponding salary intervals. For example, a 41 year old worker earning the 10th percentile salary and having account balances, contribution rates and equity allocations at the 10th percentile of the sample, would have retirement wealth of $116,390. Similarly, a 41 year old worker earning the 90th percentile salary and having account balances, contribution rates and equity allocations at the 90th percentile of the sample, would have retirement wealth of $1.4 millions.

7.2 Consumption retirement replacement ratios

We next turn our attention to the regressions of the consumption retirement replacement ratios (CRRRs), reported in Panels C and D. The coefficients in Panel C show that the CRRRs are a convex function of age, and that, unlike for retirement wealth, salary is not a statistically significant determinant of consumption replacement ratios once we add regressors to the analysis. Column (4) shows the important role of contribution rates in determining retirement adequacy. A one percentage point increase in contribution rates generates a 2.67 ppts increase in CRRR, corresponding to a consumption level 2.67 ppts higher in all retirement years. The size of the account and the equity share have the expected positive and statistically significant coefficients, but the economic magnitudes of their effect is smaller: a $10,000 increase in account balance corresponds to 69 basis points increase in CRRR, while a 10 ppts increase in the equity share corresponds, all else equal, to a 58 bps increase in CRRR.

Similar to the findings on median retirement wealth, a longer tenure at the firm has all else equal a negative effect on CRRRs: a 5 year increase in tenure corresponds to a 4.87% lower CRRR. Column (5) of Panel C shows that a more generous employer match, proxied by a higher tier one percentage match rate, is associated to a large increase in retirement consumption: a 10 ppts higher employer match generates a 2.95 ppts higher

[37]Financial literacy scores are available at the state level, while information on the fraction of the population with high school, bachelor, or advance degrees is available at the zip code level.

annual retirement consumption. Regressions available upon request indicate that the results are robust to more complex specifications of the employer matching contribution scheme, and that the effect of higher fees is negative but not statistically significant. The same column shows that all else equal workers employed at firms that are private, older, and have higher capital expenditures and net income tend to have higher CRRRs on average. On the contrary, workers at larger firms and firms with more employees have on average lower CRRRs. Finally, Column (7) shows that workers living in areas with higher financial literacy and with a higher fraction of college educated people tend to have higher CRRRs.

Panel D of Table 11 provides the calculations of CRRRs for workers with various profiles, similarly to the analysis reported in Panel B for the median wealth at retirement. The most striking result is that younger workers are more likely to have CRRRs close to or greater than 1, while workers on their 40s and older are more likely to experience significant shortfalls. For example, based on the specification in Column (7) of Table C, the worker of median age (41), median salary for that age and average values of account size, contribution rates, equity share, tenure, and other firm-level characteristics has an expected median CRRR of 0.81. The higher her risk aversion, the bigger the additional shortfall, measured in CEQR terms, would be. The situation is particularly worrisome for older workers who are closer to retirement and have less time to make changes to their savings and investment decisions. A worker aged 57, the 90th percentile of age, earning the median income for his age bracket and for whom the other covariates are set at the average value for his age group, can expect a median CRRR of just 0.77.

7.3 Age Splits

Table 12 reports the median consumption retirement replacement ratios (λ) and the certainty equivalent ratio (CEQR) from the baseline simulations for different age groups.

The median CEQRs are a U-shape function of age, with values of 0.89 and 0.88 for the younger and older cohorts respectively, in contrast with only 0.83 for the median cohort. However the dispersion of outcomes increases significantly with age. The difference in CRRRs (CEQRs) between the 10th and 90th percentiles increases from 0.67 (0.41) for the younger cohort to 1.01 (0.61) for the oldest one.

This increase in dispersion is primarily driven by the left tail of the distribution. The values of CRRRs and CEQRs at the $90th$ and $75h$ percentiles reveal the same u-shape pattern observed at the median. On the contrary, the values at the left tail decrease monotonically with age. For the CRRRs, they fall from 1.08 to 0.83 and from 0.96 to 0.67, respectively for the $25th$ and $10th$ percentiles. Almost 90% of those in the younger cohort, ages 20 to 35, have median CRRRs of 1 or higher, while only about 50% of those in the older groups have the same level of retirement preparadness.

The increase in dispersion is probably to expected, since it reflects differences in behavior and plan features over many more years. However, the fact that is concentrated on the left tail of the distribution is particularly concerning, since these individuals that have less time to adjust their current wealth accumulation path. Information sessions and other measures to improve retirement savings behavior will likely have a better chance of improving the final outcome of younger agents. Those who are close to retirement have much fewer years left to benefit from any potential changes.

Based on the regression results described in the previous Section, one important factor behind these differences is heterogeneity in the features of the pension plans themselves, with younger individuals being enrolled in more generous plans. We find that this is indeed the case, although the differences are not too large. Younger cohorts are enrolled in plans where the level of the matching contributions matching is more generous. Their employers match, on average, 66% of their contributions up to a limit of 3.2% and 9% up to an additional 0.8%. By comparison, for the rest of the population the employers match is, on average, 60% of the contributions up to a limit of 3.2% and 8% up to an additional 0.7%.

8 Counterfactual Experiments

8.1 Methodology

In this section we attempt to quantify the impact of alternative policy interventions to improve retirement wealth accumulation, by performing a series of counterfactual experiments.

One limitation of this approach is that it is subject to the Lucas critique. Since we are not using a structural model with optimizing agents, we are not computing their optimal responses to the policy changes, but rather we are assuming that the stochastic processes for contributions and portfolio allocations will remain unchanged after the policy implementation. Assuming a structural model could potentially avoid the Lucas critique, but ultimately its predictions would be reliable only if it captured the behavior of the individuals in our sample reasonably well, i.e. it matched the contribution rates and portfolio allocations that we observe, not only in the aggregate but also at the individual level. Given that individuals in our sample do not seem to behave optimally along several dimensions (e.g. contribution rate and asset allocation), such a model would be extremely difficult to develop, and might be of limited value in capturing real life retirement savings. Indeed, the empirical evidence on this issue suggest that individuals often respond very passively to changes in the features of their 401(k) plan, both in terms of contribution rates and investment decisions (e.g. Choi, J., D. Laibson and B. Madrian (2009) , Choi, J., D. Laibson, B. Madrian and A. Metrick (2004), Choi, J., D. Laibson, B. Madrian and A. Metrick (2003) and Madrian and Shea (2001)).

Finally, in all our counterfactual experiments we will keep non-retirement wealth ($W_{65}^{FW} + \theta W_{65}^{HW}$) constant at the level estimated in the baseline scenario. We view our results as a best-case scenario, since some workers, when forced to increase their contributions to DC accounts, might respond by saving less in other accounts. Chetty et al (2014) provide evidence that the amount of crowding out of non-retirement savings induce by an induced increase in retirement savings depends on the whether the policy aims at changing savings rates by active or passive choice. They find that policies that rely upon individuals to take an action to take advantage of the incentives offered cause crowding out, while policies that raise retirement contributions if individuals take no action increase wealth accumulation substantially, because of inertia. Therefore, it is certainly not unreasonable to expect that the workers might only marginally adjust their non-retirement savings if faced with some of these changes.

8.2 Removing penalty-free withdrawals at 59 1/2

Munnell and Webb (2015) show that individuals withdraw significant amounts from their retirement accounts before age 65. Restricting these withdrawals could therefore potentially help decrease the large shortfalls in wealth accumulation that we have documented. While strong arguments can be made for allowing individuals to withdraw funds due to hardship or a job separation, we consider a less severe measure, namely removing the ability to withdraw funds from age 59 1/2 onwards without a justification.[38]

Table 13 shows that this measure would have the largest impact on the wealth accumulation of the workers in the bottom half of the distribution, and would cause increases in wealth at age-65 ranging between 15% and 20%. The reason is that both the probability of a withdrawal and the percentage of the account value being withdrawn are decreasing functions of wealth (see section 3.2). Nevertheless, the increases in CRRRs and CEQRs would be higher for workers who were already better-off in the baseline scenario, since the fraction of retirement consumption financed by DC wealth is increasing in total wealth.[39] Overall, the results in Table 13 show that preventing individuals from withdrawing funds from their DC accounts after age 59 1/2 without justification can increase annual retirement consumption levels by 5% to 10% in the worst scenarios. These results confirm the importance of reducing "leakages" as documented by Munnell and Webb (2015). Despite these large effects, even after implementing this policy about 2/3 of the workers would still end up with a CEQR below 1, and 25% of them would still have a median CRRR below 1, due to the low CRRRs and CEQRs in our baseline results. In addition, as pointed out above, our results could be worse if we allowed some crowding-out of non-DC wealth.

8.3 Minimum contribution rates

In this section we explore the effect on retirement preparedness of a mandatory minimum contribution rate of either 2.5% or 5%. For comparison's sake, the average contribution rate in our sample is 6.3%, the median is 5.2%, and the 25th percentile is 2.2%.

[38] Withdrawals after age 60 due to hardship or job seperation would still be allowed.
[39] The fraction financed by social security decreases with wealth.

Panel A of Table 14 shows that imposing a minimum contribution rates of 2.5%, or even 5%, has a negligible effect on the retirement savings of the workers in our sample. The increases in consumption retirement replacement ratios never exceed 0.02 and, as discussed above, such increases would be lower or inexistent if we allowed for crowding out of non-retirement wealth. To check whether these results are due to the fact that for the those close to retirement these measures might be coming too late, and that by averaging across all ages we are not seeing the large positive impact for the younger cohorts, in Panel C, we report results across different age groups for the case of a 5% minimum contribution rate. We find that while for workers younger than 35 the CRRRs increase by about 0.04, for all other age groups the improvements are very small.[40]

These results might seem surprising given that in our sample many workers have contribution rates lower than 2.5% and 5%. However, this is true mostly for younger workers who also tend to have lower income. As income increases over the life-cycle, individuals also increase their average contribution rates, and indeed most workers in our sample contribute in excess of these thresholds.[41]

Imposing higher minimum contribution rates for all individuals could have undesired effects. Early in the life cycle most savings are precautionary in nature and should not be invested in an illiquid retirement account. Carroll (1997), Gourinchas and Parker (2002), and Gomes, Michaelides and Polkovnichenko (2009) show that the optimal retirement saving rate of the young can be much lower than 5%. Forcing young workers to contribute 7% or 8% to their DC accounts is suboptimal and could lead several of them to opt-out of the pension plan altogether. Thus, we explore the possibility of setting an age-dependent minimum contribution rate. More precisely, we consider the following rule

$$k_{\min} = 4.5\% + (age - 21) * 0.25\% \tag{37}$$

where the minimum contribution age averages to 10% between ages 21 to 65, but starts at a low level of 4.5% and increases gradually to 15.5% just before retirement, when the worker

[40] A 0.04 increase in CRRR represents to a 4% increase in annual consumption *every year* during retirement.

[41] In our sample,58% of workers younger than 35 have contribution rates below 5%, while only 43%of older workers do.

can presumably afford to save more.

The results are reported in Table 15 and show reasons for optimism. Panel A reports increases in certainty equivalent ratios of about 3 percentage points for those in the left tail of the distribution. More importantly, Panel B shows that the gains are equally distributed across all age groups, and, for those closer to retirement, the gains are particularly high at the left tail of the distribution.

8.4 Increase in contributions

In this section we study the impact of an increase in the actual contributions, by either 2 or 5 percentage points. We do not regard this exercise as evaluating a specific policy suggestions, as it would be hard to force individuals to increase their current contributions by a specific amount/percentage. Instead, our goal is to evaluate the additional savings effort required to address the shortfalls that emerged from our baseline results.

The results reported in Table 16 are promising. A 2 percentage points increase in contributions improves retirement consumption levels by 2% to 9%. A 5 percentage points increase raises the standard-of-living at retirement by an amount between 4% to 20%. It is worth noting that a 5 ppts increase in retirement contributions represents a quite significant savings effort. Also, the improvements are highest for those who were already better off. Compared to the baseline results in Table 7, the percentage of workers that are not saving enough for retirement (CEQR less than 1) falls from 3/4 to about 2/3. While this is a quite significant improvement, these figures are still worrisome and highlight the magnitude of the current under-savings problem.

Panel C shows how the results of an increase in contribution rates of 2 ppts vary across age groups. We find that for younger workers, even this moderate increase in contribution rates has a very large impact, with increases in CRRR between 0.09 to 0.15, and even for those in 30 to 39 age group annual retirement consumption would increase by about 4% to 5%.

9 Conclusions

In this paper we explore retirement savings adequacy in the US using a large panel dataset comprising the contribution rates, salary, tenure, account value, plan features, and asset allocations of more than 300 thousand US workers. We find that based on their current account balances, income, saving, and investment behavior, about 3/4 of the workers in our sample are not saving enough for retirement. Several factors contribute to the cross-sectional dispersion of outcomes across individuals. The most significant ones are the heterogeneity in the generosity of employer contributions and individual saving rates and asset allocations.

Our results are robust to various alternative calibrations. Only if we assume both low risk aversion and very high discount rates, we find that the median worker is saving enough. While the picture of retirement preparedness in the U.S. emerging from our analysis is somber, there are various reasons to believe it is an understatement of the paucity of retirement savings, as based on data from the Bureau of Labor Statistics only 65% of private sector workers have access to a retirement plan, and only 48% participate in it. Furthermore, we have not included in our analysis risks such as potential reductions in social security benefits, or higher future medical costs.

Finally, the analysis we have conducted here is in many ways exploratory, and many open questions remain. We have only analyzed a few policies aimed at increasing retirement savings, missing, among others, postponing retirement, mandatory automatic enrollment for all workers, and financial education. In future work we also plan to explore a wider range of preference parameters and return environments, and to allow for more asset classes.

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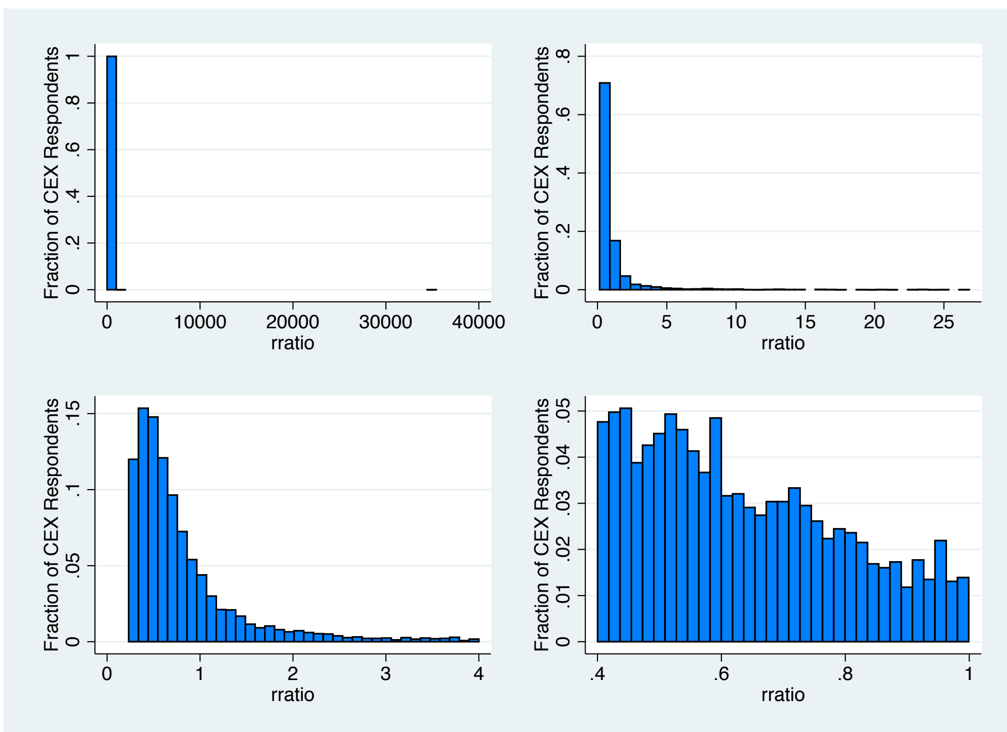
Figure 1
Distribution of Total Expenditures over Salary in the Consumer Expenditure Survey and in our Sample

Panel A illustrates the distribution of total expenditures over salary in the Consumer Expenditure Survey for various ranges of this ratio, while Panel B illustrates the distribution of fitted total expenditures over salary in our sample for those same ranges. The fitted values are computed based on the coefficients of a regression of total expenditures on a flexible specification of age and salary, reported in Table 6. The sample is based on our data and the 2006-2011 Waves of the Consumer Expenditure Survey (CEX) and comprises all respondents between the age 20 of and 65. Total expenditure is defined as the sum of food and alcohol, tobacco, apparel and services, entertainment, personal care, housing and shelter, health, reading and education, transportation, cash and pension contributions, and miscellaneous. Since the CEX measures expenditures at the household level, we use the methodology proposed by Deaton and Zaidi (2002) to calculate adult equivalents for each household and convert household-level into individual-level expenditures. The top left quadrant of Panel A graphs the ratio of total expenditures over salary for all values of the ratios; the top right quadrant restricts the ratios to the 1st-99th percentile range; the bottom left quadrant restricts the ratios to the 5th-95th percentile range; while the bottom right quadrant restricts the ratios to the 25th-75th percentile range, corresponding to ratios between 0.4 and 1. Panel B reports the ratio of fitted total expenditures over salary generated based on the coefficients from the CEX regressions performed on the 25th-75th percentile range.

Panel A - Distribution of Total Expenditures over Salary in the Consumer Expenditure Survey



Panel B - Distribution of Fitted Values of Total Expenditures over Salary in our Sample

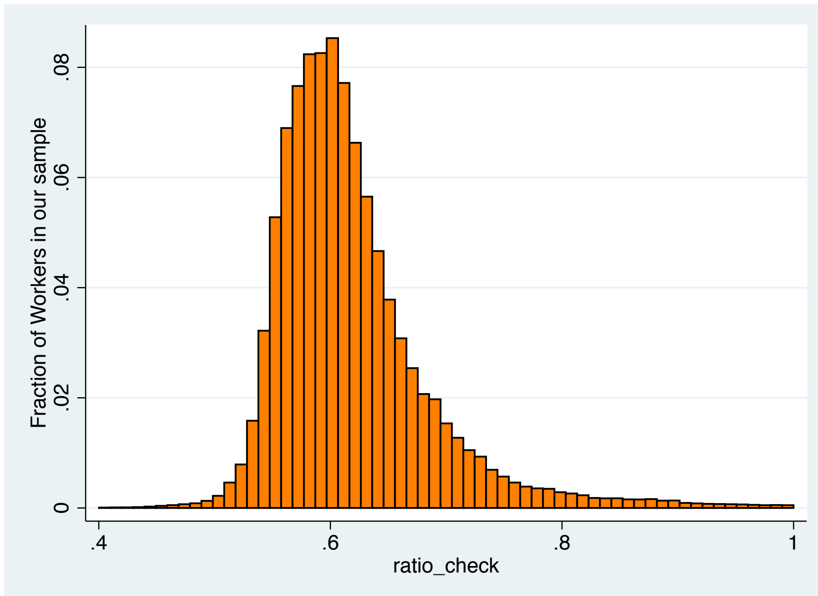


Table 1
Summary Statistics

Panel A presents the mean, median, standard deviation, 5^{th}, 25^{th}, 75^{th} and 95^{th} percentiles and number of observations for the full dataset (Panel A), our sample (Panel B) the baseline sample (Panel C). Our sample comprises the last sample observation for all workers with valid tenure data, who earn more than the minimum wage salary, and whose individual characteristics are not missing. The baseline sample is comprised by the subset of workers in sample working at firm that only offer defined contribution plans. Panel D reports the summary statistics for the firms who offer both DC and DB plans and the ones that offer only DC plans, respectively. All variables are defined in the Appendix.

Panel A – All Data

	Mean	Std Dev	5th Percentile	25th Percentile	Median	75th Percentile	95th Percentile	Obs
Age	45.388	11.907	26.000	36.000	46.000	54.000	64.000	19,480,608
Salary	57,184	46,868	15,272	32,397	46,859	71,768	125,738	14,741,368
Tenure at the firm	10.486	10.555	0.123	2.033	7.225	15.992	31.838	13,712,690
Contribution Rate	0.065	0.068	0.000	0.005	0.056	0.091	0.187	14,741,368
Account Balance	62,653	113,564	283	5,325	22,153	73,092	255,756	19,480,608
% invested in Bonds	20.689	20.492	0.000	4.000	14.000	33.000	62.000	19,480,608
% invested in Equity	64.959	32.422	0.000	46.000	76.000	90.000	100.000	19,480,608
Bond fees	0.278	0.181	0.040	0.124	0.226	0.450	0.529	19,480,608
Equity fees	0.339	0.223	0.038	0.184	0.292	0.469	0.755	19,460,357
Median House Value (Zillow)	269,176	209,779	81,300	138,500	205,800	331,600	655,100	15,459,599

Panel B – Our sample

	Mean	Std Dev	5th Percentile	25th Percentile	Median	75th Percentile	95th Percentile	Obs
Age	42.442	11.293	24.000	33.000	43.000	51.000	60.000	1,557,920
Salary	56,739	48,002	14,315	31,065	46,540	71,690	125,043	1,557,920
Tenure at the firm	9.850	9.467	0.077	2.134	6.912	14.981	29.545	1,557,920
Contribution Rate	0.069	0.068	0.000	0.023	0.056	0.100	0.196	1,557,920
Account Balance	56,588	109,829	160	2,145	14,559	63,419	251,734	1,557,920
% invested in Bonds	19.360	19.306	0.000	4.000	13.000	30.000	57.000	1,557,920
% invested in Equity	67.000	31.166	0.000	49.000	78.000	90.000	100.000	1,557,920
Bond fees	0.264	0.179	0.030	0.117	0.240	0.437	0.522	1,557,920
Equity fees	0.334	0.225	0.047	0.177	0.271	0.476	0.759	1,557,920
Median House Value (Zillow)	256,438.291	203,851.720	79,300.000	131,200.000	190,700.000	312,900.000	631,300.000	1,557,920

Panel C – Baseline sample

	Mean	Std Dev	5th Percentile	25th Percentile	Median	75th Percentile	95th Percentile	Obs
Age	41.323	11.380	24.000	32.000	41.000	50.000	60.000	371,739
Salary	54,522	40,004	16,675	30,978	44,599	69,721	117,706	371,739
Tenure at the firm	7.780	8.319	0.192	1.647	4.753	10.847	26.266	371,739
Contribution Rate	0.063	0.064	0.000	0.022	0.052	0.087	0.188	371,739
Account Balance	42,443	97,553	202	1,244	7,557	38,040	203,952	371,739
% invested in Bonds	25.612	20.942	0.000	9.000	20.000	46.000	63.000	371,739
% invested in Equity	61.928	30.794	0.000	44.000	70.000	89.000	99.000	371,739
Bond fees	0.253	0.171	0.080	0.090	0.210	0.429	0.514	371,739
Equity fees	0.327	0.204	0.058	0.193	0.277	0.398	0.732	371,739
Median House Value (Zillow)	320,801.037	239,415.004	89,000.000	155,600.000	244,800.000	428,600.000	745,500.000	371,739

Panel D – Firm Summary Statistics

	Mean	Median	Std Dev	Obs	Mean	Median	Std Dev	Obs
Private	0.568	1.000	0.497	183	0.593	1.000	0.495	59
Foreign Parent	0.142	0.000	0.350	183	0.169	0.000	0.378	59
Firm Age	73.029	71.500	44.427	170	61.563	48.000	41.747	56
Assets	55,955.348	7,238.679	241,462.372	108	23,732.156	2,867.432	67,193.587	35
Employees	26,941	8,200	60,944	169	19,389	6,596	43,714	55
Capital Expenditures	949.834	319.102	1,321.633	89	859.716	127.393	1,432.365	27
Net Income	347.365	176.836	4,217.621	108	572.292	151.798	1,497.600	35
Leverage	29.335	28.297	20.825	89	29.260	28.916	17.552	27
Investment Intensity	4.479	3.750	3.439	89	4.688	3.583	3.630	27

Table 2
Employer Contributions

This Table presents summary statistics for the parameters characterizing the employer contribution schemes in our sample. k^{e0}_i denotes the portion of the employer contribution independent from the employee's own contributions, expressed as a fraction of the worker's salary, while the other parameters capture the matching portion of the employer contribution (K_i^{match}), which is specified as

$$K_i^{match} = \begin{cases} \kappa_i^{e1} * k_{it} & \text{if } k_{it} \leq \overline{k}_i^{e1} \\ \kappa_i^{e1} * \overline{k}_i^{e1} + \kappa_i^{e2} * (k_{it} - \overline{k}_i^{e1}) & \text{if } \overline{k}_i^{e1} < k_{it} \leq \overline{k}_i^{e2} + \overline{k}_i^{e1} \\ \kappa_i^{e1} * \overline{k}_i^{e1} + \kappa_i^{e2} * \overline{k}_i^{e2} + \kappa_i^{e3} * Min\{k_{it} - (\overline{k}_i^{e2} + \overline{k}_i^{e1}), \overline{k}_i^{e3}\} & \text{if } k_{it} > \overline{k}_i^{e2} + \overline{k}_i^{e1} \end{cases}$$

	Selected Sample					DC-only sample				
Variable	Mean	Std.Dev.	25th	50th	75th	Mean	Std.Dev.	25th	50th	75th
k_i^{e0}	1.83%	3.80%	0.0%	0.0%	2.0%	1.58%	2.23%	0.0%	0.0%	5.0%
κ_i^{e1}	72%	57%	50%	60%	100%	63%	45%	0.0%	100%	100%
$\overline{k}_i^{e1}$	3.82%	6.80%	1%	4%	6%	3.13%	2.57%	0.0%	4.5%	6.0%
κ_i^{e2}	16%	27%	0%	0%	25%	9%	19%	0%	0%	0%
$\overline{k}_i^{e2}$	1.35%	2.06%	0%	0%	3%	0.79%	1.83%	0.0%	0.0%	0.0%
κ_i^{e3}	1%	5%	0%	0%	0%	0%	0%	0%	0%	0%
$\overline{k}_i^{e3}$	0.06%	0.53%	0%	0%	0%	0.00%	0.02%	0.0%	0.0%	0.0%

Table 3
Estimation of Leakage Parameters

This table presents the calculations underlying the estimation of the parameters for the leakage events. Panel A covers unemployment and job separation events, while Panel B covers withdrawals from age 59 1/2 onwards. The salary decile thresholds in Panel B are $17,381, $24,954, $30,640, $36,036, $42,404, $50,567, $60,201, $ 73,763, and $93,540. Column (2) and (3) are based on Table 2 in Munnell and Webb (2015) and Vanguard's *How America Saves* for year 2013. Column (4) is based on Engelhardt (2003), who estimates that in case of unemployment, the probability of cashing out is 46.7 % higher than for job switches. All other calculations are based on our data.

	(1)*	(2)*	(3)	(4)	(5)	(6)	(7)	(8)
Age	% of Participants cashing out upon job separation	% of available $ in account that is cashed out	**% of Participants cashing out upon unemployment****	**% of Participants cashing out upon job separation different than unemployment**	**Total Assets available to these age categories (from our dataset)**	**# of people**	**Average Account Value**	**Total Asset Available to those who left**
20s	35%	15%	**43.84%**	**30.03%**	$ 3,290,000,000	397,908	$ 8,268	$ 542,514,420
30s	32%	11%	**39.97%**	**27.38%**	$ 18,800,000,000	681,738	$ 27,577	$ 2,460,416,160
40s	32%	10%	**39.83%**	**27.28%**	$ 46,700,000,000	787,604	$ 59,294	$ 5,416,597,570
50s	24%	7%	**29.82%**	**20.42%**	$ 75,100,000,000	729,114	$103,002	$ 8,582,180,170
60s	19%	4%	**23.61%**	**16.17%**	$ 29,800,000,000	261,404	$114,000	$ 3,757,270,420
70s	26%	6%	**32.45%**	**22.22%**	$ 2,520,000,000	21,727	$115,985	$ 411,013,512
All Ages	**28.80%**	**7%**	**35.90%**	**24.59%**	**$ 176,210,000,000**	**2,879,495**	**$ 61,195**	**$ 22,395,991,443**

	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)
Age	**prob of unemployment**	**# of people becoming unemployed**	**prob of job switch or retirement**	**# of people switching jobs**	**Amount of Total Asset Withdrawn by those who left**	**# of People Withdrawing upon unemployment**	**Average Amount Withdrawn**	**Fraction of Own Account Withdrawn**	**# of People Withdrawing upon job switch**
20s	**5.94%**	23,621	**10.55%**	41,993	$ 81,377,163	10,356	$ 3,544	**42.86%**	12,609
30s	**4.80%**	32,752	**8.28%**	56,469	$ 270,645,778	13,091	$ 9,479	**34.38%**	15,460
40s	**4.36%**	34,331	**7.24%**	57,021	$ 541,659,757	13,675	$ 18,529	**31.25%**	15,557
50s	**4.35%**	31,710	**7.08%**	51,611	$ 600,752,612	9,456	$ 30,042	**29.17%**	10,541
60s	**4.79%**	12,516	**7.82%**	20,442	$ 150,290,817	2,956	$ 24,000	**21.05%**	3,306
70s	**6.02%**	1,309	**10.29%**	2,235	$ 24,660,811	425	$ 26,766	**23.08%**	497
All Ages	**4.73%**	**136,239**	**7.98%**	**229,740**	**$ 1,567,719,401**	**48,910**	**$ 14,874**	**24.31%**	**56,492**

Panel B – Withdrawal from age 59 ½ onwards

Salary Threshold	Average Account value	# of people	Cumulative # of People	Total Account $$ in that salary decile	Fraction withdrawn by salary decile	Probability of withdrawing by salary decile
Less than $17,381	$ 28,201.39	28,317	28,317	$ 798,578,761	0.47	17.70%
Between $17,381 and $24,954	$ 28,554.39	28,310	56,627	$ 808,374,781	0.46	17.70%
Between $24,954 and $30640	$ 46,779.13	29,029	85,656	$ 1,357,951,365	0.28	13.00%
Between $30,640 and $36,036	$ 60,647.59	27,598	113,254	$ 1,673,752,189	0.22	13.00%
Between $36,036 and $42,404	$ 71,740.23	28,312	141,566	$ 2,031,109,392	0.18	9.49%
Between $42,404 and $50,567	$ 95,148.48	28,422	169,988	$ 2,704,310,099	0.14	9.49%
Between $50,567 and $60,201	$ 121,029.00	28,211	198,199	$ 3,414,349,119	0.11	4.75%
Between $60,201 and $73,763	$ 155,783.50	28,307	226,506	$ 4,409,763,535	0.08	4.75%
Between $73,763 and $93,540	$ 210,436.00	28,318	254,824	$ 5,959,126,648	0.06	2.50%
More than $93,540	$ 322,656.10	28,307	283,131	$ 9,133,426,223	0.04	2.50%

Table 4
Estimation of Outside Wealth

This Table reports the summary statistics (Panel A) and the regression coefficients (Panel B) used in the estimation of outside wealth for each individual in our sample. The sample is based on our data and the 2010 Wave of the Health and Retirement Study (HRS) and comprises all married individuals between the age 62 of and 67.

Panel A – Summary statistics

	Account Value at Last Employer	Account Value at Last Employer, if >0	Total Retirement Wealth	Total Retirement Wealth, if >0	Total Account Value in our sample at the end of 2010 for workers of age >=62 & <=67
Mean	120,843.81	121,373.83	103,066.58	125,992.75	121,011.50
Std. Dev	223,700.48	224,047.13	311,246.68	216,389.62	197,142.90
10th pctile	3,000.00	3,000.00	0.00	6,000.00	707.65
25th pctile	12,000.00	12,000.00	0.00	19,000.00	11,086.34
Median	45,117.50	46,000.00	5,000.00	51,000.00	52,639.49
75th pctile	138,100.00	139,500.00	100,000.00	148,000.00	156,789.10
90th pctile	300,000.00	300,000.00	300,000.00	300,000.00	316,010.70
N of Obs	2,748.00	2,736.00	22,035.00	9,219.00	49,891.00

Panel B – Regression analysis

	(1) Total Outside Wealth	(2) Total Outside Wealth	(3) Total Outside Wealth	(4) Total Outside Wealth
Total Retirement Wealth	0.117***	0.109***	0.107***	0.103***
	[6.752]	[6.789]	[6.204]	[6.503]
Salary			1.784***	1.772***
			[7.271]	[7.708]
Constant	116,607***	136,353***	88,735***	99,544***
	[9.896]	[10.24]	[7.249]	[7.179]
Observations	1,894	1,271	1,894	1,271
Adjusted R^2	0.023	0.034	0.049	0.077
Conditional on Total Retirement Wealth>0>0	No	Yes	No	Yes

Table 5
Estimation of Housing Equity

This Table reports the summary statistics (Panel A) and the regression coefficients (Panel B) used in the estimation of housing equity for each individual in our sample. The sample is based on our data and the 2010 Wave of the Health and Retirement Study (HRS) and comprises all married individuals between the age 62 of and 67.

Panel A – Summary statistics

	Mean	**Std Dev**	**10th Percentile**	**25th Percentile**	**Median**	**75th Percentile**	**90th Percentile**	**Obs**
LTV for all Real Estate	0.266	0.425	0.000	0.000	0.065	0.442	0.760	2,294
LTV 1st Residence	0.274	0.433	0.000	0.000	0.057	0.468	0.782	2,294
Value of 1st Residence in the HRS	227,542.232	249,980.558	50,000.000	95,000.000	170,000.000	275,000.000	450,000	2,322
Value of Other Real Estate in the HRS	38,106.814	171,393.398	0.000	0.000	0.000	0.000	89,000	2,322
Total Value of Real Estate in the HRS	265,649.046	331,396.090	50,000.000	100,000.000	177,000.000	300,000.000	550,000	2,322
Median House Value in the Zip code in our sample (from Zillow)	260,598.262	191,755.734	100,400.000	138,000.000	198,100.000	325,200.000	493,500	42,875

Panel B – Regression analysis

	(1)	(2)	(3)	(4)
	Homeowner	Homeowner	LTV 1st Residence	LTV for all Real Estate
Total Retirement Wealth	2.16e-06***	1.23e-06***	-1.63e-08	-1.74e-08
	[5.586]	[3.176]	[-1.147]	[-1.185]
Salary	-3.04e-07	-1.52e-06	3.79e-07*	3.55e-07*
	[-0.186]	[-1.446]	[1.854]	[1.647]
Constant	1.215***	1.540***	0.267***	0.259***
	[23.03]	[18.19]	[25.44]	[19.78]
Observations	1,894	1,271	1,739	1,216
Adjusted R^2	0.0548	0.0352	0.001	0.002
Conditional on Total Retirement Wealth>0>0	No	Yes	NA	NA

Table 6
Estimation of Working-age Consumption

This Table reports the regression coefficients used in the estimation of working age consumption for each individual in our sample. The sample is based on our data and the 2006-2011 Waves of the Consumer Expenditure Survey (CEX) and comprises all respondents between the age 20 of and 65. Total expenditure is defined as the sum of food and alcohol, tobacco, apparel and services, entartainment, personal care, housing and shelter, health, reading and education, transportation, cash and pension contributions, and miscellaneous. Since the CEX measures expenditures at the household level, we use the methodology proposed by Deaton and Zaidi (2002) to calculate adult equivalents for each household and convert household-level into individual-level expenditures. To avoid the effect of outliers and unusual circumstances, we limit the regressions to the interquartile range of the ratio of total expenditure over salary.

	(1)	(2)	(3)	(4)	(5)
	Total Expenditure	Total Expenditure	Total Expenditure	Total Expenditure	Total Expenditure
Respondent Age	52.45***	52.19***	49.69***		
	[3.575]	[3.559]	[3.392]		
Salary	0.504***	0.504***	0.549***	0.553***	
	[96.83]	[96.95]	[41.83]	[42.18]	
$Salary^2$			-2.61e-07***	-2.76e-07***	
			[-3.725]	[-3.944]	
Age 30-39				-1,369**	-12,437***
				[-2.451]	[-8.046]
Age 40-49				-763.0	-9,173***
				[-1.405]	[-6.152]
Age 50-59				120.2	-9,500***
				[0.220]	[-6.317]
Age 60-65				501.5	-9,187***
				[0.696]	[-4.427]
Salary*Age 20-29					0.261***
					[6.311]
$Salary^2$*Age 20-29					8.42e-07***
					[3.315]
Salary*Age 30-39					0.605***
					[20.18]
$Salary^2$*Age 30-39					-7.03e-07***
					[-3.968]

Salary*Age 40-49					0.501***
					[19.37]
Salary^2*Age 40-49					1.39e-08
					[0.100]
Salary*Age 50-59					0.539***
					[21.06]
Salary^2*Age 50-59					-1.67e-07
					[-1.266]
Salary*Age 60-65					0.540***
					[11.69]
Salary^2*Age 60-65					-1.76e-07
					[-0.794]
Constant	2,321***	2,654***	1,162	3,686***	13,593***
	[3.393]	[3.482]	[1.551]	[6.257]	[11.40]
Years Fixed Effects	N	Y	N	N	N
Observations	2,253	2,253	2,253	2,253	2,253
Adjusted R-squared	0.810	0.811	0.811	0.812	0.787

Table 7
Baseline Results

This table shows the results from our baseline simulations. Columns (2) to (6) present the results for different percentiles of the distribution of the consumption retirement replacement ratio (λ) across realizations for the same individual. Columns (8) to (12) report the same statistics but for wealth accumulation at age 65 ($W^T{}_{65}$), and column (7) reports the certainty equivalent ratio. The rows represent percentiles of the distribution across individuals.

	CRRR (λ)					CEQR	$W^T{}_{65}$				
	10%	20%	30%	40%	50%		10%	20%	30%	40%	50%
10th Percentile	0.54	0.61	0.68	0.73	0.78	0.68	117	132	148	164	182
25th Percentile	0.6	0.69	0.76	0.84	0.91	0.76	152	180	208	238	270
50th Percentile	0.69	0.8	0.9	1	1.11	0.86	234	287	339	394	456
75th Percentile	0.8	0.94	1.06	1.2	1.35	0.99	419	526	625	730	850
90th Percentile	0.92	1.08	1.24	1.4	1.59	1.14	668	848	1017	1199	1412

Table 8
Results with Bequest Motive and with No Housing Wealth Availability

Panel A reports the results from assuming a target bequest of $100K (in age-65 present value terms) and that only savings in excess of this amount can be used to finance consumption after retirement. Panel B reports the results from assuming all housing equity is left unused (ϑ=0). Columns (2) through (6), and (8) through (12), present the results for different percentiles of the distribution of λ across realizations for the same individual, from the 10[th] lowest percentile to the median. Columns (7) and (13) report the CEQR from the two experiments. The rows represent percentiles of the distribution across individuals.

	Panel A - 100K Bequest						Panel B: No Housing Wealth					
	CRRR (λ)					CEQR	CRRR (λ)					CEQR
	10%	20%	30%	40%	50%		10%	20%	30%	40%	50%	
10th Percentile	0.29	0.36	0.41	0.48	0.54	0.37	0.46	0.53	0.58	0.63	0.68	0.58
	-0.25	*-0.25*	*-0.27*	*-0.25*	*-0.24*	*-0.31*	*-0.08*	*-0.08*	*-0.10*	*-0.10*	*-0.10*	*-0.10*
25th Percentile	0.36	0.46	0.54	0.63	0.7	0.45	0.49	0.58	0.65	0.71	0.79	0.63
	-0.24	*-0.23*	*-0.22*	*-0.21*	*-0.21*	*-0.31*	*-0.11*	*-0.11*	*-0.11*	*-0.13*	*-0.12*	*-0.13*
50th Percentile	0.5	0.61	0.71	0.83	0.94	0.6	0.54	0.65	0.75	0.85	0.96	0.68
	-0.19	*-0.19*	*-0.19*	*-0.17*	*-0.17*	*-0.26*	*-0.15*	*-0.15*	*-0.15*	*-0.15*	*-0.15*	*-0.18*
75th Percentile	0.65	0.79	0.93	1.06	1.21	0.78	0.63	0.78	0.91	1.05	1.20	0.76
	-0.15	*-0.15*	*-0.13*	*-0.14*	*-0.14*	*-0.21*	*-0.17*	*-0.16*	*-0.15*	*-0.15*	*-0.15*	*-0.23*
90th Percentile	0.79	0.96	1.11	1.28	1.48	0.94	0.75	0.93	1.09	1.25	1.45	0.87
	-0.13	*-0.12*	*-0.13*	*-0.12*	*-0.11*	*-0.20*	*-0.17*	*-0.15*	*-0.15*	*-0.15*	*-0.14*	*-0.27*

Table 9
Alternative Preference Parameters

This Table reports the results from repeating the baseline simulations for different combinations of the preference parameters: risk aversion, discount factor and share of wealth invested in the risky asset. Panels A and B report the median consumption retirement replacement ratio across simulations for the median individual in the sample. Panel A reports the results from alternative asset allocations during retirement, 0%, 50%, or 100% investment in the risky asset, for the baseline risk aversion coefficient of 5. Panel B reports the results for values of risk aversion, 2, 5, and 10, for the baseline risky asset allocation of 50%. Panel C reports the median consumption retirement replacement ratio for individuals in the 10th and 30th percentiles of the distribution, for risk aversion of 2 and retirement risky share of 50%. The rows show how the results vary for different values of the discount factor parameter, from 0.9 to 0.99.

	Panel A: α^R			Panel B: γ			Panel C: λ		
	γ = 5, Median λ			α^R = 0.5, Median λ			γ = 2, α^R = 0.5		
	0%	50%	100%	10%	5%	2%	10%	30%	50%
β=0.99	0.84	0.99	0.97	0.78	0.99	1.24	0.76	1	1.24
β=0.975	0.87	1.01	0.99	0.82	1.01	1.35	0.82	1.09	1.35
β=0.95	0.98	1.11	1.09	0.85	1.11	1.54	0.94	1.24	1.54
β=0.925	1.05	1.2	1.16	0.9	1.2	1.75	1.06	1.4	1.75
β=0.9	1.13	1.29	1.25	0.97	1.3	0.196	1.18	1.56	1.96

Table 10
Lower Expected Returns

This Table reports the results from repeating our baseline simulations assuming the future expected returns on both stocks and bonds will be 1 ppt lower relative to the baseline calibration. Columns (2) to (4) report the results for different percentiles of the distribution of the consumption retirement replacement ratio (λ) across realizations for the same individual. Columns (6) to (8) report the same statistics but for wealth accumulation at age 65 (W^{T}_{65}), while column (5) reports the certainty equivalent ratio. The rows represent different percentiles of the distribution across individuals. Below each entry we report differences relative to the baseline case. For consumption replacement ratios and CEQR, these differences are measured in absolute terms (e.g. $\lambda^{benchmark} - \lambda^{alternative\ scenario}$), while for wealth accumulation these differences are reported as percentage changes ($W^{benchmark} - W^{alternative\ scenario} - 1$).

	CRRR (λ)			CEQR	W^{T}_{65}		
	10%	30%	50%		10%	30%	50%
10th Percentile	0.53	0.65	0.75	0.66	115	143	173
	-0.02	*-0.03*	*-0.03*	*-0.02*	*-2%*	*-3%*	*-5%*
25th Percentile	0.59	0.74	0.88	0.74	147	197	250
	-0.01	*-0.03*	*-0.04*	*-0.02*	*-3%*	*-5%*	*-7%*
50th Percentile	0.66	0.85	1.04	0.83	223	311	408
	-0.02	*-0.05*	*-0.08*	*-0.03*	*-5%*	*-8%*	*-11%*
75th Percentile	0.76	0.99	1.24	0.95	38	557	746
	-0.04	*-0.08*	*-0.11*	*-0.04*	*-9%*	*-11%*	*-12%*
90th Percentile	0.89	1.15	1.44	1.1	604	897	1227
	-0.04	*-0.09*	*-0.15*	*-0.04*	*-10%*	*-12%*	*-13%*

Table 11
Cross-Sectional Regressions

This Table reports the coefficients from cross-sectional regressions of age-65 wealth accumulation ($W^T{}_{65}$) and the median consumption retirement replacement ratio (λ), obtained from our baseline simulations, on multiple individual and plan and firm level characteristics from our original data. Panel A reports the coefficients from the age-65 wealth accumulation regressions while Panel B provides calculations of the median age-65 wealth accumulation for workers with various profiles. More precisely, Column (1) of Panel B reports median age-65 wealth accumulation for a worker of median age, median salary and at the average of the other covariates for that age bracket (40-42); Column (2) of Panel B reports it for a worker of median age, 10th percentile salary and at the average of the other covariates for that age bracket (40-42); Column (3) of Panel B reports it for a worker of Worker of median age, 90th percentile salary and at the average of the other covariates for that age bracket (40-42); Column (4) of Panel B reports it for a worker at the 10th percentile of age, median salary and at the average of the other covariates for that age bracket (25-27); Column (5) of Panel B reports it for a worker at the 10th percentile of age and salary, and at the average of the other covariates for that age bracket (25-27);); Column (6) of Panel B reports it for a worker at the 10th percentile of age, at the 90th percentile of salary, and at the average of the other covariates for that age bracket (25-27); Column (7) of Panel B reports it for a worker at the 90th percentile of age, median salary, and at the average of the other covariates for that age bracket (56-58); Column (8) of Panel B reports it for a worker at the 90th percentile of age, at the 10th percentile of salary, and at the average of the other covariates for that age bracket (56-58); Column (9) of Panel B reports it for a worker at the 90th percentile of age and salary, and at the average of the other covariates for that age bracket (56-58). Similarly, Panel C reports the coefficients from the consumption retirement replacement ratio regressions, while Panel D provides calculations of the median consumption retirement replacement ratios for workers with same profiles as in Panel B.

Panel A - Age-65 Wealth Accumulation ($W^T{}_{65}$) Regressions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Median $W^T{}_{65}$	Median $W^T{}_{65}$	Median $W^T{}_{65}$	Median $W^T{}_{65}$	Median $W^T{}_{65}$	Median $W^T{}_{65}$	Median $W^T{}_{65}$
Age	-39.22***	-32.83***	-29.34***	-23.64***	-17.04***	-19.50***	-15.66***
	[-8.820]	[-6.700]	[-7.101]	[-5.009]	[-6.015]	[-3.734]	[-5.463]
Age squared	0.400***	0.289***	0.226***	0.210***	0.142***	0.170***	0.127***
	[8.766]	[5.568]	[4.456]	[3.875]	[4.715]	[2.824]	[4.268]
Salary	0.0128***	0.0114***	0.0108***	0.0104***	0.0115***	0.0100***	0.0112***
	[14.78]	[12.40]	[12.73]	[12.64]	[10.53]	[11.26]	[10.97]
Salary squared	-6.25e-09***	-5.60e-09***	-5.14e-09***	-4.98e-09***	-1.05e-08***	-4.73e-09***	-1.03e-08***
	[-4.843]	[-4.661]	[-4.986]	[-4.827]	[-6.988]	[-4.718]	[-6.988]
Account Balance		0.00130***	0.000682***	0.00129***	0.00145***	0.00131***	0.00143***
		[5.276]	[3.397]	[5.713]	[4.547]	[8.149]	[4.441]
Contribution Rate			3,203***	3,058***	3,233***	2,917***	3,212***
			[11.64]	[11.56]	[15.69]	[12.12]	[16.00]
Tenure				-15.12***	-17.80***	-14.98***	-17.40***
				[-8.736]	[-5.464]	[-7.308]	[-5.076]
Equity Share				0.712**	0.725*	0.947***	0.731**
				[2.086]	[2.110]	[3.637]	[2.229]

% employer match, 1st tier					3.440***		3.269***
					[3.934]		[4.127]
company the worker is employed at is private					166.6***		153.3***
					[3.575]		[3.531]
Firm Age					1.556**		1.797***
					[2.727]		[3.379]
Total Assets					-0.00159***		-0.00121***
					[-5.072]		[-4.934]
Capital Expenditure					0.0376***		0.0301***
					[3.947]		[3.748]
Net Income					0.0228***		0.0180***
					[3.962]		[3.214]
# of Employees					-0.000563**		-0.000528**
					[-2.349]		[-2.264]
Financial Literacy at the state level							2.862**
							[2.590]
% with advanced degree in the worker's zip code							2.313***
							[3.349]
% with bachelor degree or more in the worker's zip code							1.665**
							[2.441]
% with high school degree or more in the worker's zip code							-2.165**
							[-2.715]
Constant	841.6***	802.1***	623.9***	501.0***	-102.5	414.5***	-121.9
	[8.793]	[7.994]	[7.659]	[4.648]	[-0.930]	[5.055]	[-1.126]
Observations	350,859	350,859	350,859	350,859	195,397	350,859	191,389
Adjusted R-squared	0.586	0.625	0.745	0.781	0.834	0.815	0.839
Firm Fixed Effects	No	No	No	No	No	Yes	No
Firm Clustered SE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Panel B – Median Age-65 Wealth Accumulation (W^T_{65}) for Selected Worker Profiles

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Based on Column (1) of Panel A								
Age	41	41	41	26.000	26.000	26.000	57.000	57.000	57.000
Salary	48323.290	23492.630	103315.800	34292.290	19195.150	65624.680	53270.040	24053.150	106953.900
Median W^T_{65}	508.773	201.542	1161.753	524.522	335.995	906.695	570.677	210.182	1205.237
Ratio of Median Worker Wealth to 10th and 90th percentiles		2.524	0.438		1.561	0.578		2.715	0.473
Spread across ratios			2.086			0.983			2.242
	Based on Column (4) of Panel A								
Age	41	41	41	26.000	26.000	26.000	57.000	57.000	57.000
Salary	48323.290	23492.630	103315.800	34292.290	19195.150	65624.680	53270.040	24053.150	106953.900
Account Balance	10556.540	1583.652	46269.950	2528.786	710.986	5328.661	35332.270	3057.190	171567.500
Contribution Rate	0.052	0.034	0.068	0.034	0.023	0.067	0.063	0.043	0.112
Tenure	5.918	2.734	5.875	3.066	2.329	1.937	11.121	3.496	16.107
Equity Share	75.000	79.000	96.000	73.000	59.000	78.000	60.000	60.000	64.000
Median W^T_{65}	**509.600**	**243.344**	**1151.517**	**490.641**	**303.497**	**926.669**	**488.363**	**208.404**	**1257.965**
Ratio		*2.094*	*0.443*		*1.617*	*0.529*		*2.343*	*0.388*
Spread across ratios			*1.652*			*1.087*			*1.955*
	Based on Column () of Panel A								
Age	41	41	41	26.000	26.000	26.000	57.000	57.000	57.000
Salary	48323.290	23492.630	103315.800	34292.290	19195.150	65624.680	53270.040	24053.150	106953.900
Account Balance	10556.540	1583.652	46269.950	2528.786	710.986	5328.661	35332.270	3057.190	171567.500
Contribution Rate	0.052	0.034	0.068	0.034	0.023	0.067	0.063	0.043	0.112
Tenure	5.918	2.734	5.875	3.066	2.329	1.937	11.121	3.496	16.107
Equity Share	75.000	79.000	96.000	73.000	59.000	78.000	60.000	60.000	64.000
% Employer Match	65.261	76.256	66.206	66.237	55.546	47.717	55.970	73.198	59.464
Private Company	0.428	0.355	0.423	0.430	0.522	0.531	0.492	0.459	0.450
Firm Age	58.612	52.237	61.283	56.738	56.170	69.951	68.498	53.729	79.360
Total Assets	76082.280	70724.960	66124.130	78956.640	70118.510	56320.140	59235.300	74186.580	56960.200

Capital Expenditure	2692.652	2324.690	2266.610	2800.561	2467.323	3048.215	2485.750	2626.364	2821.844
Net Income	2463.469	2190.563	2572.961	2991.847	2035.896	2759.390	1835.898	2264.084	1745.772
# of Employees	68730.090	87278.310	53436.590	71062.260	101228.200	34760.450	51026.620	79551.860	35826.590
Median W^{T}_{65}	**483.731**	**198.083**	**1165.343**	**438.831**	**179.687**	**934.913**	**464.680**	**183.523**	**1305.854**
Ratio		*2.442*	*0.415*		*2.442*	*0.469*		*2.532*	*0.356*
Spread across ratios			*2.027*			*1.973*			*2.176*
	Based on Column (7) of Panel A								
Age	41	41	41	26.000	26.000	26.000	57.000	57.000	57.000
Salary	48323.290	23492.630	103315.800	34292.290	19195.150	65624.680	53270.040	24053.150	106953.900
Account Balance	10556.540	1583.652	46269.950	2528.786	710.986	5328.661	35332.270	3057.190	171567.500
Contribution Rate	0.052	0.034	0.068	0.034	0.023	0.067	0.063	0.043	0.112
Tenure	5.918	2.734	5.875	3.066	2.329	1.937	11.121	3.496	16.107
Equity Share	75.000	79.000	96.000	73.000	59.000	78.000	60.000	60.000	64.000
% Employer Match	65.261	76.256	66.206	66.237	55.546	47.717	55.970	73.198	59.464
Private Company	0.428	0.355	0.423	0.430	0.522	0.531	0.492	0.459	0.450
Firm Age	58.612	52.237	61.283	56.738	56.170	69.951	68.498	53.729	79.360
Total Assets	76082.280	70724.960	66124.130	78956.640	70118.510	56320.140	59235.300	74186.580	56960.200
Capital Expenditure	2692.652	2324.690	2266.610	2800.561	2467.323	3048.215	2485.750	2626.364	2821.844
Net Income	2463.469	2190.563	2572.961	2991.847	2035.896	2759.390	1835.898	2264.084	1745.772
# of Employees	68730.090	87278.310	53436.590	71062.260	101228.200	34760.450	51026.620	79551.860	35826.590
Financial Literacy	40.497	39.825	40.635	40.807	40.266	40.912	40.565	39.912	40.970
% with advanced degree in the worker's zip code	12.515	9.432	17.712	11.181	9.549	15.237	11.618	10.701	15.452
% with bachelor degree or more in the worker's zip code	33.746	27.150	44.637	30.837	27.712	39.168	31.646	29.868	39.499
% with high school degree or more in the worker's zip code	87.591	84.655	91.300	85.168	83.687	86.776	87.758	86.228	90.046
Median W^{T}_{65}	**489.001**	**196.688**	**1175.908**	**437.749**	**181.090**	**938.112**	**462.766**	**182.012**	**1305.089**
Ratio		*2.486*	*0.416*		*2.417*	*0.467*		*2.543*	*0.355*
Spread across ratios			*2.070*			*1.951*			*2.188*

Panel C - Median Consumption Retirement Replacement Ratio (λ) Regressions

	(1) Median λ	(2) Median λ	(3) Median λ	(4) Median λ	(5) Median λ	(6) Median λ	(7) Median λ
Age	-0.0535***	-0.0494***	-0.0464***	-0.0428***	-0.0392***	-0.0415***	-0.0383***
	[-14.41]	[-12.38]	[-17.94]	[-16.82]	[-14.56]	[-19.87]	[-14.45]
Age squared	0.000564***	0.000492***	0.000438***	0.000429***	0.000391***	0.000416***	0.000382***
	[13.88]	[11.53]	[14.75]	[15.59]	[15.46]	[17.38]	[16.30]
Salary	1.75e-06***	8.30e-07***	3.59e-07*	6.73e-08	1.13e-07	-9.11e-08	-2.32e-07
	[6.477]	[3.370]	[1.793]	[0.318]	[0.270]	[-0.439]	[-0.568]
Salary squared	-0**	-0	-0	0	-0	0	-0
	[-2.059]	[-1.347]	[-0.471]	[0.0195]	[-0.957]	[0.655]	[-0.541]
Account Balance		8.36e-07***	3.03e-07**	6.95e-07***	8.12e-07***	6.89e-07***	7.99e-07***
		[4.501]	[2.408]	[4.640]	[4.036]	[5.922]	[3.871]
Contribution Rate			2.759***	2.661***	2.828***	2.578***	2.804***
			[15.83]	[15.98]	[13.77]	[14.84]	[13.74]
Tenure				-0.00975***	-0.0109***	-0.00902***	-0.0105***
				[-7.830]	[-4.529]	[-7.594]	[-4.020]
Equity Share				0.000583*	0.000753**	0.000817***	0.000743**
				[1.853]	[2.699]	[4.309]	[2.723]
% employer match, 1st tier					0.00295***		0.00279***
					[4.393]		[4.306]
Private Company					0.130***		0.120***
					[3.514]		[3.474]
Firm Age					0.00135***		0.00151***
					[3.173]		[3.677]
Total Assets					-6.06e-07**		-3.21e-07
					[-2.384]		[-1.528]
Capital Expenditure					1.57e-05**		9.28e-06*
					[2.638]		[1.885]
Net Income					1.12e-05**		7.77e-06**
					[2.806]		[2.177]
# of Employees					-5.01e-07***		-4.69e-07***
					[-3.051]		[-2.933]
Financial Literacy							0.00374***
							[3.809]

% with advanced degree in the worker's zip code							-0.000391
							[-0.771]
% with bachelor degree or more in the worker's zip code							0.00242***
							[3.488]
% with high school degree or more in the worker's zip code							-0.00117
							[-1.451]
Constant	2.011***	1.985***	1.832***	1.746***	1.280***	1.708***	1.165***
	[26.68]	[24.72]	[30.46]	[22.91]	[13.37]	[35.93]	[10.63]
Observations	350,859	350,859	350,859	350,859	195,397	350,859	191,389
Adjusted R-squared	0.139	0.202	0.556	0.616	0.716	0.708	0.730
Firm Fixed Effects	No	No	No	No	No	Yes	No
Firm Clustered SE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Panel D – Median Consumption Retirement Replacement Ratios (λ) for Selected Worker Profiles

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
					Based on Column (1) of Panel C				
Age	41.000	41.000	41.000	26.000	26.000	26.000	57.000	57.000	57.000
Salary	48323.290	23492.630	103315.800	34292.290	19195.150	65624.680	53270.040	24053.150	106953.900
Median l	**0.843**	**0.801**	**0.932**	**1.059**	**1.033**	**1.111**	**0.881**	**0.831**	**0.967**
Ratio of Median Worker Wealth to 10th and 90th percentiles		*1.052*	*0.905*		*1.025*	*0.953*		*1.059*	*0.911*
Spread across ratios			*0.147*			*0.072*			*0.148*
					Based on Column (4) of Panel C				
Age	41.000	41.000	41.000	26.000	26.000	26.000	57.000	57.000	57.000
Salary	48323.290	23492.630	103315.800	34292.290	19195.150	65624.680	53270.040	24053.150	106953.900
Account Balance	10556.540	1583.652	46269.950	2528.786	710.986	5328.661	35332.270	3057.190	171567.500
Contribution Rate	0.052	0.034	0.068	0.034	0.023	0.067	0.063	0.043	0.112
Tenure	5.918	2.734	5.875	3.066	2.329	1.937	11.121	3.496	16.107
Equity Share	75.000	79.000	96.000	73.000	59.000	78.000	60.000	60.000	64.000
Median l	**0.844**	**0.820**	**0.928**	**1.029**	**0.997**	**1.135**	**0.822**	**0.819**	**1.005**
Ratio		*1.029*	*0.909*		*1.032*	*0.906*		*1.004*	*0.818*
Spread across ratios			*0.119*			*0.126*			*0.185*
					Based on Column (5) of Panel C				
Age	41.000	41.000	41.000	26.000	26.000	26.000	57.000	57.000	57.000
Salary	48323.290	23492.630	103315.800	34292.290	19195.150	65624.680	53270.040	24053.150	106953.900
Account Balance	10556.540	1583.652	46269.950	2528.786	710.986	5328.661	35332.270	3057.190	171567.500
Contribution Rate	0.052	0.034	0.068	0.034	0.023	0.067	0.063	0.043	0.112
Tenure	5.918	2.734	5.875	3.066	2.329	1.937	11.121	3.496	16.107
Equity Share	75.000	79.000	96.000	73.000	59.000	78.000	60.000	60.000	64.000
% employer match, 1st tier	65.261	76.256	66.206	66.237	55.546	47.717	55.970	73.198	59.464
Private Company	0.428	0.355	0.423	0.430	0.522	0.531	0.492	0.459	0.450
Firm Age	58.612	52.237	61.283	56.738	56.170	69.951	68.498	53.729	79.360
Total Assets	76082.280	70724.960	66124.130	78956.640	70118.510	56320.140	59235.300	74186.580	56960.200
Capital Expenditure	2692.652	2324.690	2266.610	2800.561	2467.323	3048.215	2485.750	2626.364	2821.844

Net Income	2463.469	2190.563	2572.961	2991.847	2035.896	2759.390	1835.898	2264.084	1745.772
# of Employees	68730.090	87278.310	53436.590	71062.260	101228.200	34760.450	51026.620	79551.860	35826.590
Median l	**0.798**	**0.774**	**0.904**	**0.970**	**0.889**	**1.093**	**0.775**	**0.784**	**1.007**
Ratio		*1.031*	*0.883*		*1.092*	*0.888*		*0.989*	*0.770*
Spread across ratios			*0.148*			*0.204*			*0.219*
	Based on Column (7) of Panel C								
Age	41.000	41.000	41.000	26.000	26.000	26.000	57.000	57.000	57.000
Salary	48323.290	23492.630	103315.800	34292.290	19195.150	65624.680	53270.040	24053.150	106953.900
Account Balance	10556.540	1583.652	46269.950	2528.786	710.986	5328.661	35332.270	3057.190	171567.500
Contribution Rate	0.052	0.034	0.068	0.034	0.023	0.067	0.063	0.043	0.112
Tenure	5.918	2.734	5.875	3.066	2.329	1.937	11.121	3.496	16.107
Equity Share	75.000	79.000	96.000	73.000	59.000	78.000	60.000	60.000	64.000
% employer match, 1st tier	65.261	76.256	66.206	66.237	55.546	47.717	55.970	73.198	59.464
Private Company	0.428	0.355	0.423	0.430	0.522	0.531	0.492	0.459	0.450
Firm Age	58.612	52.237	61.283	56.738	56.170	69.951	68.498	53.729	79.360
Total Assets	76082.280	70724.960	66124.130	78956.640	70118.510	56320.140	59235.300	74186.580	56960.200
Capital Expenditure	2692.652	2324.690	2266.610	2800.561	2467.323	3048.215	2485.750	2626.364	2821.844
Net Income	2463.469	2190.563	2572.961	2991.847	2035.896	2759.390	1835.898	2264.084	1745.772
# of Employees	68730.090	87278.310	53436.590	71062.260	101228.200	34760.450	51026.620	79551.860	35826.590
Financial Literacy	40.497	39.825	40.635	40.807	40.266	40.912	40.565	39.912	40.970
% with advanced degree in the worker's zip code	12.515	9.432	17.712	11.181	9.549	15.237	11.618	10.701	15.452
% with bachelor degree or more in the worker's zip code	33.746	27.150	44.637	30.837	27.712	39.168	31.646	29.868	39.499
% with high school degree or more in the worker's zip code	87.591	84.655	91.300	85.168	83.687	86.776	87.758	86.228	90.046
Median l	**0.805**	**0.775**	**0.913**	**0.973**	**0.894**	**1.098**	**0.777**	**0.786**	**1.006**
Ratio		*1.039*	*0.882*		*1.089*	*0.886*		*0.988*	*0.772*
Spread across ratios			*0.157*			*0.202*			*0.216*

Table 12
Consumption Replacement Ratios and Certainty Equivalent Ratios Across Age Groups

This Table reports the median consumption retirement replacement ratios (λ) and the certainty equivalent ratio (CEQR) from the baseline simulations for different age groups. The rows represent different percentiles of the distribution across individuals.

	Median CRRR (λ)				Median CEQR			
	20-34	35-49	50-64	All	20-34	35-49	50-64	All
10th Percentile	0.96	0.76	0.67	0.78	0.75	0.67	0.63	0.68
25th Percentile	1.08	0.87	0.83	0.91	0.81	0.74	0.74	0.76
50th Percentile	1.25	1.03	1.03	1.11	0.89	0.83	0.88	0.86
75th Percentile	1.45	1.24	1.32	1.35	1.02	0.94	1.05	0.99
90th Percentile	1.63	1.47	1.68	1.59	1.16	1.07	1.24	1.14

Table 13
Removing Age 59 ½ Early Withdrawals

This Table reports the results from repeating our baseline simulations disallowing age 59 ½ early withdrawals. Columns (2) to (4) report the results for different percentiles of the distribution of the consumption retirement replacement ratio (λ) across realizations for the same individual. Columns (6) to (8) report the same statistics but for wealth accumulation at age 65 (W^T_{65}), while column (5) reports the certainty equivalent ratio. The rows represent different percentiles of the distribution across individuals. Below each entry we report differences relative to the baseline case. For consumption replacement ratios and CEQR, these differences are measured in absolute terms (e.g. $\lambda^{benchmark} - \lambda^{alternative\ scenario}$), while for wealth accumulation these differences are reported as percentage changes ($W^{benchmark} - W^{alternative\ scenario} - 1$).

	CRRR (λ)			CEQR	W^T_{65}		
	10%	30%	50%		10%	30%	50%
10th Percentile	0.59	0.71	0.83	0.73	136	179	216
	0.04	*0.04*	*0.05*	*0.05*	*0.16*	*0.21*	*0.19*
25th Percentile	0.66	0.84	1	0.83	180	249	317
	0.06	*0.08*	*0.09*	*0.07*	*0.18*	*0.2*	*0.17*
50th Percentile	0.75	0.99	1.21	0.93	274	390	510
	0.06	*0.09*	*0.1*	*0.07*	*0.17*	*0.15*	*0.12*
75th Percentile	0.86	1.15	1.44	1.07	461	672	902
	0.06	*0.09*	*0.09*	*0.08*	*0.1*	*0.08*	*0.06*
90th Percentile	0.99	1.31	1.69	1.23	706	1061	1463
	0.06	*0.08*	*0.1*	*0.09*	*0.06*	*0.04*	*0.04*

Table 14
Setting the Minimum Contribution Rates to 2.5% and 5%

Panel A reports the results from assuming a mandatory minimum contribution rate of 2.5%, while Panel B reports the results from assuming a mandatory minimum contribution rate of 5%. Columns (2) through (4), and (6) through (8) present the results for different percentiles of the distribution of λ across realizations for the same individual, from the 10th lowest percentile to the median. Columns (5) and (9) report the CEQR from the two experiments. Panel C reports the results for the minimum contribution rate of 5% for different age groups. The rows represent percentiles of the distribution across individuals. Below each entry we include differences from the baseline case.

	Panel A - 2.5% Minimum Contribution				Panel B: 5% Minimum Contribution				Panel C: 5% Minimum Contribution Across Age Groups					
	CRRR (λ)			CEQR	CRRR (λ)			CEQR	Median CRRR (λ)			Median CEQR		
	10%	30%	50%		10%	30%	50%		20-34	35-49	50-64	20-34	35-49	50-64
10th Percentile	0.55	0.68	0.78	0.68	0.55	0.69	0.79	0.69	1	0.78	0.69	0.76	0.68	0.64
	0.01	*0*	*0*	*0*	*0.01*	*0.01*	*0.01*	*0.01*	*0.04*	*0.02*	*0.02*	*0.01*	*0.01*	*0.01*
25th Percentile	0.6	0.76	0.93	0.76	0.61	0.78	0.94	0.77	1.12	0.89	0.83	0.82	0.74	0.75
	0	*0*	*0*	*0*	*0.01*	*0.01*	*0.02*	*0.01*	*0.04*	*0.02*	*0*	*0.01*	*0*	*0.01*
50th Percentile	0.69	0.9	1.11	0.86	0.69	0.9	1.13	0.87	1.29	1.04	1.03	0.9	0.83	0.88
	0	*0*	*0*	*0*	*0*	*0*	*0.01*	*0.01*	*0.04*	*0.01*	*0*	*0.01*	*0*	*0*
75th Percentile	0.8	1.06	1.35	1	0.8	1.08	1.36	1	1.48	1.24	1.33	1.03	0.95	1.05
	0	*0*	*0*	*0.01*	*0*	*0.01*	*0.01*	*0.01*	*0.03*	*0*	*0.01*	*0.01*	*0.01*	*0*
90th Percentile	0.93	1.24	1.59	1.15	0.93	1.24	1.6	1.15	1.67	1.47	1.68	1.17	1.07	1.24
	0	*0*	*0*	*0.01*	*0*	*0*	*0.01*	*0.01*	*0.04*	*0*	*0*	*0.01*	*0*	*0*

Table 15
Age-Dependent Contribution Rate

This Table reports the results from setting an age-dependent minimum contribution rate k_{min} = 4.5% + (age - 21) * 0.25% Panel A reports the results for the full sample. Columns (2) to (4) present the consumption retirement replacement ratios (λ) for different percentiles of the distribution across realizations for the same individual, and column (5) presents the certainty equivalent ratio (CEQR). Panel B reports the results by age group. Columns (6) to (8) report the median consumption retirement replacement ratios (λ), while columns (9) to (11) report the certainty equivalent ratios. The rows represent different percentiles of the distribution across individuals. Below each entry we report the differences relative to the baseline case.

	Panel A - All				Panel B - By Age Group					
	CRRR (λ)			CEQR	Median CRRR (λ)			Median CEQR		
	10%	30%	50%		20-34	35-49	50-64	20-34	35-49	50-64
10th Percentile	0.56	0.71	0.83	0.71	1.01	0.83	0.72	0.77	0.7	0.67
	0.02	*0.04*	*0.05*	*0.03*	*0.05*	*0.07*	*0.05*	*0.02*	*0.03*	*0.04*
25th Percentile	0.63	0.8	0.96	0.79	1.13	0.93	0.86	0.83	0.77	0.77
	0.02	*0.04*	*0.05*	*0.03*	*0.05*	*0.06*	*0.03*	*0.02*	*0.03*	*0.03*
50th Percentile	0.7	0.93	1.15	0.88	1.3	1.08	1.06	0.92	0.85	0.9
	0.01	*0.03*	*0.04*	*0.02*	*0.05*	*0.05*	*0.03*	*0.03*	*0.02*	*0.02*
75th Percentile	0.81	1.09	1.38	1.01	1.49	1.27	1.34	1.04	0.97	1.06
	0.01	*0.02*	*0.02*	*0.02*	*0.04*	*0.04*	*0.02*	*0.02*	*0.03*	*0.01*
90th Percentile	0.94	1.26	1.63	1.16	1.68	1.49	1.69	1.18	1.09	1.25
	0.01	*0.03*	*0.04*	*0.02*	*0.05*	*0.02*	*0.01*	*0.02*	*0.02*	*0.01*

Table 16
Increasing the Saving Rate

This Table reports the results from increasing the saving rate by 2 and 5 ppts, respectively. Panel A reports the results for the 2 ppts increase, while Panel B reports the results for the 5 ppts increase. Columns (2) to (4) / (6) to (8) present the consumption retirement replacement ratios (λ) for different percentiles of the distribution across realizations for the same individual, and column (5) / (9) presents the certainty equivalent ratio (CEQR). Panel C reports the results by age group for the case with a 2 ppts increase. The rows represent different percentiles of the distribution across individuals. Below each entry we report the differences relative to the baseline case.

	Panel A - 2 ppts Increase in Contribution Rates				Panel B - 5 ppts Increase in Contribution Rates				Panel C - 2ppts Increase in Contribution Rates, by Age Group					
	CRRR (λ)			CEQR	CRRR (λ)			CEQR	Median CRRR (λ)			Median CEQR		
	10%	30%	50%		10%	30%	50%		20-34	35-49	50-64	20-34	35-49	50-64
10th Percentile	0.56	0.7	0.81	0.71	0.59	0.74	0.86	0.74	0.56	0.7	0.81	0.59	0.74	0.86
	0.02	*0.03*	*0.04*	*0.03*	*0.04*	*0.06*	*0.09*	*0.06*	*0.02*	*0.03*	*0.04*	*0.04*	*0.06*	*0.09*
25th Percentile	0.61	0.8	0.96	0.79	0.64	0.84	1.03	0.82	0.61	0.8	0.96	0.64	0.84	1.03
	0.01	*0.04*	*0.05*	*0.03*	*0.04*	*0.08*	*0.11*	*0.06*	*0.01*	*0.04*	*0.05*	*0.04*	*0.08*	*0.11*
50th Percentile	0.71	0.94	1.18	0.89	0.74	0.99	1.25	0.92	0.71	0.94	1.18	0.74	0.99	1.25
	0.03	*0.04*	*0.06*	*0.03*	*0.05*	*0.09*	*0.14*	*0.06*	*0.03*	*0.04*	*0.06*	*0.05*	*0.09*	*0.14*
75th Percentile	0.83	1.11	1.43	1.02	0.85	1.18	1.51	1.05	0.83	1.11	1.43	0.85	1.18	1.51
	0.03	*0.05*	*0.07*	*0.03*	*0.05*	*0.11*	*0.16*	*0.06*	*0.03*	*0.05*	*0.07*	*0.05*	*0.11*	*0.16*
90th Percentile	0.95	1.29	1.68	1.17	0.98	1.36	1.79	1.2	0.95	1.29	1.68	0.98	1.36	1.79
	0.03	*0.05*	*0.09*	*0.03*	*0.05*	*0.13*	*0.2*	*0.06*	*0.03*	*0.05*	*0.09*	*0.05*	*0.13*	*0.2*