Stock Market Returns and Annuitization: a Case of Myopic Extrapolation

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Abstract

With the earliest cohorts of the Baby Boomers starting to retire, how to manage retirement wealth is a major financial decision that millions of individuals will soon face. In this setting, I provide novel evidence on the time-series determinants of the decision to annuitize. More specifically, I document a strong *negative* relationship between stock market returns and annuitization. Using a new dataset with more than 103,000 actual payout decisions, I find that positive stock market returns decrease the likelihood of employees choosing an annuity over a lump sum, and vice versa. More precisely, only *recent* market performance drives annuitization with almost no weight assigned to returns two years before the decision date. Several explanations can account for these findings: wealth effects generated by movements of the stock market; endogenous timing of retirement; volatility of stock market returns and time varying risk aversion; and expectations about labor income or inflationary periods. After addressing these explanations, I present evidence consistent with employees extrapolating from recent stock market returns. I conclude showing that this *myopic* extrapolation – based on very recent stock market performance – can bear serious welfare consequence and significantly reduce retirement wealth if, for example, individuals annuitize too early because of a market drop. Policy interventions focused at promoting voluntary annuitization as a potential retirement income solution should carefully account for this tendency.

Keywords: Household Finance, Retirement Income, Annuities, Myopic Extrapolation, Wealth Effects

JEL Classifications: D14, G11, G22, H55

1 Introduction

Thirty-one million Americans are expected to retire within the next ten years (Reno and Lavery, 2009). Employees enrolled in defined benefit plans would traditionally receive at retirement lifetime income in the form of an annuity. In defined contribution plans - nowadays the most common retirement plans - retirees have greater autonomy in managing their retirement wealth and can decide how to invest and how much to withdraw.

This greater autonomy comes with an often-overlooked challenge: retirees from defined contribution plans will directly bear their longevity risk or the risk of outliving one's retirement wealth. To understand the potential magnitude of this risk, we can look at the distribution of life expectancy at age 65. The difference between the 10th and 90th percentile of this distribution is equal to 22 years for men (dying at 70 versus 92). Similar data hold for women (see Benartzi, Previtero and Thaler, 2011).

By providing lifetime income, annuities are a straightforward way to hedge longevity risk. Not surprisingly, economists have investigated annuitization for almost 60 years (Yaari, 1965). However, our knowledge about this important decision is mostly theoretical and still limited on the empirical side. This paper tries to fill this void, looking at the (time-series) determinants of the decision to annuitize.

Annuities sales largely fluctuate over time. The booms in annuity sales after the recent financial crisis and in the aftermath of the dot-com bubble suggest that past stock market returns might influence the decision to annuitize. In Figure 1, I plot quarterly data from individual annuity sales (in real dollars) and the one-year lag stock market returns. As we can see, the correlation between the two time-series is striking (-.748)

The three goals of this paper stem from this stylized fact in the data. First, I quantify how strong and how robust - across different samples and overtime - is the effect of stock market returns on annuitization. Second, I aim at identifying what is driving it (e.g., wealth effects vs. naïve beliefs about future returns). Last, I highlight the potential implications of this effect on retirees' welfare.

Toward these goals, I primarily use a novel dataset made available by an anonymous data provider specifically for my analysis. I investigate seven years from 2002 to 2008 of actual

payout decisions of over 103,000 retirees enrolled in 112 different DB plans from 63 different companies. To check the robustness of my results and their external validity outside of this sample, I rely on two additional datasets: i) a defined benefit plan from IBM with over 18,000 actual retirement decisions between 2001 and 2009; ii) and quarterly individual annuities sales between 1985 and 2009 form LIMRA International. Four sets of results emerge from my analysis.

First, I document a strong *negative* relationship between stock market returns and annuitization: positive stock market returns decrease significantly the propensity to choose an annuity over the lump sum, and vice versa. This result is robust to the inclusion of a host of different control variables: age, gender, tenure, benefit amount, interest rates,[1] calendar months, and fixed effects for retirement plans and metropolitan statistical area (MSA) of residency. The result is also economically significant: an increase of one standard deviation in the average stock market return decreases the likelihood to annuitize by about 6 percentage points. Similar results in magnitude emerge from the analysis of the IBM retirement plan and the individual annuity sales from LIMRA.

Second, only *very recent* stock market returns drive the decision to annuitize. Adapting the approach in Malmendier and Nagel (2011), I estimate directly from the data the weighting function of the monthly stock market returns in the five years prior to retirement. The weight assigned to the monthly return declines very quickly with time. The weight 12 months before the payout decision is about one-third of the weight given to the return in the month prior to the decision date; almost no weight is assigned to returns older than two years.

Third, wealth effects are not likely to drive my results. A limitation of the data is that I do not directly observe the overall wealth of employees, but only the retirement benefits in their defined benefit plan. Since it is safe to assume that wealth variation is positively correlated with past stock market returns, we do face a potential omitted variable bias depending on the sign of the relationship between wealth variation and annuitization. Using median house prices at the Metropolitan Statistical Area (MSA) as a proxy for wealth, I found a positive relationship between variation in real estate prices and annuitization. I provide more compelling evidence looking at the effect of the negative (exogenous) wealth shock due to the Hurricane

[1] I use the composite long-term Treasury Bonds rate, the discount rate mandated by the Internal Revenue Code.

Katrina. Using a differences-in-differences approach, I found that employees retiring in the states afflicted - Florida, Mississippi, Alabama and Louisiana - are about 8.2 percentage points less likely to choose an annuity compared to retirees in the neighboring states. Both results are consistent with a positive relationship between variation in wealth and annuitization and with precautionary motives and bequests motives (Bernheim, 1991; Sinclair and Smetters, 2004; Ameriks et al., 2011; Lockwood, 2012). Hence, the estimates of the effect of stock market returns on annuitization - if anything - seem to biased downward.

Fourth, I consider whether beliefs about future stock market returns are driving my results: employees might believe that recent trends in the stock market will continue in the future. This belief can alter the relative attractiveness of the lump sum versus the annuity, an irreversible investment in a fixed income product. To test this hypothesis, I use data from the Confidence Index,[2] that collects beliefs from individual investors on future stock market returns. Using the main sample, I find that one standard deviation increase in the index implies a decrease in the probability of selecting an annuity by 9.8 percentage points. After I control also for past returns, the effect of beliefs dramatically shrinks and it is not statistically significant. These results suggest that past stock returns affect annuitization by changing beliefs. A falsification test, using beliefs from institutional instead of individual investors does not hold any result and, thus, confirms the story that naïve beliefs might be driving the decision to annuitize. Although indirect,[3] this evidence makes extrapolation from recent returns a plausible interpretation of the evidence in my data.

This paper connects to several strands of literature. Consistent with my results, several studies have documented the influence of past stock market returns in various settings: investors' beliefs and stockholdings (Vissing-Jorgensen, 2003); investments by young mutual fund managers (Greenwood and Nagel, 2009); mutual fund flows (Chevalier and Ellison, 1997; Sirri and Tufano, 1998); IPO subscriptions (Kaustia and Knupfer, 2008); asset allocation (Benartzi, 2001; Benartzi and Thaler, 2007) and saving rates in 401(k) plans (Choi, Laibson, Madrian, Metrick, 2009). Three major differences separate my study from this literature on

[2] The Confidence Index is collected from the Yale International Center for Finance. I thank Robert Shiller for making available the data on his website (http://www.econ.yale.edu/~shiller/data.htm).

[3] Two limitations in my data do not allow me to directly test for this explanation. First, I observe neither how employees invest the lump sum nor how they invest additional financial resources. Second, I do not have direct access to the employees in my dataset and I cannot survey them about future stock market expectations.

the influence of past stock market returns. First, I document a case of myopic extrapolation: only very recent stock market returns affect annuitization. Second, I find that the extrapolation bias drives also a critical and - due to adverse selection - irreversible decision. Last, making the wrong decision can bear serious welfare consequences. For example, annuitizing too early after a market drop similar to the one experienced in the recent financial crisis can reduce, according to my back-of-the-envelope calculations, the retirement wealth by as much as 10 percent.

This paper relates also to the extensive literature on the annuity puzzle and the real driver of the decision to annuitize. While there are several theoretical attempts at explaining why annuitization levels are lower than economics models would predict, the related empirical evidence is scant (for a review see Brown, 2007 and Benartzi, Previtero and Thaler, 2011). Empirical studies on annuitization tend to rely on surveys (Ameriks et al., 2011) or on international markets such as the UK where retirement wealth is mandatorily annuitized (Finkelstein and Poterba, 2004; Inkman et al., 2011). This paper is among the first to provide actual data on annuitization in a setting with no default options (another contemporaneous paper is Chalmers and Reuter, 2009). Moreover, while empirical studies of annuitization have mostly focused on cross-sectional determinants of annuitization, I focus on the time-series determinants of annuitization.

With the boomers approaching retirement and the US and world governments looking to provide some guidance on retirement income decisions, studying annuitization and financial decisions of the elderly is as timely as ever. My results document that recent stock market performance has the potential to substantially sway retirees away or towards annuitization. Policy interventions focused at promoting voluntary annuitization as a potential retirement income solution should carefully consider this tendency.

The paper proceeds as follows. Section 2 describes the data and report summary statistics. Section 3 introduces the empirical evidence on the relationship between stock market returns and annuitization, and documents its robustness. Section 4 is devoted to interpreting this evidence. In Section 5, I discuss the potential implications of my findings for retirees' welfare and I conclude.

2 Data Summary and Statistics

2.1 Retirement Payout Options in Defined Benefit Plans

DB plans guarantee fixed benefits, typically based on an employee's tenure at the company and pre-retirement level of income. While DB plans are compelled to offer participants the option to receive an annuity, some DB plans *also* offer a lump sum payout option. These plans are the focus of this paper.

The accrued benefits are usually defined in terms of an annuity, beginning at the plan retirement age (typically age 65). The lump sum distributions are determined as the present value of the future annuity payments to which the employee is entitled. The Internal Revenue Code (IRC) prescribes the interest rate and the unisex mortality table that the plan must use to determine the conversion from an annuity to a lump sum payment. A plan might decide to pay a larger lump sum, but is prohibited from paying less than the minimum amount derived under the IRC assumptions. For the majority of our sample period (2002-2007), the interest rate prescribed was the rate on 30-year Treasury bonds. The Pension Protection Act has revised the interest rate (changing it to a mix of short and long rates) and the mortality tables. As a consequence, starting in 2008, the value of lump sums will progressively decrease over the years.[4]

2.2 Summary Statistics

I investigate the relationship between stock market returns and annuitization across three different samples: a large number of DB plans from an anonymous data provider (main sample); a DB plan from IBM; and individual annuity sales as collected by LIMRA International.

The main sample includes the actual payout decisions of over 103,000 employees enrolled in DB plans that offer the option to choose between an annuity and a lump sum. The payout decisions span seven years (2002-2008) and 112 different retirement plans offered by 63 different companies.[5] Due to data collection issues and to the addition of new plans over time, the

[4] According to congressional estimates, the value of the lump sum will decline by about 1 percent in 2008 (Purcell, 2007). I will include year fixed effects to account for this change introduced by the Pension Protection Act.

[5] While a company can offer more than one DB plan, the same plan cannot be offered by two different companies.

panel of plans is unbalanced.[6] Therefore, I do not observe all 112 plans for the entire seven-year period. At the employee level, I observe: i) some demographic information: age, gender, tenure at the company and zip code of residency; ii) the actual payout decision: payout form, benefit amount and benefit start date; and iii) identifiers for the retirement plan and company offering it.

The IBM data provides over 18,000 actual payout decisions from their DB plan. Three reasons make this dataset of particular interest. First, while in the main dataset the decision between an annuity and a lump sum is mutually exclusive, here employees can choose partial annuitization (i.e., a mix of the two). Second, the decisions span nine years, from 2000 to 2008, and allow me to investigate an additional stock market downturn, the one related to the Internet bubble. Last, I observe additional demographic information, such as income before retirement and detailed information on education.

LIMRA International, a worldwide association of insurance and financial services companies, provides estimates on total individual annuities sold in the US.[7] In my analysis, I use fixed annuity sales between the first quarter of 1985 and the second quarter of 2009 and immediate fixed annuity sales starting from 1992. I deflate the sales into June 2009 dollars using the Consumer Price Index.

In Table I, I introduce descriptive statistics. In the main sample, 49 percent of employees select an annuity. In the IBM plan, 88 percent of employees make a similar choice, 6 percent choose a lump sum and the remaining 6 percent select a mix of the two. Among the 112 plans covered in my main sample, some plans present a high annuitization rate, similar to the one I find in the IBM plan. Considering the wide dispersion of annuitization rates across plans, I use retirement plan fixed effects to control for (non time varying) unobservable features of the plans that can drive the decision to annuitize.

I do not observe total wealth of employees, but only the retirement benefits in the specific DB plan.[8] The age and the tenure of employees across the two datasets are respectively 58-60

[6] To check if missing data for some plans or additional plans bias my results, I run all the analyses in the paper using only data from plans that are in my sample for at least four years. All my results are confirmed in this sub-sample.

[7] Depending on the different type of annuities, LIMRA estimates coverage between 85 and 95 percent of the total sales.

[8] I cannot exclude that some of these employees are also enrolled in a DC plan offered by the same employer. However, when both plans are offered the contributions of the employer to the DC plan – in the form of matching

years and 25-30 years. This evidence supports the fact that this payout decision represents a relevant fraction of their total retirement wealth. To support this claim, I use data from three waves of the Survey of Consumer Finances (2001, 2004 and 2007).[9] Observations are weighed using SCF sample weights, to represent the U.S. population. The mean and median values of retirement benefits in the main sample – \$188,130 and \$86,460 respectively – are of the same order of magnitude of the average and median net financial wealth for retirees in the SCF – \$259,200 and \$15,360.[10] All these considerations extend to the IBM sample, in which employees have significantly higher benefits.

To control for the omission of total wealth in my results, I use the median house prices at the MSA level. Looking at the data from the SCF, we can see how home equity represents a large fraction of total wealth of respondents, about 40 percent of the sum of home equity and net financial wealth (\$167,460 and \$259,200). Therefore, including in my regressions DB benefit amounts and median house prices is likely to significantly reduce the omitted variable bias.

3 Empirical Results

3.1 Methodology

Using the datasets previously described, I estimate an equation of the following general form:

$$Ann_{ijt} = \alpha + \beta A_t(\lambda) + \gamma' x_{it} + \varepsilon_{it} \tag{1}$$

Ann_{ijt} is a binary variable equal to one if employee i enrolled in plan j at time t chooses an annuity. I explain this decision using: a weighted average of the past stock market returns, $A_t(\lambda)$; a vector of control variables, x_{it}; and an error term, ε_{it}. Following Malmendier and Nagel (2009), I estimate directly from the data the following weighting function of monthly

funds – are generally limited as are the voluntary contributions made by employees.

[9] I obtained the survey from the Board of Governors of the Federal Reserve System.

[10] While the DB benefits in my sample are measured at the employee level, the data from the SCF are reported at the household level (generally husband and wife). Data in Columns 5 and 6 are from respondents that are retired and with age lower than 75 years. In Columns 7 and 8, I report similar results using data from respondents with age between 50 and 75 years – the same age range of the Main Sample – regardless of their retirement status.

stock returns, R_{t-k}, for the period lag (expressed in months) prior to the decision date:

$$A_t(\lambda) = \sum_{k=1}^{lag-1} w(k,\lambda) R_{t-k}, \text{ with } w(k,\lambda) = \frac{(lag-k)^{\lambda}}{\sum_{k=1}^{lag-1}(lag-k)^{\lambda}} \tag{2}$$

As Figure II shows, this functional form for the weighting function is very flexible and parsimonious. Depending on the value of just one parameter, λ, I can obtain decreasing, increasing or constant weights for past monthly stock returns.[11] Therefore, the parameters of interest in my analysis are two, β and λ. This procedure allows me to estimate them simultaneously from the data. On one hand, a β statistically different from zero implies that employees take into account past stock market returns in their payout decisions. On the other, the more positive the lambda is, the higher are the weights that employees assign to more recent returns.

From Equations 1 and 2, we can see that the estimating equation is not linear in the parameter λ. Therefore, I use non-linear least squares and select the λ that minimizes the sum of squared residuals.[12] As in Malmendier and Nagel (2009), to ensure that I find the global minimum, I first estimate Equation 1 for tightly spaced values of λ. Then, I use the value of λ that minimizes the sum of squared residuals as the starting value in the optimization process.

In my analyses, I assume a lag period equal to 60 months before the decision date. The results are robust for different choices of this relevant period, either longer or shorter than 60 months. As an additional robustness check, I try different functional forms for the weighting function. Quadratic or logistic specifications result in significantly higher sums of squared residuals compared to the functional form I use.

[11] With $\lambda<0$, the weighting function is always increasing and convex the further we go back in time. If $\lambda=0$, I have constant weights. With $\lambda>0$, the weighting function is decreasing going back in time (concave for $\lambda<1$, linear for $\lambda=1$, convex for $\lambda>1$).

[12] Even if the outcome variable is binary, I use linear probability models (i.e., OLS estimation). The results presented in the paper are robust to the use of Logit models. I report the reasons for my choice in the next paragraph.

3.2 Stock Market Returns and Annuitization

I use a non-linear regression model to estimate the effect of past returns on annuitization in the DB plans from the main sample,

$$Ann_{ijt} = \alpha + \beta A_t(\lambda) + \gamma' x_{it} + \delta' z_{jt} + \xi' t_t + \varepsilon_{it} \tag{3}$$

I introduce the estimates of the parameters of interest (β and λ) in Column 1 of Table II.[13] The vector of individual control variables – x_{it} – includes: age, gender, benefit amount and tenure. The vector of time-varying plan control variables – z_{jt} – consists of: the average of age, gender and benefit amount, and the number of employees separating for a given year for each plan. The vector of time-varying controls – t_t – includes: long-term interest rates, calendar months and year fixed effects.[14]

Column 1 documents how the coefficient of the weighted average of past (monthly) stock returns, β, is both statistically and economically significant. One percentage point (pp) increase in the average stock market return decreases the likelihood of selecting an annuity by about 5.6 pp.[15] Alternatively, a change from the 25th to the 75th percentile of the past 60-month average stock market return distribution (about 1.71 pp) implies a change in the probability of selecting an annuity of about -5.627*1.71 pp≈ -9.6 pp. Analogously, a change from the 10th to the 90th percentile (about 2.62 pp) implies a change in the probability of annuitization of about -5.627*2.62 pp≈ -14.8 pp. To look at the magnitude of this coefficient in perspective, note that one year of age increases the likelihood of annuitizing by 2.4 pp; being female increases the likelihood of selecting the annuity by about 4.2 pp; and an increase in the benefit amount of $100,000 increases the likelihood of annuitization by 3.3 pp.

The coefficient of the weighting parameter, λ, is statistically different from zero. Figure III plots the weights corresponding to a value of λ equal to 5.16. Such value implies that the

[13] The coefficients of the control variables have the signs that one would expect given the previous literature. I report them in the Online Appendix Table OA1, available from my website: http://personal.anderson.ucla.edu/alessandro.previtero

[14] To proxy for interest rates, I use the average long-term composite Treasury Bond in the six months before the separation date. As specified in Section 2, this is a good proxy for the discount rate that the employers are required to use in the conversion between the annuity and the lump sum. I use calendar month fixed effect to control for the fact that some plans might allow particular payout forms only in specific periods. I use year fixed effect to mitigate the concern that the number of plans varies across years.

[15] The standard deviation of the weighted (using the weights from Column 1) 60-month average stock market return is 1.1 percent.

weights assigned to past stock market returns decrease over time with higher weight given to the most recent returns. For example, for stock market returns six months before their decision date, employees assign a weight about two-thirds of the weight they give to returns one month prior to the decision. The weights are practically zero after about two years.

The use of non-linear regressions implies that I'm modeling the decision to annuitize with a linear probability model (i.e., OLS estimation). Despite a binary dependent variable, I prefer this choice over the commonly used Logit or Probit models for three reasons, two substantial and one formal. First, I can use fixed effects without incurring the incidental parameters problem.[16] Second, I can directly obtain unbiased coefficients for interaction terms (Ai and Norton, 2003). Last, this choice makes it easier to directly assess economic magnitudes by simply multiplying β with the variation in the past returns.[17] Estimating Equation 3 with a Logit model does not materially change my results. In this case, one needs to use maximum likelihood estimation and select the values of β and λ that maximize the likelihood function.

To account for cross-sectional and inter-temporal dependence in my data, I cluster the standard errors in Table II across fifteen company size/time groups. More precisely, I partition the data in quintiles based on company size[18] and three 28-month periods. Combining these two partitions, I obtain fifteen groups with observations in the same quintile of company size and the same period belonging to one group.

I derive this approach from Bester, Conley and Hansen (2009). They provide simulation evidence that using cluster covariance estimators – as the ones I use in my analyses – outperforms conventional inference procedures when the data exhibit cross-sectional and temporal dependence. The key prerequisite in their methodology is to construct (a small number of) groups whose averages are approximately independent.[19] I choose a partition meant to satisfy this requirement.[20] First, from Figure III we can see how the weight given to stock market returns after 28 months is approximately zero (precisely 0.004). Second, I conservatively clus-

[16] From the simulations in Greene (2004), the problem of incidental parameters should be limited in my data.

[17] I previously determined the effect of a movement from the 10th to the 90th percentile in the past returns distribution, by simply multiplying this variation by β. Using Logit models, this determination would imply to estimate first and separately the likelihood of annuitizing at the 10th and 90th percentiles.

[18] I compute the company size using the number of employees separating from each company in my sample period.

[19] The Fama-MacBeth (1973) procedure represents a well-known application of this idea of partitioning the data into researcher-defined groups to overcome dependence problems.

[20] There are three additional restrictions on the groups. They need to be: i) mutually exclusive; ii) exhaustive; iii) and contiguous.

ter across company size quintiles to take into account not only dependence of the data within the same plan or the same company, but also potential dependence within the same company size.[21] My results are robust to the use of different partitions of the data, such as clusters based on geographical location of the employees and time. These robustness checks are reported in the Online Appendix Table OA2.[22]

In Columns 2-4, I do not directly estimate a value for λ. After fixing the weighting parameter (λ=5.16), equation 3 becomes linear and can be estimated using a linear probability model.[23] In Column 2, I add retirement plan fixed effects to control for unobservable (non time-varying) plan characteristics that can influence employee decisions. In this specification, β can be interpreted as the effect of returns on the probability of taking an annuity *within* the same plan. Notwithstanding the use of plan fixed effects, β remains both statistically and economically significant.

In Column 3, I add Metropolitan Statistical Area (MSA) fixed effects to control for unobservable variables at the MSA level. Column 4 adds both MSA and retirement plan fixed effects. In all the specifications, the stock return coefficient β is statistically and economically significant: one standard deviation variation in the weighted average stock market return (equal to about 1.1 pp) implies a variation in the likelihood of selecting an annuity that varies between 4.4 and 5.3 pp. Standard errors in Columns 2-4 are clustered across the 15 company size/time groups, as previously described.

3.3 Stock Market Returns, Annuitization and Financial Education

In Table III, I report the estimates for the IBM DB plan of the following non-linear regression model:

$$Ann_{ijt} = \alpha + \beta A_t(\lambda) + \gamma' x_{it} + \xi' t_t + \varepsilon_{it} \tag{4}$$

The dependent variable is binary: it equals 1 if the employee receives benefits entirely as an

[21] The size of the company is likely to have an effect on the decision to annuitize. For example, larger companies might offer additional saving vehicles – such as 401(k) – or information seminars on managing retirement wealth. Moreover, financial institutions are also more likely to target bigger companies with a customized offer of retirement income solutions.

[22] The Online Appendix is available from the author's website: http://personal.anderson.ucla.edu/alessandro.previtero

[23] The inclusion in the regressions of hundreds of fixed effects makes it computationally burdensome to estimate non-linear least squares.

annuity, 0 otherwise (i.e., part or all of benefits taken as a lump sum).[24] $A_t(\lambda)$ is the weighted average of stock market return. The vector of individual control variables – x_{it} – includes: age, gender, benefit amount, tenure, income and years of education. The vector of time-varying controls – t_t – includes: long-term interest rates and calendar months fixed effects.

Looking at the estimates in Column 1, we can see how the stock returns coefficient β is both statistically and economically significant. A change from the 25th to the 75th percentile of the past 60-month weighted average stock market return (about 1 percentage point, pp) implies a change in the probability of selecting an annuity of about -2.608*1.00 pp≈ -2.6 pp. In the same fashion, moving from the 10th to the 90th percentile (about 2.33 pp) implies a change in the probability of annuitization of about -2.608*2.33 pp≈ -6.1 pp. To consider this economic magnitude in perspective, note that five additional years of education decrease the likelihood of selecting an annuity by about 1.5 pp. The estimate of the weighting parameter (λ=1.02) is statistically different from zero and implies almost linearly decreasing weights for the past returns.

I cluster all the standard errors in Table III across eight geographical region/time groups. To ensure independency across group averages, I partition the data in the four US Census Regions[25] and two 51-month periods. First, with a value of λ equal to 1.02, the weight given to stock market returns after 51 months is approximately zero (precisely 0.005). Second, I cluster across regions to take into account not only dependence of the data *within* the same working location, but also potential dependence within the same geographical area of residency. These results are robust to the use of different geographical partitions (using nine Census Divisions) or different time periods (three 34-month periods).

In Column 2, I fix the weighting parameter (λ =1.02) and I add working location fixed effects to control for (non time-varying) unobservable variables at the working location level. With these controls, β can be interpreted as the effect of returns on annuitization within the same working location. This effect remains both economically and statistically significant, implying that stock returns affect annuitization across all the different working locations and not merely in some of them.

[24] I find similar results if I use as dependent variable the percentage of retirement wealth annuitized. Since the left-hand variable is censored in this case, I estimate a Tobit model.

[25] Northeast, Midwest, South, West. For more details see: http://www.census.gov/geo/www/us_regdiv.pdf.

In Columns 3-6, I investigate if financial education mitigates the effect of past stock market returns on annuitization. In Columns 3 and 4, I categorize employees as financially educated if they have received any financial education in their studies. The coefficient of interest is the interaction between financial education and past stock market returns. From Column 3, we can see how this coefficient is not statistically significant and we cannot reject the null hypothesis that the effect of stock market returns is the same for employees with or without financial education. Note that failing to reject the null does not depend on the way I estimate the standard errors. With less conservative standard errors,[26] the interaction coefficient becomes significant but *negative*: if anything, the effect of stock market returns seems stronger for financially educated employees.

In Column 4, I allow not only a different β, but also a different λ for financially educated employees. Under this specification, my previous results are confirmed and I also obtain a higher value of λ for financially educated employees (i.e., they more heavily weight more recent returns). In Columns 5 and 6, I replicate qualitatively the evidence that financial education does not mitigate the effect of stock market returns, using having an MBA as a proxy for financial education.

3.4 Stock Market Returns and Individual Annuity Sales

In Table IV, I investigate the relationship between stock market returns and individual annuity sales. More precisely, I estimate the following non-linear regression model:

$$Ann_{ijt} = \alpha + \beta A_t(\lambda) + \xi' t_t + \varepsilon_{it} \tag{5}$$

The dependent variable is the deflated quarterly annuity sales. $A_t(\lambda)$ is the weighted average of stock market returns. The vector of time-varying controls – t_t – includes: long-term interest rates, an indicator variable equal to 1 for the NBER recession periods and calendar quarter fixed effects.[27] In Column 1, the dependent variable is the log of real sales of fixed annuities (both deferred and immediate). One percent point (pp) variation in the quarterly

[26] Clustered at the working location level or double clustered at the working location and month level (Petersen, 2009).

[27] The indicator variable controls for the business cycles, while calendar quarters control for potential effects of incentives to advisors selling annuities related to calendar periods (for example half-year or year-end).

average stock market return translates to a 10.6 percent reduction in the sales of fixed annuities, a result statistically and economically significant. The value of λ, 1.25, implies weights for stock market returns are almost linearly decreasing over the past five years. Since I have only time series data, I do not have to worry about cross-sectional dependence in the data. Therefore, I use Newey-West (1987) standard errors to account for serial correlation up to 20 quarters (five years) in the data.

In Column 2, I replicate these results using immediate annuity sales as the dependent variable. Here one percentage point increase in stock market return implies a 5.3 percent reduction in annuity sales. While immediate annuity sales are in nature closer to the decision to annuitize in DB plans, the data from Limra included in this category also the sales of structured settlements.[28] Settlement sales are less likely to be affected by stock market returns. This fact can explain why I obtain a lower estimate for β and a noisy estimate for λ.

4 Interpretation of the Evidence

4.1 Omitted Variables Bias

The results in the previous section can seriously suffer from an omitted variables bias. For example, I do not observe the overall wealth of employees but only their DB plan retirement benefits. If employees have financial wealth invested in the stock market, my estimates of the stock returns coefficient, β, might be severely biased.

To understand the direction of the bias, consider the hypothetical case in which the decision to annuitize depends *only* on $A_t(\lambda)$, the weighted average of stock market returns, and W_{it}, the additional financial wealth:[29]

$$Ann_{it} = \alpha + \beta^* A_t(\lambda) + \rho W_{it} + \varepsilon_{it} \tag{6}$$

If I regress annuitization only on stock market returns, the omitted variables bias will be equal to (Angrist and Pischke, 2008):

[28] The breakdown between the two categories is available only from 2001. Structured settlements are essentially annuities paid to compensate injury victims for their losses.

[29] I will focus only on the potential bias in my variable of interest, the stock returns coefficient β. Note that given my large sample size, the estimates of this coefficient remain consistent even when another regressor is endogenous (Wooldridge, 2002)

$$\frac{Cov\left(Ann_{it}, A_t\left(\lambda\right)\right)}{V\left(A_t\left(\lambda\right)\right)} = \beta^* + \rho\delta_{W\,\mathrm{Re}\,t} \tag{7}$$

in which δ is the coefficient from regressing wealth on stock market returns. From Equation 7, we can see how the bias in the estimates depends on the product between the effect of wealth on annuitization – ρ – and the effect of stock market returns on wealth – δ.

More generally, my estimates in the previous section are too conservative if the effect of the omitted variable on annuitization and the effect of the stock market returns on the omitted variable have the same sign.[30] If they have opposite signs, my estimates can be "too large" or eventually of the wrong sign. In the next paragraphs, I deal with the omission of additional (financial) wealth. . In the remainder of the paper, I consider the effects of omitting stock market volatility and expectations about human capital and inflation.

4.2 Wealth Effects

While I can safely assume a positive relationship between stock returns and financial wealth, the effect of a wealth shock on annuitization is less straightforward. Mitchell et al. (1999) show that more risk-averse people should be willing to pay more for annuities. With wealth-dependent risk aversion, as wealth increases – and risk aversion decreases – employees should value an annuity less and be less likely to choose it.

However, bequests and precautionary motives can influence the decision to annuitize (Bernheim, 1991; Sinclair and Smetters, 2004). If employees avoid annuitization to bequeath or to better handle liquidity needs – such as health shocks – an increase in wealth might actually attenuate liquidity concerns and increase the likelihood of annuitization.

To overcome the lack of information on the total wealth of employees, I follow two different approaches. First, I use house price appreciation across different Metropolitan Statistical Areas to proxy a wealth shock.[31] Second, I use the exogenous shock to wealth caused by a natural disaster whose consequences were largely unanticipated (i.e., Hurricane Katrina).

After matching median house prices by MSA[32] with payout data from the main sample,

[30] Recall that I estimate a *negative* relationship between stock returns and annuitization.

[31] Both Hurst and Lusardi (2004) and Lusardi and Mitchell (2007) use variation in real estate prices as an instrument for wealth. The former paper investigates the effects of liquidity constraints on entrepreneurship; the latter the effects of wealth on financial planning.

[32] I obtain the real estate data from the National Association of Realtors (www.realtor.org).

I obtain a final dataset of 58,897 observations, about 57 percent of my original observations. In Column 1 of Table V, I document that this smaller sample does not cause any selection issue: the estimates of the stock return coefficient, β, and of the weighting parameter, λ, are remarkably similar to the previous ones (see Table II, Column 1. In Columns 2-5, for simplicity I fix λ to this estimated value (5.1) and I use linear probability models.

In Column 2, I document that the coefficient of past returns, β, remains statistically and economically significant *after* controlling for *levels* and *variations* in median house prices. One standard deviation increase in the weighted average of returns (about 1.1 percentage point, pp) implies a decrease in the probability of choosing an annuity by 6.7 pp. Both variables related to real estate prices have a non negligible effect on annuitization. One standard deviation variation in the one-year lag of median house prices (about $125,600) *reduces* the likelihood of choosing the annuity by 4.1 pp. A similar variation in the past 12-month appreciation of real estate values (about 11 pp) implies an increase in the likelihood of annuitizing by about 2.0 pp. As in Table II, standard errors are clustered across 15 company size/time groups, from partitioning the data in company size quintiles and three 28-month periods.

These results highlight the importance of jointly controlling for levels and variations in real estate values. The coefficient of levels of house prices is driven by cross-sectional variations across MSA and tells us the employees living in areas with higher prices – and therefore more likely to be wealthier – are less likely to choose an annuity. Using data from Defined Contribution plans from the Health and Retirement Study, Brown (2001) finds a similar (small) negative relationship between annuitization and financial net worth. Among others, the author suggests that this relationship might be driven by wealthier individuals: i) having less need for the "insurance" offered by the annuity; and ii) believing they can earn higher returns than offered by the annuity. Both are plausible explanations for this result in my data.[33]

The coefficient of variation of house prices is driven by time series variation in prices: for a given level of real estate prices, employees that have experienced higher increases in prices are more likely to take an annuity. Therefore, precautionary motives seem also relevant in explaining the decision to annuitize. This positive relationship between variation in wealth and annuitization provides evidence against the potential explanation that an increase in wealth –

[33] In the analysis of the IBM data I find a (small) statistically significant negative relationship between annuitization and both income and education.

caused by by stock market returns – is driving my main results.

In Columns 3 and 4, I control for levels and variation in median house prices over longer horizons, respectively two and three years. Similar to what I find for stock returns, the effect of the variation in house prices on annuitization decreases going back in time and is not significant after three years.[34]

In Column 5, I include retirement plan fixed effects. Under this specification, the effect of real estate prices on annuitization is driven by employees enrolled in the same plan but living in different areas. I still find statistically significant results for the effects of levels and variations of house prices on annuitization but – as we might expect – the magnitudes are smaller.

4.3 The Effect of an Exogenous Shock to Wealth: Evidence from Hurricane Katrina

In August 2005, Hurricane Katrina caused more than 1,800 deaths and an estimated $81 billion in total property damage, particularly concentrated in four states: Florida, Mississippi, Alabama and Louisiana (Knabb, Rhome and Brown, 2005). Even though the Gulf Area has witnessed several hurricanes over the years, Katrina was unprecedented in terms of damages caused.[35] For this reason, I use this event as a proxy for an exogenous shock to the wealth of the employees living in that area at the time of retirement.

Methodologically I use a differences-in-differences approach to estimate the *casual* effect on annuitization of a shock to wealth due to the hurricane.[36] Table VI reports these results. In Column 1, I estimate the same model in Equation 3 with the addition of three explanatory variables: i) "Katrina Date," equal to 1 after the hurricane; ii) "Katrina States," equal to 1 for the four states afflicted by the hurricane; and iii) their interaction. This interaction represents our coefficient of interest. In Column 1, I document that this coefficient is economically and statistically significant: the hurricane decreases the likelihood of selecting an annuity by 8.2 percentage points (pp).

[34] In additional analyses not tabulated, I find similar non significant results for horizons of four and five years.

[35] The second costliest Atlantic hurricane, Andrew (1982), caused less than half of the total property damage (in 2005 US dollars) of Katrina.

[36] In essence, this approach compares the likelihood of annuitization pre- and post-hurricane of the employees living in the Treatment States (i.e., the four states primarily affected by the hurricane), with the difference in the likelihood of annuitization in the same period for the Control States (i.e., states not affected by the hurricane). For more details see Angrist and Piscke (2008).

The standard errors are clustered across 12 region/time groups, obtained by combining the four US Census Regions and three 28-month periods. I prefer this partition over the one based on company size, because it allows me to handle serial correlation among the choices of employees before and after the event (Bertrand, Duflo, and Mullainathan, 2004). With this partition, four of the 12 groups include *at the same time* employees before and after the hurricane, with one of these groups including employees living in the four Katrina States before and after. Therefore, with this approach I can account for serial correlation of decisions within the same geographical areas *and* for cross-sectional correlation of decisions very close in time. As we would expect, if I simply follow the procedure suggested in Bertrand, Duflo, and Mullainathan (2004) and cluster the errors at the state level, the estimates of the standard errors – that ignore cross-sectional correlations – go down.

Instead of using data on property damage at the county level, I opt for a coarser classification at the state level. On the one hand, my classification adds a lot of noise to the estimation: obviously not all the counties in the four states have been affected by the hurricane in the same way. This choice biases my results toward not finding any effect of the hurricane on annuitization. On the other hand, natural disasters can cause all the employees in the states involved – not only the ones that have directly experienced damages – to reassess the risk of property damage and to increase their demand of property-related insurance contracts (Browne and Hoyt, 2000).[37]

In Column 2, I test if immediate liquidity needs are driving my results. In some areas – such as the entire state of Louisiana – the shock to wealth might have been so dramatic as to entirely prevent some employees from selecting an annuity. I check for this possibility by excluding from the analysis all the employees (1,440) that are located in Louisiana. As expected, the coefficient of interest – the interaction between Katrina States and Date – is lower than what I find earlier. Nonetheless, it remains economically and statistically significant: employees retiring after the hurricane in the three states affected are 7.6 pp less likely to select an annuity.

In Column 3, I check if changes in life expectancy due to the hurricane explain my findings: employees might prefer a lump sum after the hurricane because they might expect to live less

[37] As a consequence of the hurricane, the demand for insurance products can also increase in our control states. If this is the case, my results will again be biased toward not finding any effect of the hurricane on annuitization.

and not because of the negative wealth shock that they have experienced.[38] To control for this alternative explanation, I rely on the evidence that demand of life insurance increases after disasters in the states directly affected by the event and *also* in neighboring states (Fier and Carson, 2009).

Consequently, I include in my estimate an indicator variable "Neighboring States" equal to 1 for the neighboring states where minor casualties were recorded (Texas, Kentucky, Ohio and Georgia). The interaction between this variable and "Katrina Date" will capture the effect of changes in life expectancy on annuitization, under the identifying assumption that these changes are similar in the "Katrina States" and in the other four neighboring states that have recorded casualties. While the interaction coefficient for the Katrina states remains significant, the one for the neighboring states is not. Therefore, the effect of a change in life expectancy on annuitization appears negligible.[39]

Column 4 replicates similar results, excluding the state of Louisiana from the analysis. After controlling jointly for stringent liquidity needs and potential changes in life expectancy, there is still a negative effect of the hurricane on the probability of annuitizing. This result appears consistent with the effect of the hurricane being mostly a wealth shock and with a *positive* relationship between wealth shock and annuitization (in this case a negative shock *reduces* annuitization).

4.4 Timing of Retirement

In most cases, employees can choose endogenously when to retire. Therefore, our results might be largely (or exclusively) driven by those employees that time the stock market in their decision to retire. In Table VII, I investigate the effect of endogenous timing of retirement using data from main sample (Columns 1 and 2) and IBM (Columns 3 and 4).

In Column 1, I estimate Equation 3 with the addition of: i) a dummy variable (Exact Age)[40] equal to 1 if the employee retires on his or her birthday; and ii) the interaction between this indicator variable and stock market returns.[41] Under the assumption that employees

[38] Note that this is true only if the annuity offered does not fully adjust to this new lower (perceived) life expectancy. I can safely assume that this is the case, because the mortality tables used are not state-specific.

[39] As a robustness check, I obtain similar results running a differences-in-differences estimation between the Katrina states and neighboring states, excluding all the remaining states.

[40] In my sample there are almost 18,000 employees in this category.

[41] The value of λ is fixed at the estimate from Table II, Column 1 (5.16). Analogously, in Columns 3 and 4,

retiring on their birthday are less likely to be "market-timing" their retirement date compared to those retiring on other dates, this interaction represents the coefficient of interest. It has the expected sign, but it is not statistically significant at the conventional levels. Therefore, I cannot reject the null hypothesis that the relationship between returns and annuitization is the same for employees retiring on their birthday as for employees retiring on any other date. Standard errors are clustered across 15 company size/time groups, obtained from partitioning the data in company size quintiles and three 28-month periods.[42] In Column 2, I add to this specification retirement plan fixed effects to confirm that this result is common across plans and not driven by any plan in particular.

In Columns 3 and 4, I provide similar evidence using a subsample of the IBM employees, for whom I can observe the reason of separation, whether voluntary or not (i.e., employees let go by the company). I estimate Equation 4 with the addition of a dummy variable – Laid-off –, equal to 1 if the employees were let go.[43] Consistent with what I found before, the interaction between the variable, laid-off, and stock market returns is not statistically significant and I cannot reject the null hypothesis that the effect of stock market returns on annuitization is the same for employees retiring voluntarily and employees who were let go.

When it comes to annuitization and stock market returns, employees who retire on their birthday or who are laid-off do not seem to behave differently than employees retiring voluntarily. This evidence suggests the effect of market returns on annuitization is not limited to those employees that can time their retirement.

4.5 Stock Market Volatility

In Table VIII, I investigate the effect that the omission of stock market volatility produces on my estimates. A negative correlation between volatility and returns in the short term[44] together with time-varying risk aversion can bias my results. According to this alternative explanation, the higher volatility in a down market might increase the risk aversion of employees and, consequently, their willingness to annuitize.

the value of λ is fixed at the estimate from Table III, Column 1 (1.02).

[42] Note that the failure to reject the null is not driven by the way I estimate the standard errors. I find similar results using less conservative estimates.

[43] There are 7,394 employees that fall in this category (about 47 percent of the subsample).

[44] See Glosten, Jagannathan and Runkle (1993).

In Columns 1 and 2, I estimate Equation 3 with the addition of the average stock market volatility over the previous three and six months respectively. I document that the effect of stock market returns remains statistically and economically significant even after controlling for returns volatility. As in the previous analyses, standard errors are clustered across 15 company size/time groups. Column 3 confirms that this result is not driven by a few specific plans.

In Columns 4 and 5, I document that adding the three or six months average volatility to the estimates in Equation 5 does not change the results. The sales of fixed annuities are driven by stock market returns and not by their volatility. In analyses not tabulated, I find that this result holds also for the sale of immediate fixed annuities.

4.6 Expectations about Labor Income and Inflation

In analyses reported in Online Appendix Table OA3,[45] I also control for the potential effects on my results of expectations about labor income and inflation. Positive stock market returns can generate better labor income expectations. Better prospects might cause employees to be more willing to choose a lump sum and to forfeit the implicit insurance associated with an annuity. As we can see from Equation 7, a positive correlation between stock returns and labor expectations together with a negative correlation between these expectations and annuitization can bias my results.

To test if there is a positive relationship between labor income and annuitization, I complete the main sample data with information on median income at the MSA level.[46] Adding both levels and the variations in income does not change the results in my baseline estimations. While the coefficient of stock returns remains significant, shocks to income have no effect on annuitization.

Employees with expectations of high future inflation might prefer to select a lump sum, because it allows them to better hedge the inflation risk (annuities are typically in nominal terms). A positive trend in the stock market can indeed generate expectation of higher inflation. As in the previous case, a positive correlation between stock returns and inflation expectations

[45] The results are available from the author's website: http://personal.anderson.ucla.edu/alessandro.previtero

[46] The median income estimates are from the Department of Housing and Urban Development (HUD). They are available from the Federal Financial Institutions Examination Council (FFIEC) on their website (http://www.ffiec.gov/default.htm).

together with a negative relationship between inflation expectations and annuitization can produce a bias in my results. Using data on long-term inflation expectations,[47] I do not find that these expectations affect the decision to annuitize and, in turn, my main results.

4.7 Extrapolation from Recent Stock Market Returns

Recent stock market returns can affect beliefs about future returns. After negative returns, employees might believe that this trend will continue in the future and, consequently, find more attractive the annuity, essentially a fixed-income financial product. The opposite can happen after a positive trend in the market.

In Table IX, I test for this possibility using a measure of investor beliefs about future returns, the Confidence Index. This index corresponds to the percentage of *individual* investors expecting an increase in the Dow Jones (Industrial) in the coming year.[48] In Column 1, I estimate my baseline model from Equation 3, replacing past stock market returns with the six-month average of the Confidence Index. One standard deviation increase in the index implies a 9.8 percent points (pp) decrease in the probability of selecting an annuity. This result is not only statistically significant, but also comparable in magnitude with the effect I find for past returns in Table II.[49] Note that the standard errors in Table IX are clustered across the 15 company size/ time groups to allow for the same type of cross-sectional and serial correlation assumed earlier.

In Column 2, I add to the previous specification the average of past stock market returns. After controlling for past returns, the effect of beliefs about future returns dramatically shrinks and it is not statistically significant. This evidence suggests that the effect of beliefs on annuitization is mainly driven by previous returns. In Column 3, using retirement plan fixed effects, I confirm that this finding is robust not only across but also *within* retirement plans.

In Columns 4-6, I use data from a confidence index computed in the same manner but with answers from *institutional* investors. Beliefs from institutional investors have a marginal effect

[47] The data are from the Federal Reserve Bank of Philadelphia that conducts a quarterly survey (Survey of Professional Forecasters) , a quarterly survey on long-term (10 years) inflation expectations (10 years).conducted by the Federal Reserve Bank of Philadelphia.

[48] The Confidence Index data are available on Robert Shiller's website (http://www.econ.yale.edu/~shiller/data.htm).

[49] For example, recall that a change from the 10th to 90th percentile of the distribution of the average past returns implies a reduction in the probability of annuitization by 14.8 pp. An analogous variation for the average Confidence Index implies a reduction of about 16.1 pp.

on annuitization: this coefficient in Column 4 is of the right sign but smaller in magnitude and noisily estimated. Nonetheless, this effect is significant in explaining annuitization *within* retirement plans (see Column 6 in which I add plan fixed effects) and it is not reduced when I add past returns (see Column 5). Beliefs from institutional investors have information useful in understanding annuitization. Different than individual investor beliefs, this information is not easily captured by previous past returns.[50]

The evidence in Table IX suggests that past stock returns affect annuitization by changing beliefs. This result makes extrapolation a plausible interpretation of the evidence in my data. Consistent with this interpretation, several studies document the influence of past stock market returns on financial decisions. Using data from the UBS/Gallup survey between 1998 and 2002, Vissing-Jørgensen (2003) documents that expected returns were high when the market was at its peak, with investors that have directly experienced higher returns having the highest expectations. These beliefs affected actions: investors with higher expected returns for Internet stocks tilted more of their portfolio toward this asset class. Using data from the same survey from 1998 to 2007, Malmendier and Nagel (2009) find that the average stock market returns during a lifetime have an impact on beliefs about future stock market returns, with higher weights assigned to more recent returns.

Additional evidence in the domain of retirement savings is consistent with this interpretation. Benartzi (2001) shows that employees are more likely to invest their retirement funds in their company stock after the company shares have experienced abnormally high returns. Benartzi and Thaler (2007) document that during the Internet bubble, new 401(k) participants' allocation to equity was highest at the market's peak. In a plan that offered a technology fund, participants were investing in this fund most aggressively at its peak. Choi et al. (2009) document that after experiencing positive returns in their 401(k) accounts, employees increase their retirement saving rates.

Lastly, someone might argue that an interpretation based on extrapolation might contradict my previous results for the real estate market. In Table V, I find that after an increase in real estate prices, employees are *less* likely to choose a lump sum payment. If employees tend to extrapolate from past experience, a legitimate question is why after a positive growth in real

[50] As a simple test, I run a regression of the confidence index on past stock returns. The coefficient is significant for individual investors, while it is not for institutional investors.

estate prices they do not choose a lump sum to invest in real estate. I believe that this different behavior is due to inherent differences between the real estate and stock market: liquidity; entry and monitoring costs; and minimum investment required. Consistent with my results, Mian and Sufi (2009) document how, in the period 2002-2006, homeowners were borrowing against the increase in home equity and how the money extracted was not used to purchase new real estate.

5 Conclusion

Managing savings after retirement is a daunting maximization problem that involves decisions about investment, consumption and (longevity) risk management. The welfare consequences of these decisions can be remarkable. Hornef et al. (2009) document that investors can obtain substantial welfare gains – up to 40 percent of their financial wealth – by adjusting portfolio allocation and purchasing variable annuities gradually over time.[51] In the presence only of fixed annuities, Milevsky and Young (2002) calculate that the value of the (real) option to defer annuitization can be as high as 20 percent of retirement wealth.

Using these estimates, I can make a back-of-the-envelope calculation of the welfare consequences associated with the effect of stock returns on annuitization. As an example, I consider two employees: one retiring before the credit crises, in December 2007, and the other a year later, in December 2008. Holding everything else equal, my estimates imply that the employee retiring in December 2008 is about 25 percentage points (pp) more likely to choose an annuity.[52] Multiplying this change in probability by the wealth losses associated with immediate full annuitization from the previous studies, I can obtain an estimate of welfare reduction that ranges between 5 and 10 percent.

A limitation of my data is that I do not observe how employees manage and invest the lump sum payment. Investigating how people handle their wealth after retirement seems a promising venue for future research. In this paper, I look at annuitization – only one of the major decisions employees face during their retirement. Decisions about asset allocation

[51] The authors consider variable payout annuities, a payout product that offers both an investment element and a longevity insurance element. For more details, refer to the cited paper.

[52] Using estimates from Column 1 in Table II, the difference in the past return average between the two employees is equal to 4.1 pp. Therefore, the effect of returns on annuitization is equal to -5.627*4.1 pp $\approx$ -23.3 pp.

and investing, or consumption and spending rates are equally important. While behaviors associated with saving for retirement have been widely studied and analyzed, we need to deepen our knowledge about what happens in the other half of the equation, after people retire.

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Table I
Summary Statistics

Annuity is a binary variable equal to 1 if the annuity is chosen. Age is equal to the age of the employee at the benefit start date. Female is an indicator variable equal to 1 if the employee is female. Tenure is the number of years the employee has worked for the company. DB Benefits is the total amount of the benefits accrued to the employee. Median House Price is the median house price in the Metropolitan Statistical Area (MSA) of residency at the moment of separation. I can match house prices only for 70,587 employees in my sample. Income is the total yearly income for the employee in the year of separation. Years of Education represents years of education completed. Business Education is an indicator variable equal to 1 if the employee obtained any financial education (either a bachelor's degree with a major in economics or accounting, or a master's degree in economics or in business administration). MBA is an indicator variable equal to 1 if the employee obtained a master's degree in business administration. Sample Size is the total number of observations for each sample. The data from the Survey of Consumer Finances (SCF) represent average across three waves of the survey (2001, 2004 and 2007). Observations are weighed using SCF sample weights, so to be representative of the U.S. population. Data in Columns 5 and 6 are from respondents that are retired and with age lower than 75 years. Data in Columns 7 and 8 are from respondents with age between 50 and 75 years, regardless their retirement status. Age and Female are referred to the person answering the survey. Net Financial Wealth and Home Equity are measured at the household level.

		Main Sample		IBM		SCF (retirees)		SCF (age 50-75)	
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Unit	Mean	Median	Mean	Median	Mean	Median	Mean	Median
Annuity	0-1	0.49	0.00	0.88	1.00				
Age	1	59.83	60.00	58.33	57.86	70.20	70.13	60.63	59.60
Female	0-1	0.44	0.00	0.25	0.00	0.32	0.00	0.27	0.00
Tenure	1	24.52	25.66	28.92	30.59				
DB Benefits	$1,000	188.13	86.46	413.04	387.1				
Net Financial Wealth	$1,000					259.2	15.36	262.79	6.72
Median House Price	$1,000	213.33	166.10						
Home Equity	$1,000					167.46	97.37	163.89	87.4
Income	$1,000			101.07	95.93				
Years of Education	1			15.22	16				
Business Education	0-1			0.12	0				
MBA	0-1			0.06	0				
Sample Size	1	103,516	103,516	18,688	18,688	932	932	5,835	5,835

Table II
Stock Market Returns and Annuitization (Main Sample)

This table reports results from Non-linear Least Squares (Col. 1) or OLS (Col. 2-4) regressions. The dependent variable is a binary indicator which equals 1 if the employee chooses an annuity. Demographic Controls include: age, gender, tenure and benefit amount. Interest Rates is the composite return on long-term Treasury Bonds. Plan Controls include for each year the average age, gender, benefits and number of employees retiring in that specific plan. Column 1 includes Demographic Controls, Interest Rates, Calendar Months Fixed Effects and Plan Controls. In Column 2, I add Plan Fixed Effects. In Column 3, I add fixed effects for the Metropolitan Statistical Area (MSA) of the employee at separation. In Column 4, I add both Plan and MSA fixed effects. Standard errors are clustered across 15 company size/time groups. More precisely, I partition the data in quintiles based on company size and three 28-month periods. Combining these two partitions, I obtain fifteen groups with observations in the same quintile of company size and the same period belonging to one group. See the text for more detail on this methodology and for the motivation of using Linear Probability Models. For ease of interpretation, all the coefficients - except λ - are multiplied by 100. They can be interpreted as 1 percentage variation in the probability of annuitization corresponding to 1 unit change in the corresponding independent variable. The unit of past stock market returns is 1 percentage point, equivalent approximately to one standard deviation variation.

	(1)	(2)	(3)	(4)
Past stock return coefficient β	-5.627***	-4.336**	-4.815**	-3.949**
	(1.513)	(1.609)	(1.921)	(1.623)
Weighting parameter λ	5.163***	5.163	5.163	5.163
	(0.827)			
Demographic Controls	Yes	Yes	Yes	Yes
Interest Rates	Yes	Yes	Yes	Yes
Calendar Months F. E.	Yes	Yes	Yes	Yes
Years F. E.	Yes	Yes	Yes	Yes
Plan Controls	Yes	Yes	Yes	Yes
Plan F.E.	No	Yes	No	Yes
MSA F.E.	No	No	Yes	Yes
Observations	103,516	103,516	89,396	89,396
R-squared	0.192	0.390	0.242	0.415

Standard errors in parentheses. Constant included.

* significant at 10%; ** significant at 5%; *** significant at 1%.

Table III
Stock Market Returns and Annuitization (IBM Sample)

This table reports results from Non-linear Least Squares or OLS (Column 2) regressions. The dependent variable is a binary indicator which equals 1 if the employee chooses full annuitization. Demographic Controls include: age, gender, benefit amount and income. Education is the number of years of education completed. Financially Educated (MBA) is an indicator variable equal to 1 if the employee received any financial education (an MBA). Interest Rates is the composite return on long-term Treasury Bonds. Column 2 includes Working Location Fixed Effects. Standard errors are clustered across eight geographical region/time groups. More precisely, I partition the data in the four US Census Regions and two 51-month periods. Combining these two partitions, I obtain eight groups with observations in the same region and the same period belonging to one group. See the text for more detail on this methodology and for the motivation of using Linear Probability Models. For ease of interpretation, all the coefficients - except λ - are multiplied by 100. They can be interpreted as 1 percentage variation in the probability of annuitization corresponding to 1 unit change in the corresponding independent variable. The unit of past stock market returns is 1 percentage point, equivalent approximately to one standard deviation variation.

	(1)	(2)	(3)	(4)	(5)	(6)
Past stock return β	-2.608***	-2.227***	-2.483 ***	-2.350***	-2.663***	-2.641**
	(0.696)	(0.452)	(0.396)	(0.616)	(0.590)	(0.854)
Weighting par. λ	1.022***	1.022	1.059***	0.969***	0.956***	0.891***
	(0.188)		(0.286)	(0.096)	(0.171)	(0.079)
Financially Educated			-0.005	-0.134		
			(0.914)	(0.873)		
Past stock ret.*Fin. Ed.			-1.074	-1.437		
			(0.830)	(0.839)		
Weight. par.*Fin. Ed.				4.336**		
				(1.401)		
MBA					-0.772	-1.018
					(0.112)	(0.862)
Past stock ret.*MBA					-0.378	-1.187
					(0.899)	(0.900)
Weight. par.*MBA						7.779
						(4.278)
Education	Yes	Yes	Yes	Yes	Yes	Yes
Demographic Controls	Yes	Yes	Yes	Yes	Yes	Yes
Interest Rates	Yes	Yes	Yes	Yes	Yes	Yes
Calendar Month F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Work. Loc. F. E.	No	Yes	No	No	No	No
Observations	18,671	18,671	18,671	18,671	18,671	18,671
R-squared	0.134	0.162	0.134	0.135	0.135	0.1313

Standard errors in parentheses. Constant included.

* significant at 10%; ** significant at 5%; *** significant at 1%.

Table IV
Stock Market Returns and Individual Annuities Sales (LIMRA Sample)

This table reports results from Non-linear Least Squares regressions. In Column 1, the dependent variable is the log of real quarterly sales of Fixed Annuities. In Column 2, the dependent variable is the log of real quarterly sales of Fixed Immediate Annuities. Interest Rates is the composite return on long-term Treasury Bonds. Recession is an indicator variable equal to 1 during the NBER recession periods. Newey-West robust standard errors in parentheses. For ease of interpretation, all the coefficients - except λ - are multiplied by 100. They can be interpreted as 1 percentage variation in the probability of annuitization corresponding to 1 unit change in the corresponding independent variable. The unit of past stock market returns is 1 percentage point, equivalent approximately to one standard deviation variation.

Sample Period:	1985Q1-2009Q2	1992Q1-2009Q2
Dependent Variable:	Fixed Annuities (Ln)	Fixed Immediate Annuities (Ln)
	(1)	(2)
Past stock return coefficient β	-10.629 ***	-5.282***
	(0.872)	(1.712)
Weighting parameter λ	1.258***	0.398
	(0.184)	(0.223)
Interest Rates	Yes	Yes
Recession	Yes	Yes
Calendar Quarters F. E.	Yes	Yes
Observations	98	70
R-squared	0.760	0.608

Standard errors in parentheses. Constant included.

* significant at 10%; ** significant at 5%; *** significant at 1%.

Table V
Stock Market Returns, Annuitization and Wealth (Main Sample)

This table reports results from Non Linear Least Squares (Col. 1) and OLS regressions. The dependent variable is a binary indicator which equals 1 if the employee chooses an annuity. The median house prices are collected at the MSA where the employee lived at separation. Variations in Median House Prices are computed from the Lagged Value until the time of retirement. Demographic Controls include: age, gender tenure and benefit amount. Interest Rates is the composite return on long-term Treasury Bonds. Column 5 includes retirement plan fixed effects. Standard errors are clustered across fifteen company size/time groups. More precisely, I partition the data in quintiles based on company size and three 28-month periods. Combining these two partitions, I obtain fifteen groups with observations in the same quintile of company size and the same period belonging to one group. See the text for more detail on this methodology and for the motivation of using Linear Probability Models. For ease of interpretation, all the coefficients - except λ - are multiplied by 100. They can be interpreted as 1 percentage variation in the probability of annuitization corresponding to 1 unit change in the corresponding independent variable. I use the following units: i) 1 percentage point for past stock market returns; ii) $100,000for Median House price; iii) 10 percentage points for Variation in Median House Price. All the units correspond approximately to one standard deviation variation.

Lag in Median House Prices:		1 Year	2 Years	3 Years	1 Year
	(1)	(2)	(3)	(4)	(5)
Past stock return β	-5.801**	-6.079**	-5.963**	-6.135**	-4.730*
	(2.123)	(2.505)	(2.512)	(2.498)	(2.331)
Weighting parameter λ	5.095**	5.095	5.095	5.095	5.095
	(2.022)				
Lagged Median House Price		-3.260***	-3.802***	-4.419***	-1.229**
		(0.720)	(0.795)	(0.861)	(0.473)
Δ Median House Price		1.873*	1.122**	0.482	1.118**
		(0.951)	(0.437)	(0.429)	(0.509)
Dem. Controls	Yes	Yes	Yes	Yes	Yes
Interest Rates	Yes	Yes	Yes	Yes	Yes
Cal. Months F. E.	Yes	Yes	Yes	Yes	Yes
Years F. E.	Yes	Yes	Yes	Yes	Yes
Plan Controls	Yes	Yes	Yes	Yes	Yes
Plan F.E.	No	No	No	No	Yes
Observations	58,897	58,897	58,897	58,897	58,897
R-squared	0.166	0.174	0.174	0.173	0.376

Standard errors in parentheses. Constant included.

* significant at 10%; ** significant at 5%; *** significant at 1%.

Table VI
Stock Market Returns, Annuitization and Exogenous Wealth Shock: Evidence from the Hurricane Katrina (Main Sample)

This table reports results from OLS regressions. The dependent variable is a binary indicator which equals 1 if the employee chooses an annuity. Katrina Date is an indicator variable equal to 1 after 9/2005. Katrina States is an indicator variable equal to 1 if the employee lived in Florida, Mississippi, Louisiana or Alabama at the decision date. Neighboring States is an indicator variable if the employee lived in Texas, Kentucky, Ohio or Georgia. Demographic Controls include: age, gender, benefit amount and tenure. Interest Rates is the composite return on long-term Treasury Bonds. Standard errors are clustered across 12 geographical region/time groups. More precisely, I partition the data in the four US Census Regions and three 28-month periods. Combining these two partitions, I obtain 12 groups with observations in the same region and the same period belonging to one group. See the text for more detail on this methodology and for the motivation of using Linear Probability Models.For ease of interpretation, all the coefficients - except λ - are multiplied by 100. They can be interpreted as 1 percentage variation in the probability of annuitization corresponding to 1 unit change in the corresponding independent variable. The unit of past stock market returns is 1 percentage point, equivalent approximately to one standard deviation variation.

Sample:	All States	All States (without LA)	All States	All States (without LA)
	(1)	(2)	(3)	(4)
Past stock return β	-5.713**	-5.637**	-5.667**	-5.590**
	(2.062)	(2.079)	(2.072)	(2.088)
Weighting parameter λ (Fixed)	5.163	5.163	5.163	5.163
Katrina Date	3.708	3.434	3.911	3.639
	(3.422)	(3.284)	(3.601)	(3.458)
Katrina States	5.131*	4.196	5.918**	4.975*
	(2.544)	(2.342)	(2.600)	(2.396)
Katrina Date*Katrina States	-8.195***	-7.623***	-8.310***	-7.735***
	(2.195)	(2.183)	(2.104)	(2.170)
Neighboring States			3.427**	3.434**
			(1.353)	(1.375)
Katrina Date*Neigh. States			-0.661	-0.662
			(2.227)	(2.239)
Interest rates	Yes	Yes	Yes	Yes
Year F. E., Month F.E.	Yes	Yes	Yes	Yes
Dem. and Plan Controls	Yes	Yes	Yes	Yes
Observations	95,997	94,557	95,997	94,557
R-squared	0.197	0.195	0.197	0.195

Standard errors in parentheses. Constant included.

* significant at 10%; ** significant at 5%; *** significant at 1%.

Table VII
Stock Market Returns, Annuitization and Timing of Retirement

This table reports results from OLS regressions. The dependent variable is a binary indicator which equals 1 if the employee chooses an annuity. Exact Age is an indicator variable equal to 1 if the benefits start on the birthday of the employees. Laid-off Workers is an indicator variable equal to 1 if the employees did not decide voluntarily to retire. Demographic Controls include: age, gender, benefit amount and tenure (plus income and education years in Columns 3 and 4). Interest Rates is the composite return on long-term Treasury Bonds. In Columns 1 and 2, standard errors are clustered across 15 company size/time groups, based on company size quintiles and three 28-month periods. In Columns 3 and 4, standard errors are clustered across eight geographical region/time groups, based on the four US Census Regions and two 51-month periods. See the text for more detail on this methodology and for the motivation of using Linear Probability Models. Column 2 includes retirement plan fixed effects; Column 4 working location fixed effects. For ease of interpretation, all the coefficients - except λ - are multiplied by 100. They can be interpreted as 1 percentage variation in the probability of annuitization corresponding to 1 unit change in the corresponding independent variable. The unit of past stock market returns is 1 percentage point, equivalent approximately to one standard deviation variation.

Sample:	Main Sample		IBM	
	(1)	(2)	(3)	(4)
Past stock return β	-6.992**	-5.225**	-3.303***	-3.043***
	(2.932)	(2.363)	(0.816)	(0.640)
Weighting parameter λ (Fixed)	5.163	5.163	1.022	1.022
Exact Age	-3.264	-5.95		
	(9.302)	(8.203)		
Past stock return*Exact Age	4.287	2.426		
	(3.589)	(2.544)		
Laid-off Workers			-0.984*	-0.996**
			(0.436)	(0.323)
Past stock return * Laid-off Work.			0.656	0.893
			(0.826)	(0.729)
Interest Rates	Yes	Yes	Yes	Yes
Demographic Controls	Yes	Yes	Yes	Yes
Year F. E.and Calendar Month F.E.	Yes	Yes	Yes	Yes
Plan Controls	Yes	Yes		
Plan F.E.	No	Yes		
Working Location F.E.			No	Yes
Observations	103,516	103,516	15,802	15,802
R-squared	0.193	0.391	0.137	0.169

Standard errors in parentheses. Constant included.

* significant at 10%; ** significant at 5%; *** significant at 1%.

Table VIII
Stock Market Returns, Volatility and Annuitization

This table reports results from OLS regressions. In Columns 1 and 2 the dependent variable is a binary indicator which equals 1 if the employee chooses an annuity; in Columns 3 and 4 is the log of real quarterly sales of Fixed Annuities. S&P 500 Volatility equals the volatility of the S&P500 index over the referred time horizon. Demographic Controls include: age, gender, benefit amount and tenure. Interest Rates is the composite return on long-term Treasury Bonds. Recession is an indicator variable equal to 1 during the NBER recession periods. In Columns 1 and 2, standard errors are clustered across 15 company size/time groups, based on company size quintiles and three 28-month periods. See the text for more detail on this methodology and for the motivation of using Linear Probability Models. In Column 3 and 4, I report Newey-West robust standard errors. Column 3 includes retirement plan fixed effects. For ease of interpretation, all the coefficients - except λ - are multiplied by 100. They can be interpreted as 1 percentage variation in the probability of annuitization corresponding to 1 unit change in the corresponding independent variable. I use the following units: i) 1 percentage point for past stock market returns; ii) one standard deviation for volatility.

Sample:	Main Sample			Limra	
	(1)	(2)	(3)	(4)	(5)
Past stock return coefficient β	-5.632***	-3.995**	-3.416**	-11.240***	-11.313***
	(1.857)	(1.705)	(1.511)	(0.967)	(0.744)
Weighting parameter λ (fixed)	5.163	5.163	5.163	1.258	1.258
S&P500 Volatility std	0.167			-0.031***	
(3 months)	(0.998)			(0.010)	
S&P500 Volatility std		2.014	1.268		0.030
(6 months)		(2.372)	(1.867)		(0.018)
Interest rates	Yes	Yes	Yes	Yes	Yes
Calendar Months/Quarters F.E.	Yes	Yes	Yes	Yes	Yes
Year F. E.	Yes	Yes	Yes		
Dem. and Plan Controls	Yes	Yes	Yes		
Plan F.E.	No	No	Yes		
Recession				Yes	Yes
Observations	103,516	103,516	103,516	98	98
R-squared	0.192	0.192	0.39	0.67	0.671

Standard errors in parentheses. Constant included.

* significant at 10%; ** significant at 5%; *** significant at 1%.

Table IX
Beliefs about Stock Market Returns and Annuitization

This table reports results from OLS regressions. The dependent variable is a binary indicator which equals 1 if the employee chooses an annuity. Confidence Index is the (six-month average) percentage of investors expecting an increase in the Dow Jones Industrial in the coming year. Columns 1-3 report this percentage for individual investors; Columns 4-6 for institutional investors. Demographic Controls include: age, gender, benefit amount and tenure. Interest Rates is the composite return on long-term Treasury Bonds. Standard errors are clustered across 15 company size/time groups, based on company size quintiles and three 28-month periods. See the text for more detail on this methodology and for the motivation of using Linear Probability Models. For ease of interpretation, all the coefficients - except λ - are multiplied by 100. They can be interpreted as 1 percentage variation in the probability of annuitization corresponding to 1 unit change in the corresponding independent variable. I use the following units: i) one percentage point for past stock market returns; ii) one standard deviation for the confidence index.

Sample:	Individual Investors			Institutional Investors		
	(1)	(2)	(3)	(4)	(5)	(6)
Confidence Index	-9.803**	-2.771	-4.199	-3.217	-2.611	-3.170*
	(4.570)	(3.920)	(3.266)	(1.930)	(1.661)	(1.490)
Past stock return β		-5.168**	-3.614**		-5.732***	-4.492**
		(1.761)	(1.299)		(1.871)	(1.565)
Weighting parameter λ		5.163	5.163		5.163	5.163
Interest rates	Yes	Yes	Yes	Yes	Yes	Yes
Calendar Months and Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Dem. and Plan Controls	Yes	Yes	Yes	Yes	Yes	Yes
Plan F.E.	No	No	Yes	No	No	Yes
Observations	101,053	101,053	101,053	101,053	101,053	101,053
R-squared	0.186	0.190	0.389	0.184	0.190	0.390

Standard errors in parentheses. Constant included.

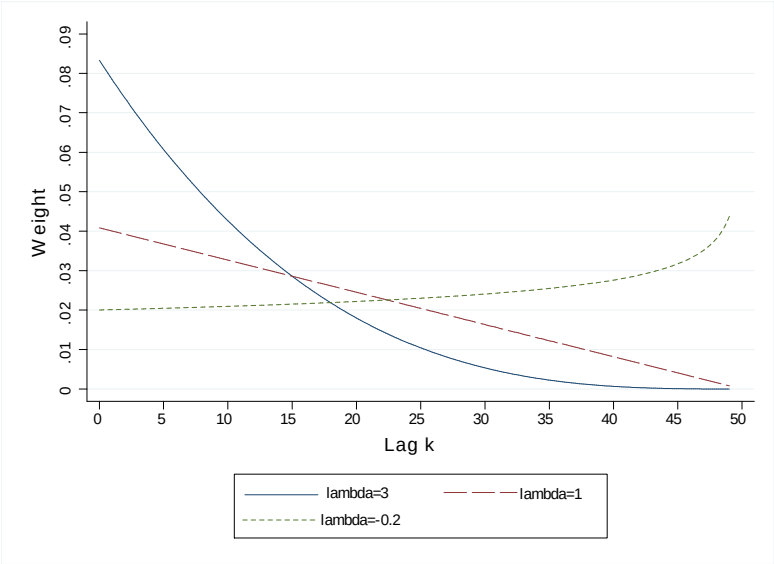
* significant at 10%; ** significant at 5%; *** significant at 1%.

Figure I
Annuity Sales and Past Stock Market Returns

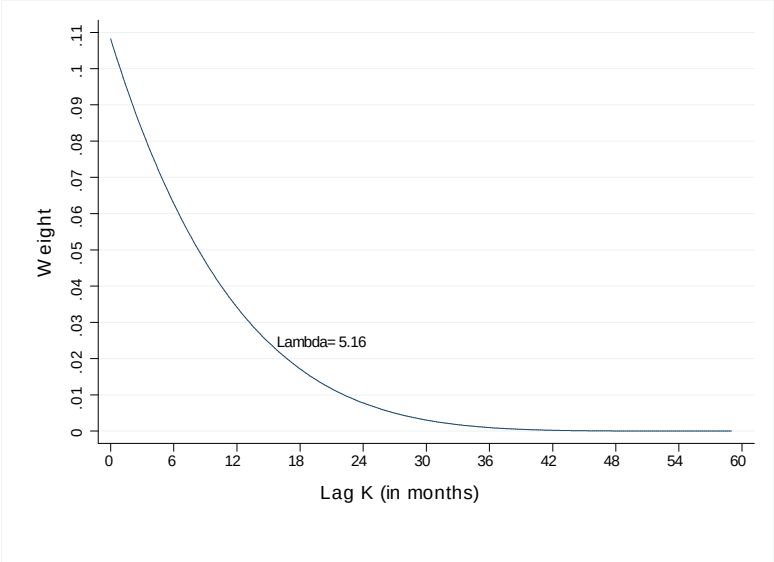
This graph plots the past twelve months returns on the S&P500 index (solid line) and the quarterly fixed annuity sales (dotted line). Annuity sales are deflated using the 2009 CPI.

Figure II
Past Stock Market Returns Weighting Function

This graph shows how the weighting function of past monthly stock market returns varies for different values of the parameter λ.



Source: Adapted from Malmendier and Nagel (2009)

Figure III
Estimated Weighting Function (Main Sample Data)

This graph plots the weighting function of past monthly stock market returns with the value of λ estimated in Table II.