Supplemantary Online Appendix for
Stock Returns and Annuitization at Older Ages

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1 Methodology

A Weigthing Function of Past Stock Returns

Using the data sets described in the paper, we estimate an equation of the following general form:

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

where Ann_{ijt} is a binary variable equal to one if employee i enrolled in plan j at time t chooses an annuity. We explain this decision using a weighted average $A_t(\lambda)$ of the past stock returns, a vector x_{it} of control variables, and an error term ε_{it}. Following Malmendier and Nagel (2011), we estimate directly from the data the following weighting function of monthly stock returns R_{t-k} for the period lag (expressed in months) prior to the decision date:

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

This functional form for the weighting function is very flexible and parsimonious. Depending on the value of just one parameter, λ, we can obtain decreasing, increasing or constant weights for past monthly stock returns.[1] Therefore, the two parameters of primary interest in our analysis are β and λ, to be estimated simultaneously from the data. The relative weight of recent returns is determined by λ while β captures the overall effect of weighted returns on the decision to annuitize.

From Equations 1 and 2, we can see that the estimating equation is not linear in the

[1] 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 $\lambda>1$). See Figure A.2 for a graphical representation of this weighting function.

parameter λ. Therefore, we use non-linear least squares and select the λ that minimizes the sum of squared residuals.[2] As in Malmendier and Nagel (2011), to ensure that we find the global minimum we first estimate Equation 1 for tightly spaced values of λ. Then, we use the value of λ that minimizes the sum of squared residuals as the starting value in the optimization process.

In our analyses, we assume a lag period equal to 60 months before the decision date. The results are robust to longer or shorter choices of period length. As additional robustness checks, we 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 we use use.

B Standard Errors

To account for cross-sectional and inter-temporal dependence in our data, we follow the approach developed in Bester, Conley and Hansen (2011). They provide simulation evidence that using cluster covariance estimators 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. 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. There are three additional restrictions on the groups. They need to be: i) mutually exclusive; ii) exhaustive; iii) and contiguous. We choose partitions meant to satisfy these requirements.

Standard Errors in the Main Sample. In our defined benefit plans analyses (e.g.,

[2] Even if the outcome variable is binary, we use linear probability models (i.e., OLS estimation). The results are robust to the use of Logit models. We report the reasons for this choice in the paper.

Table II, Panel A) we cluster the standard errors in fifteen company size/time groups. More precisely, we partition the data into three 28-month periods and quintiles based on company size, proxied by the number of employees separating from each company in our sample period. Combining these two partitions, we obtain fifteen groups with observations in the same quintile of company size and the same period belonging to one group.

First, from Figure A.1 we can see how the weight given to stock market returns after 28 months is approximately zero (precisely 0.004). Second, we conservatively cluster 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. 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. Our results are robust to the use of different clusters based on company size deciles and four 21-month periods; or based on time and geographical location of the employees (the four US Census Regions or the nine Divisions).

Standard Errors in the IBM Sample. In all the IBM analyses (e.g., Table II, Panel B), to ensure independence across group averages, we partition the data into the four US Census Regions (Northeast, Midwest, South, West)[3] 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, we cluster across regions to take into account not only dependence of the data *within* the same working location, but also

[3]For more details see: http://www.census.gov/geo/www/us_regdiv.pdf.

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).

Standard Errors in the Hurricane Katrina Evidence. In the analyses related to the Hurricane Katrina event, we cluster the standard errors across 12 region/time groups, obtained by combining the four US Census Regions and three 28-month periods. We prefer this partition to the one based on company size, because it allows us 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 simultaneously include 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 we 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 we simply follow the procedure suggested in Bertrand, Duflo, and Mullainathan (2004) and cluster the errors at the state level and ignore cross-sectional correlations, we estimate smaller standard errors.

C Omitted Variables Bias

The results in Section 2 of the paper can seriously suffer from an omitted variables bias. For example, we 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, our 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:[4]

$$Ann_{it} = \alpha + \beta^* A_t(\lambda) + \rho W_{it} + \varepsilon_{it} \tag{3}$$

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

$$\frac{Cov\left(Ann_{it}, A_t(\lambda)\right)}{V\left(A_t(\lambda)\right)} = \beta^* + \rho\delta_{W\,\mathrm{Re}\,t} \tag{4}$$

in which δ is the coefficient from regressing wealth on stock market returns. From Equation 4, 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.

Since we estimate a *negative* relationship between stock returns and annuitization, our estimates will be in general 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. If they have opposite signs, our estimates can be "too large" or eventually of the wrong sign. For example, in the case of wealth we can safely assume a positive relationship between stock returns and financial wealth (i.e., an increase in stock returns increases financial wealth). Therefore, our estimates will be biased if a shock in wealth reduces annuitization or, alternatively, too conservative if a variation in wealth increases annuitization. We report results consistent with this latter case in the subsection 3.A and 3.B of the paper. Later in this Appendix, we consider the effects of omitting stock

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

market volatility and expectations about labour income and inflation.

2 Additional Empirical Analyses and Robustness Checks

A Stock Market Returns and Annuitization

In Table A.I Panel A, we present results that rely on the weighting function to estimate more precisely the effect of past returns. In Column 5, the coefficient of the weighted average of past (monthly) stock returns, β, is both statistically and economically significant. A one standard deviation increase in the average stock market return (equal to 1.1 percentage points) decreases the likelihood of selecting an annuity by about 6.2 percentage points (pp). Alternatively, a change from the 25^{th} to the 75^{th} percentile of the past 60-month average stock market return distribution (about 1.7 pp) implies a change in the probability of selecting an annuity of about -9.5 pp. A change from the 10^{th} to the 90^{th} percentile (about 2.6 pp) implies a change in the probability of annuitization of about -14.6 pp.

The coefficient of the weighting parameter, λ, is statistically different from zero. Figure A.2 plots the weights corresponding to a value of λ equal to 5.2. This value implies that the weights assigned to past stock market returns decrease over time with higher weight given to the most recent returns. 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. In Columns 6 and 7, we do not directly estimate a value for λ. After fixing the weighting parameter (λ=5.2), equation 3 becomes linear and can be estimated using a linear probability model.[5]

In Panel B, we report results using the IBM sample. We confirm that the past returns coefficient β is both statistically and economically significant. A change from the 25^{th} to the 75^{th} percentile of the past 60-month weighted average stock market return (about 1 pp) implies a change in the probability of selecting an annuity of about -2.6 pp. In the same fashion, moving from the 10th to the 90th percentile (about 2.3 pp) implies a change in the probability of annuitization of roughly -6.0 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. The decline is not as steep as the one we found in Panel A. The effect of interest rates if anything become stronger with this specification. Overall, these results confirm the estimates without the weighting function.

In Table A.II, we introduce estimates that rely on Logit models instead of linear probability models (OLS). In Panel A, we document that the results are robust to either estimation method. Given the issues associated with Logit models (i.e., incidental parameters problem and difficult interpretation of the interaction coefficients), this evidence support our use of linear probability models. In Panel B, we report similar estimates from the IBM sample. We note how all the coefficients estimated here are in general smaller than the ones reported in the previous table. Moreover, the effect of past returns becomes stronger if we include returns more distant in time. This is perfectly consistent with our estimation of the weighting parameter in this sample: a weighting coefficient of roughly 1 implies linearly decreasing weights going as far back as five years before retirement (our cutoff for recent returns). Last, we observe here some discrepancy between

[5] Estimating models with non-linear least squares hold the same results.

the estimates using Logit models and linear probability models. The fact that about 88 percent of IBM employees choose an annuity can account for these differences. Recall that in the main sample the average annuitization rate is close to 50 percent and, hence, our estimates from Logit and LPM models are very close. The use of retirement plan fixed effects accounts for this heterogeneity across retirement plans and guarantees that our results are not driven by any specific plan.

B Stock Market Returns and Individual Annuity Sales

In Table A.III, we investigate the relationship between stock market returns and individual annuity sales. We analyze data on fixed annuity sales between the first quarter of 1985 and the second quarter of 2009 and immediate fixed annuity sales starting from 1992. We deflate the sales into June 2009 dollars using the Consumer Price Index. The data on annuity sales are collected by LIMRA International, a worldwide association of insurance and financial services companies. Depending on the annuity type, LIMRA estimates coverage between 85 and 95 percent of the total annuity sales in the US.

More precisely, we 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. 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). In Column 1, the dependent variable is the log of real sales of fixed annuities (both deferred and immediate). A one percent point (pp) increase in the quarterly average stock market return translates into a 10.6 percent reduction in the sales of fixed annuities, a result statistically and economically significant. A value of λ equal to 1.25 implies weights for stock market returns are almost linearly decreasing over the past five years. Since we have only time series data, we do not have to worry about cross-sectional dependence in the data. Therefore, we use Newey-West (1987) standard errors to account for serial correlation up to 20 quarters (five years) in the data.

In Column 2, we replicate these results using immediate annuity sales as the dependent variable. Here a one percentage point increase in stock market return implies a 5.3 percent reduction in annuity sales. While immediate annuity sales are in reality closer to the decision to annuitize in DB plans, the data from LIMRA also included the sales of structured settlements in this category. Structured settlements are essentially annuities paid to compensate injury victims for their losses and are, of course, less likely to be affected by stock market returns. This fact can explain why we obtain a lower estimate for β and a noisy estimate for λ.

C Additional Analyses on the Hurricane Katrina Event

In Table A.IV we test if changes in life expectancy due to the hurricane explain our findings. Natural disasters such as Hurricane Katrina could cause individuals to revise (downward) their life expectancies and, hence, to find annuities less appealing. Note that this alternative interpretation is true only if the annuities offered do not fully adjust to this new lower (perceived) life expectancy. We can safely assume that this is the case, because the mortality tables used are not state-specific. As previously discussed, data limitations prevent us from directly measuring these potential changes in life expectancy.

We rely instead on the evidence that after natural disasters the demand for life insurance increases in the states directly affected by the event and also in neighboring states (Fier and Carson, 2009). Therefore, we compare individuals that were afflicted by the hurricane with individuals that lived in neighboring areas not directly afflicted. This identification strategy assumes that both sets of individuals will revise their life expectancies in a similar way, while only the ones living in the afflicted areas would suffer a wealth shock.

In practice, we run a differences-in-differences estimation between the Katrina areas and neighboring states (Texas, Kentucky, Ohio and Georgia), excluding employees from all the remaining states. From Column 1, we can see that our results are largely unchanged and that employees living in the afflicted areas are 7.3 pp less likely to annuitize after the hurricane. As in the main analyses reported in the paper, in Column 2 we exclude employees from Louisiana, while in Columns 3 and 4 we include the company exposure to the areas afflicted by the hurricane. Our main results are robust to all these different specifications.

D Timing of Retirement

In most cases, employees can decide when to retire. Some omitted variable could jointly drive the timing of retirement and the decision to annuitize. For example, more impatient individuals could decide to retire after a positive trend in the market and also be more likely - because of their present-biased preferences - to choose a lump sum. To rule out this alternative explanation or the effect of some omitted variable that could jointly drive the timing of retirement and the decision to annuitize, we test if the effect of stock returns on annuitization is also significant for subsamples of employees less likely to time their retirement based on recent stock market conditions.

In Table A.V, we present these robustness checks. More specifically, using data from our main sample (Column 1 and 2) we hypothesize that employees retiring on their birthdays at specific and very popular retirement ages (such age 65) are less likely to time their retirement. We complement this evidence with data from the IBM sample (Columns 3 and 4), looking at employees that were let go. In Column 1, we estimate our baseline model with the addition of: i) a dummy variable (Exact Age) equal to 1 if an employee retires on her 55^{th}, 60^{th}, 62^{nd} and 65^{th} birthday; and ii) the interaction between this indicator variable and stock market returns. We obtain these four ages looking at spikes in the distribution of retirement ages. Being round numbers, age 55, 60 and 65 are natural reference points. Age 62 is the earliest and most common age at which people start claiming Social Security. About 9.2 percent of employees in our sample (N=9,556) retire on any of these birthdays. The value of λ is fixed at the estimated value from Table II, Panel A (5.16). Analogously, in Columns 3 and 4, the value of λ is fixed at the estimated value from Table II, Panel B (1.02).

We report in the last row the p-values of an F-test that investigates whether the stock return coefficient for employees retiring on their birthdays is equal to zero (i.e., sum of the main and interaction effect). The results indicate that employees retiring on less discretionary dates are also subject to the effect of stock returns (p-value=.011). We obtain similar results if we analyze only those employees that retire on their 65^{th} birthday (p-value=.083). Standard errors are clustered here across 15 company size/time groups obtained by partitioning the data into company size quintiles and three 28-month periods. In Column 2, we add retirement plan fixed effects to this specification to confirm that this result is common across plans and not driven by any plan in particular.

In Columns 3 and 4, we provide more compelling evidence using a subsample of the IBM employees for whom we can observe the reason for separation, whether voluntary or not (i.e., employees let go by the company). We estimate our baseline model with the addition of a dummy variable (Laid-off), equal to 1 if the employees were let go. There are 7,394 employees that fall in this category (about 47 percent of this subsample). Consistent with what we found before, the effect of stock market returns on annuitization is also statistically significant for employees who were let go (p-value = .008). In Column 4, we repeat a similar test adding working location fixed effects.

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

E Stock Market Volatility

In Table A.VI, we investigate the effect that the omission of stock market volatility produces on our estimates. A negative correlation between volatility and returns in the short term (Glosten, Jagannathan and Runkle, 1993) together with time-varying risk aversion can bias our 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.

In Columns 1 and 2, we estimate our baseline model with the addition of the average stock market volatility over the previous three and six months respectively. We 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, we document that adding the three or six months average volatility to the estimates about individual annuity sales (LIMRA sample) 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, we find that this result holds also for the sale of immediate fixed annuities.

F Expectations about Labor Income and Inflation

In Table A.VII, we control for the potential effects of expectations about labor income and inflation. Positive stock market returns can generate better labor income expectations, which in turn could 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 4, a positive correlation between stock returns and labor expectations together with a negative correlation between these expectations and annuitization can bias our results.

To test for a positive relationship between labor income and annuitization, we complement the main sample with information from the Survey of Consumers (University of Michigan/ Thomson Reuters). More specifically, we use regional monthly data on expectations of future family income (both nominal and real) and business conditions one and five years into the future.[6] Controlling for these beliefs does not change the results

[6]These data are available for each of the four US Census regions: Northeast, Midwest, South, and

in our baseline estimations. While the coefficient of stock returns remains significant, expectations about future income or business conditions have no effect on annuitization. As an additional robustness check, we proxy for expectations about income with the median income at the MSA level, estimated by the Department of Housing and Urban Development (HUD).[7] Using both historical levels and variations in median income does not materially change our results.

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 expectations of higher inflation. As in the previous case, a positive correlation between stock returns and inflation expectations together with a negative relationship between inflation expectations and annuitization can produce a bias in our results. Using one and five years forward expectations of inflation from the Survey of Consumers, we do not find that these expectations affect the decision to annuitize or our main results. We obtain similar results if we use data on future inflation from the Federal Reserve Bank of Philadelphia's quarterly survey on long-term (10 years) inflation expectations (the survey of Professional Forecasters).

G Does the Effect of Extrapolation Increase at Older Ages?

In the paper we report estimates of the effect of age on extrapolation, imposing the same weighting parameter for past returns, λ, across different age groups. In Table A.VIII, we remove this assumption and estimate different baseline models separately

Western. They are publicly available at http://www.sca.isr.umich.edu.

[7] They are available from the Federal Financial Institutions Examination Council (FFIEC) on their website (http://www.ffiec.gov/default.htm).

for the different age groups both in our DB plans and in the IBM sample. Instead of running the estimation on the entire sample using interaction effects, we decide to split our sample in three, as the non-linear functional form for λ would make the interaction coefficients difficult to interpret. With these new estimates we can control for systematic differences in how far back in time individuals look and confirm the magnitude of the previous results (i.e., the coefficient β). Our main result that extrapolation dramatically increases with age still holds as our estimates of β remain almost unchanged. This is not surprising given that our estimate for λ for those in their 50s and 60s are very close (4.8 versus 5.4). Although lambda for those over 70 is smaller, note that an estimate of 3.3 would still imply that the weights decrease very quickly going back in time.

In Columns 4-7, we confirm similar results for the IBM retirement plan splitting the sample between employees younger or older than 60. Results in Columns 6 and 7 are particularly relevant for our identification as they document that the effect of age on extrapolation is present also for those employees that were let go. Therefore, our results are not entirely driven by cross-sectional differences in the type of employees that voluntarily retire younger.

H Recent vs. Lifetime Stock Market Events

Our evidence appears consistent with a beliefs-based explanation: past stock market returns affect beliefs about future returns and, hence, the decision to annuitize. Understanding how individuals form and change their beliefs over time can help strengthen the micro-foundations of asset pricing models and deepen our understanding of financial markets. Toward this goal we investigate how both recent and lifetime stock market returns affect the decision to annuitize.

More specifically, in Table A.IX, we present the results of an estimation including returns experienced since birth. In Column I, we estimate the following model:

$$Ann_{ijt} = \alpha + \beta A_{it}(\lambda) + \gamma' x_{it} + \varepsilon_{it} \tag{6}$$

where Ann_{ijt} is a binary variable equal to one if employee i enrolled in plan j at time t chooses an annuity. We explain this decision using: a weighted average of the past stock market returns $A_{it}(\lambda)$; a vector of control variables x_{it}; and an error term ε_{it}. Following Malmendier and Nagel (2011), we estimate directly from the data the following weighting function of *yearly real* stock returns R_{t-k} deflated using the CPI:

$$A_{it}(\lambda) = \sum_{k=1}^{Age_{it}-1} w_{it}(k,\lambda) R_{t-k}, \text{ with } w_{it}(k,\lambda) = \frac{(Age_{it}-k)^{\lambda}}{\sum_{k=1}^{Age_{it}-1}(Age_{it}-k)^{\lambda}} \tag{7}$$

Note that here Age_{it} represents the age of employee i making the decision in year t and that this weighting function differs from the one used in all the previous equations. The effect of returns appears both statistically and economically significant with a one standard deviation increase in the lifetime experienced returns decreasing the likelihood to annuitize by 5.6 pp. Here, the estimate for lambda is 3.1, implying that weights quickly decrease with the size of the time lag. In Column 2, we modify our estimations to include returns experienced from birth up to five years before the decision to annuitize or not. Our results remain the same with an expected increase in the weighting parameter λ to 4.1.

In Column 3, we introduce both short and long-term (greater than five years) experienced returns. The effect of the recent experience remains both economically and statistically significant and remarkably similar to what was estimated in the previous tables. The effect of lifetime returns – although of the expected sign – is noisily estimated and not statistically significant at the conventional levels. In Column 4 we confirm these results after adding retirement plan fixed effects.

In Column 5, we use quintiles of lifetime returns to further investigate the long-term effects of returns. The effect of lifetime returns on annuitization appears significant only for the highest quintile. Taken together, these results tend to confirm our intuition that the effect of past stock returns on annuitization is mainly driven by the most recent returns. Lifetime experiences seem to matter significantly only for individuals that have experienced unusually high returns (i.e., the top quintile).

A major limitation of our data is that we have a relatively short time-series, 2002-2008, and limited age differences, 50 to 75 years. Nonetheless, the standard deviation of weighted average lifetime returns (using the weights estimated in Column 1 or 2) is still significant and comparable with what was found in other studies using longer time-series and higher age differences. For example, Malmendier and Nagel (2011) report a standard deviation of weighted average returns equal to 2.2 percent. We find a standard deviation equal to 0.7 percent (weights from Column 1 with lifetime returns) or to 2.3 percent (weights from Column 2 with lifetime returns up to 5 years before decision date).

Our results suggest that recent stock market events and extreme lifetime experiences affect annuitization. Consistent with our results, Malmendier, Tate and Yan (2011) find that having lived during the Great Depression has long-lasting effects of on managerial decisions. CEOs that were raised during the Great Depression are more debt averse and more likely to rely excessively on internal finance. We have very limited data to run a similar test as only 895 individuals were born before 1930 (less than one percent of our sample). Untabulated results confirm that individuals that grew up during the Great

Depression are less likely to choose an annuity. Not knowing how people invest their money if they take the lump sum, we cannot clearly identify what might be driving this specific result. We speculate that individuals that grew up during the Depression might dislike annuities partially because of the inherent counterpart risk of bankruptcy.

I Individual Welfare Consequences

Elaborating a formal model of annuitization to assess the welfare consequences of our results is beyond the scope of this paper. Nonetheless, we aim to provide some back-of-the-envelope calculations that also rely on estimates from other studies about optimal annuitization strategies.

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 instead of annuitizing all their wealth at retirement. In their estimations, the authors consider variable payout annuities, a payout product that offers both an investment element and a longevity insurance element. If variable annuities are not available and individuals can invest only in fixed annuities, Milevsky and Young (2002) estimate that the value of the (real) option to defer annuitization can be as high as 20 percent of retirement wealth. These results stem from an equity premium argument. Deferring annuitization – an investment in a fixed income product – can allow individuals to earn higher interim returns by investing in the stock market and, hence, achieve higher retirement wealth to annuitize later in life.

Moving from these estimates, we can quantify the effect of annuitizing too early due to negative recent stock market returns. As an example, we consider two employees retiring in consecutive years: the former in December 2007, before the financial crisis; the latter in December 2008, in the midst of it. Holding everything else constant and using the estimates from Table II, Panel A, Column 5, the latter employee is about 23.3 percentage points more likely to choose the annuity. The difference in the weighted past return average (with λ fixed at 5.16) between these two employees is equal to 4.1 pp. Therefore, the effect of returns on annuitization is equal to -5.6*4.1 $\approx$ -23.0. In other words, if we assume that the two employees are both male, 65 years old with 20 years of tenure and $200,000 in DB benefits, the former employee has roughly a 39 percent probability of choosing the annuity, while the latter has about a 62 percent probability.

Multiplying this change in probability by the wealth losses computed in Hornef et al. (2009) and Milevsky and Young (2002), we can obtain an estimate of welfare reduction that ranges from 4.6 to 9.2 percent (i.e., 23.0% * 20% or 40%). Another way to grasp the magnitude of this effect is to consider that in defined benefit plans, employees' benefits increase with tenure. Each additional year at work usually increases the replacement ratio between pre- and post-retirement income of about 2.0 percent. In other words, annuitizing too soon can bear a cost equivalent to having to work an additional two to almost five years to achieve the same retirement benefits.

The welfare consequences of annuitizing too early appear substantial. What about the opposite case when someone chooses the lump sum after high recent stock returns? The annuities in our main sample are roughly comparable with the annuity deals offered in the private market (for more details refer to Benartzi, Previtero, and Thaler, 2011). Hence, we do not expect any substantial loss for someone passing on the annuity offered in the retirement plan and deciding to buy an annuity from the private market later on. The only exception would be the case of someone choosing the lump sum and never buying the annuity. Given the low annuitization rates in the individual annuity market, we suspect that retirees will not actively try to buy an annuity from a financial advisor once they have passed on the easy, check-the-box annuity offered in the retirement plan. Benartzi, Previtero and Thaler (2011) elaborate on the standard and behavioral frictions that can prevent annuitization outside of retirement plans.

Yogo (2011) estimates that healthy individuals can increase their retirement wealth by about 16% if they have access to additional annuitization above and beyond the already annuitized Social Security benefits. Using our previous example, the employee retiring in December 2007 would have a lower probability of choosing the annuity and, if the retiree never annuitizes later in life, this might generate a loss in retirement wealth of about 3.7 percent (e.g., 23.0% * 16%), or the equivalent of having to work roughly 2 years longer to achieve the same benefits level.

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Table A.I
Stock Market Returns and Annuitization (Weighting Function)

This table reports results from OLS and Non-linear Least Squares (when we estimate the weighting function) regressions. The dependent variable is a binary indicator which equals 1 if the employee chooses an annuity. Interest Rates is the composite return on long-term Treasury bonds. Additional Controls include: i) demographic controls (age, gender, tenure and benefit amount); plan controls (yearly average age, gender, benefits and number of employees retiring in that specific plan); and calendar month fixed effects. Standard errors are clustered across 15 company size/time groups. In Panel B, we also include income and years of education. Standard errors are clustered across eight geographical region/time groups. See the text for more details on this methodology and the use of Linear Probability Models. All the coefficients can be interpreted as the percentage point variation in the probability of annuitization corresponding to a one standard deviation change in the corresponding independent variable.

Panel A: Defined Benefit Plans

Estimation Methodology:	without Weighting Function				with Weighting Function		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Past 12-month returns	-6.363***			-5.070***			
	(1.723)			(1.429)			
Past 24-month returns		-7.141**					
		(2.434)					
Past 36-month returns			-0.422				
			(0.479)				
Past returns coefficient β					-6.175***	-4.758**	-4.404**
					(1.661)	(1.766)	(1.792)
Weighting parameter λ					5.163***	5.163	5.163
					(0.827)		
Interest Rates	-2.227	-1.511	-2.626	-0.120	-2.518	-0.259	-0.047
	(2.344)	(2.410)	(2.032)	(1.915)	(2.210)	(1.848)	(1.772)
Additional Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Years F. E.	Yes	Yes	Yes	Yes	Yes	Yes	
Plan F.E.				Yes		Yes	
Plan/ Year F.E.							Yes
Observations	103,516	103,516	103,516	103,516	103,516	103,516	103,516
R-squared	0.193	0.190	0.186	0.391	0.134	0.389	0.410

Standard errors in parentheses. Constant included.

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

Panel B: IBM retirement plan

Estimation Methodology:	without Weighting Function			with Weighting Function		
Sample:	All Employees			All	Bus. Education	MBA
	(1)	(2)	(3)	(4)	(5)	(6)
Past 12-month returns	-1.327***					
	(0.310)					
Past 24-month returns		-1.573**				
		(0.510)				
Past 36-month returns			-1.914**			
			(0.610)			
Past returns coefficient β				-1.926***	-3.039***	-2.916*
				(0.514)	(0.771)	(1.310)
Weighting parameter λ				1.023***	2.733**	2.539
				(0.188)	(0.817)	(2.303)
Interest Rates	3.388***	3.702***	-4.291***	4.320***	3.698***	4.875***
	(0.565)	(0.611)	(0.798)	(0.909)	(0.788)	(1.022)
Additional Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	18,671	18,671	18,671	18,671	2,271	1,062
R-squared	0.131	0.132	0.133	0.134	0.133	0.165

Standard errors in parentheses. Constant included.

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

Table A.II
Stock Market Returns and Annuitization (Logit Models)

The dependent variable is a binary indicator which equals 1 if the employee chooses an annuity. In Panel A, Additional Controls include: plan controls, calendar months f.e. and year fixed effects. Standard errors are clustered across 15 company size/time groups. In Panel B, standard errors are clustered across eight geographical region/time groups. For ease of interpretation, all the coefficients - except λ - are multiplied by 100. They can be interpreted as the percentage point variation in the probability of annuitization corresponding to 1 unit change in the corresponding independent variable. We use the following units: i) one standard deviation for past returns and interest rates; ii) $100,000 for benefit amount; iii) $10,000 for income; and iv) 1 year for age, tenure and years of education.

Panel A: Defined Benefit Plans

Estimation Methodology:	Logit Models		
	(1)	(2)	(3)
Past 12-month returns	-6.484***		
	(1.869)		
Past 24-month returns		-7.291**	
		(2.728)	
Past 36-month returns			-0.368
			(0.495)
Interest Rates	-1.649	-0.903	-2.022
	(2.241)	(2.348)	(1.955)
Female	4.721***	4.729***	4.738***
	(1.221)	(1.228)	(1.212)
Age	2.347***	2.362***	2.401***
	(0.280)	(0.284)	(0.300)
Benefits Amount	5.110***	5.145***	5.173***
	(1.777)	(1.779)	(1.769)
Tenure	-0.281	-0.282	-0.285
.	(0.176)	(0.177)	(0.176)
Additional Controls	Yes	Yes	Yes
MSA F.E.			
Observations	103,516	103,516	103,516
R-squared	0.166	0.164	0.160

Standard errors in parentheses. Constant included.
* significant at 10%; ** significant at 5%; *** significant at 1%.

Panel B: IBM retirement plan

Estimation Methodology:	Logit Models		
	(1)	(2)	(3)
Past 12-month returns	-0.722***		
	(0.277)		
Past 24-month returns		-0.893*	
		(0.537)	
Past 36-month returns			-1.192**
			(0.561)
Interest Rates	3.885***	3.995***	4.295***
	(0.681)	(0.686)	(0.816)
Female	2.521***	2.545***	2.564***
	(0.471)	(0.455)	(0.458)
Age	-1.335***	-1.325***	-1.315***
	(0.066)	(0.071)	(0.073)
Benefits Amount	3.737***	3.725***	3.716***
	(0.381)	(0.371)	(0.365)
Tenure	0.121*	0.123*	0.126*
	(0.067)	(0.066)	(0.066)
Income	-0.684***	-0.678***	-0.671***
	(0.102)	(0.098)	(0.094)
Years of Education	-0.554***	-0.556***	-0.554***
	(0.144)	(0.140)	(0.138)
Observations	18,671	18,671	18,671
R-squared	0.162	0.162	0.163

SE in parentheses. Constant included. * significant at 10%; ** at 5%; *** at 1%.

Table A.III
Stock Market Returns and Individual Annuities Sales

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. Data are from LIMRA International. 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 the percentage point variation in annuity sales corresponding to 1 percentage point change in past stock returns (approximately one standard deviation variation).

Sample Period:	1985Q1-2009Q2	1992Q1-2009Q2
Dependent Variable:	Fixed Annuities (Ln)	Fixed Immediate Annuities (Ln)
	(1)	(2)
Past stock returns 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 A.IV
Additional Results on Hurricane Katrina Event

This table reports results from OLS regressions, using only data from employees in our DB plans sample. The dependent variable is a binary indicator which equals 1 if the employee chooses an annuity. After Katrina is an indicator variable equal to 1 after 9/2005. Katrina Areas is an indicator variable equal to 1 if the employee lived at the moment of separation in counties afflicted by the Hurricane. Concentration in Katrina Areas is the fraction of employees separating in the areas afflicted over the total number of separating employees in the same company. Additional Controls include: i) age, gender, tenure and benefit amount; ii) interest rates; iii) calendar months and year fixed effects; iv) time-varying plan controls. Standard errors are clustered across 12 geographical region/time groups. For ease of interpretation, all the coefficients - except λ - are multiplied by 100 and standardized. They can be interpreted as the percentage point variation in the probability of annuitization corresponding to one unit change (for indicator variables) or a one standard deviation change in the corresponding independent variable.

Sample:	Katrina Areas + Neighboring States			
		without LA		without LA
	(1)	(2)	(3)	(4)
Past stock returns β	-8.145**	-8.186**	-8.978***	-9.062***
	(2.208)	(2.224)	(1.645)	(1.642)
Weighting parameter λ (Fixed)	5.163	5.163	5.163	5.163
After Katrina	11.31***	10.54***	12.92**	12.19**
	(2.585)	(2.535)	(3.404)	(3.379)
Katrina Areas	3.373*	2.609	4.634	3.821
	(1.518)	(1.645)	(2.600)	(2.613)
After Katrina*Katrina Areas	-7.280***	-6.315**	-7.106**	-6.199**
	(1.450)	(1.616)	(2.139)	(2.287)
Concentration in Katrina Areas			-4.423	-4.474
			(4.049)	(4.062)
Additional Controls	Yes	Yes	Yes	Yes
Observations	29,619	28,162	29,619	28,162
R-squared	0.229	0.222	0.234	0.226

Standard errors in parentheses. Constant included.
* significant at 10%; ** significant at 5%; *** significant at 1%.

Table A.V
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 55, 60, 62 or 65 birthday of the employees. Laid-off Workers is an indicator variable equal to 1 if the employees did not decide voluntarily to retire. Additional Controls include: age, gender, benefit amount and tenure (plus income and education years in Columns 3 and 4); interest rates (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. For ease of interpretation, all the coefficients - except λ - are multiplied by 100. They can be interpreted as the percentage point variation in the probability of annuitization corresponding to one unit change (for indicator variables) or a one standard deviation change in the corresponding independent variable.

Sample:	Main Sample		IBM	
	(1)	(2)	(3)	(4)
Past stock returns β [A]	-5.775**	-4.564**	-3.303***	-3.043***
	(2.219)	(1.868)	(0.816)	(0.640)
Weighting parameter λ (Fixed)	5.163	5.163	1.022	1.022
Exact Age	17.958***	14.432***		
	(3.114)	(2.102)		
Past stock return*Exact Age [B]	2.412	2.136		
	(2.540)	(1.897)		
Laid-off Workers			-0.984*	-0.996**
			(0.436)	(0.323)
Past stock return * Laid-off Work. [B]			0.656	0.893
			(0.826)	(0.729)
Additional Controls	Yes	Yes	Yes	Yes
Plan/ Working Location F.E.		Yes		Yes
Observations	103,516	103,516	15,802	15,802
R-squared	0.198	0.394	0.137	0.169
p-value for F-Test				
[A]+[B] = 0	0.011**	0.040**	0.008***	0.003***

Standard errors in parentheses. Constant included.

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

Table A.VI
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&P 500 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, we report Newey-West robust standard errors. For ease of interpretation, all the coefficients - except λ - are multiplied by 100. They can be interpreted as the percentage point variation in the probability of annuitization corresponding to 1 percentage point for past stock market returns and one standard deviation for volatility.

Sample:	Main Sample			LIMRA	
	(1)	(2)	(3)	(4)	(5)
Past 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 - 3months	0.167			-0.031***	
	(0.998)			(0.010)	
S&P500 Volatility std - 6 months		2.014	1.268		0.030
		(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.			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 A.VII
Expectations about Future Income and Inflation

This table reports results from OLS regressions. The dependent variable is a binary indicator that equals 1 if the employee chooses an annuity. All the data on expectations about family income, business conditions and inflation are from the Survey of Consumers (University of Michigan/ Thomson Reuters). The data are collected monthly for each of the four US Census Regions (Northeast, Midwest, South, West). Family Income Increase is an index calculated as “Higher – Lower + 100” based on the percentage of people that have answered “higher” or “lower” to the following question: "During the next 12 months, do you expect your (family) income to be higher or lower than during the past year?"; Real Family Income Increase is an index calculated as “More – Less + 100” based on the percentage of people that have answered “more” or “less” to the following question: "During the next year or two, do you expect that your (family) income will go up more than prices will go up, about the same, or less than prices will go up?"; Short-term Business Conditions is an index calculated as “Good – Bad + 100” based on the percentage of people that have answered “good” or “bad” to the following question: “Now turning to business conditions in the country as a whole–do you think that during the next 12 months we’ll have good times financially, or bad times, or what?"; Long-term Business Conditions is an index calculated as “Good – Bad + 100” based on the percentage of people that have answered “good” or “bad” to the following question: "Looking ahead, which would you say is more likely -that in the country as a whole we’ll have continuous good times during the next 5 years or so, or that we will have periods of widespread unemployment or depression, or what?"; Short-term Inflation Expectations is the average answer to the following question: "By what percent do you expect prices to go up, on the average, during the next 12 months?"; Long-term Inflation Expectations is the average answer to the following question: "By what percent per year do you expect prices to go up, on the average, during the next 5 to 10 years?" We obtain similar results if we use the median values instead of the mean of the inflation expectations answers. Additional Controls include: age, gender tenure and benefit amount; the composite return on long-term Treasury Bonds; calendar months and year fixed effects; and time-varying plan controls. Standard errors are clustered across 15 company size/time groups. See the text for more details 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 the percentage point variation in the probability of annuitization corresponding to one percentage point variation in the independent variable.

[See table on next page]

	(1)	(2)	(3)	(4)
Past stock returns β	-6.085***	-4.398**	-6.409***	-4.848**
	(1.995)	(1.587)	(2.096)	(1.683)
Weighting parameter λ (fixed)	5.163	5.163	5.163	5.163
Family Income Increase	0.963	-0.326	0.687	-0.602
	(1.075)	(0.709)	(0.994)	(0.713)
Real Family Income Increase	1.291	1.634	1.641	2.033**
	(1.324)	(1.026)	(1.141)	(0.864)
Short-term Business Conditions	-1.337	-1.118	-1.192	-1.021
	(1.567)	(1.055)	(1.544)	(0.866)
Long-term Business Conditions	1.338	0.829	1.991	1.491
	(1.498)	(1.208)	(1.714)	(1.294)
Short-term Inflation Expectations			0.994	0.488
			(2.519)	(2.067)
Long-term Inflation Expectations			1.909	2.243**
			(1.231)	(0.848)
Additional Controls	Yes	Yes	Yes	Yes
Plan F.E.		Yes		Yes
Observations	95,997	95,997	95,997	95,997
R-squared	0.197	0.389	0.198	0.39

Standard errors in parentheses. Constant included.

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

Table A.VIII
Extrapolation from Past Returns and Annuitization at Older Ages

This table reports results from Non-linear Least Squares. The dependent variable is a binary indicator that equals 1 if the employee chooses an annuity. Additional Controls and standard errors are the ones used in the main specifications for each sample. For ease of interpretation, all the coefficients - except λ - are multiplied by 100. They can be interpreted as the percentage variation in the probability of annuitization corresponding to 1 percentage point change of past stock market returns (roughly equivalent to one standard deviation variation).

Sample:	Defined Benefit Plans			IBM retirement plan			
Age group:	50-59	60-69	70-75	<60	>60	<60	>60
Retirement reason:				All	All	Laidoff	Laidoff
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Past stock return β	-2.636***	-6.034***	-14.077***	-1.976***	-5.696***	-1.955**	-4.358**
	(0.807)	(1.693)	(3.301)	(0.523)	(1.197)	(0.736)	(1.247)
Weighting parameter λ	4.824	5.379***	3.308***	1.031***	0.539***	1.212*	0.714*
	(2.856)	(0.952)	(0.681)	(0.179)	(0.151)	(0.559)	(0.303)
Additional Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	101,053	101,053	101,053	10,561	5,241	5,156	2,234
R-squared	0.148	0.051	0.509	0.069	0.157	0.085	0.199

Standard errors in parentheses. Constant included.

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

Table A.IX
Annuitization and Lifetime Experienced Stock Market Returns

This table reports results from Non-linear Least Squares (Col. 1-2) and OLS regressions (Col. 3-6). The dependent variable is a binary indicator which equals 1 if the employee chooses an annuity. In Column 2 lifetime returns are computed up to five years before separation. For the definition of Additional Controls refer to the previous tables. Lifetime Returns Q1-Q5 are the quintiles of the weighted experienced lifetime returns (up to five years before the decision) based on the weights estimated in Column 2, with Q5 being the highest (i.e., the most positive) quintile and Q1 the lowest. In Columns 3-4, we fix the weighting parameter. In Columns 5-6, Lifetime Returns Q1 is the omitted variable. Standard errors are clustered across 15 company size/time groups. For ease of interpretation, all the coefficients - except λ - are multiplied by 100. They can be interpreted as the percentage point variation in the probability of annuitization corresponding to one unit change for indicator variables or a 1 percentage point change of past stock market returns.

	(1)	(2)	(3)	(4)	(5)	(6)
Lifetime stock return $\beta_{lifetime}$	-4.285***	-5.903***	-4.312	-4.623		
	(0.575)	(0.381)	(3.757)	(3.618)		
Weighting parameter $\lambda_{lifetime}$	3.131***	4.120***	4.120	4.120		
	(0.205)	(0.088)				
Recent stock return β_{recent}			-5.262***	-4.147***	-4.914***	-4.173***
			(1.609)	(1.403)	(1.483)	(1.455)
Weighting parameter λ_{recent} (fixed)			5.163	5.163	5.163	5.163
Lifetime Returns Q2					-5.683	-7.781
					(8.438)	(7.792)
Lifetime Returns Q3					-12.804	-4.907
					(9.319)	(8.439)
Lifetime Returns Q4					-7.293	-3.565
					(11.752)	(10.417)
Lifetime Returns Q5					-22.015*	-13.067
					(11.702)	(10.795)
Additional Controls	Yes	Yes	Yes	Yes	Yes	Yes
Plan F.E.				Yes		Yes
Observations	101,053	101,053	101,053	101,053	101,053	101,053
R-squared	0.128	0.129	0.193	0.391	0.196	0.392

Standard errors in parentheses. Constant included.

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

Figure A.1
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.

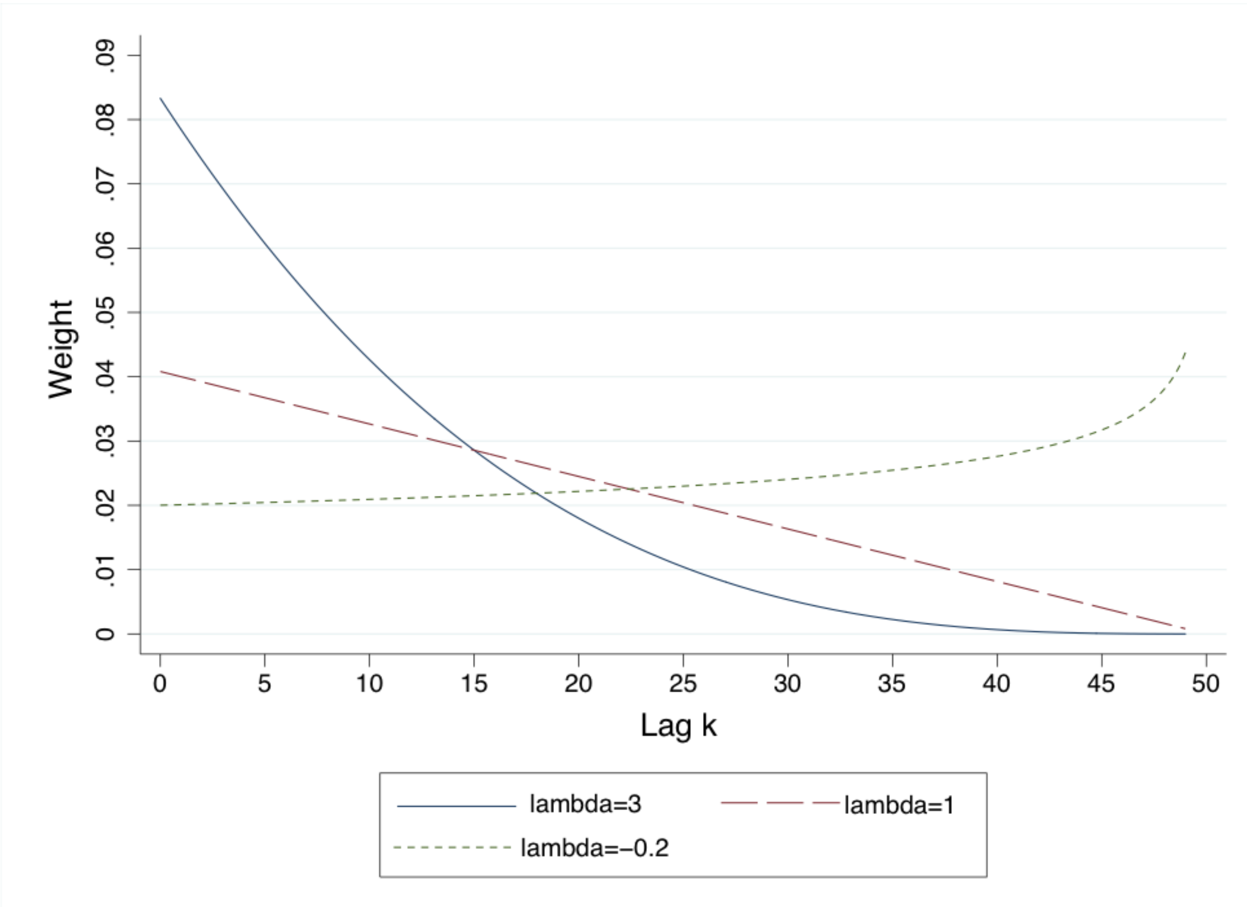

Figure A.2
Estimated Weighting Function (Main Sample Data)

This graph plots the weighting function of past monthly stock market returns with the value of λ estimated in Table AI., PanelI A.