Three Essays on Financial Decision-Making of Older Households

By

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A dissertation submitted in partial fulfillment
of the requirements for the degree of
Doctor of Philosophy
(Economics)
in the University of Michigan
2016

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In the memory of my grandfather

ACKNOWLEDGEMENTS

First and foremost, I would like to thank my advisor Matthew D. Shapiro for his continued guidance and support throughout my Ph.D. I was privileged to have him as my advisor. I also thank my committee members, Andrew Caplin, John Laitner, and Stefan Nagel, for their insightful comments and support. Guodong Chen, Michael Gelman, Chenyue Hu, Gretchen Lay, Tong Yob Nam, Christian Proebsting, and Fudong Zhang provided moral support as well as academic insights. I also acknowledge financial support from the Korea Foundation for Advanced Studies and the National Institute of Aging (P01-AG026571). Finally, I am heavily indebted to my family, in particular to my wife Jungeun, for their unconditional support.

The second chapter of this dissertation is co-authored with John Ameriks, Gabor Kezdi, and Matthew D. Shapiro. The third chapter is co-authored with John Ameriks, Andrew Caplin, Matthew D. Shapiro, and Christopher Tonetti.

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Abstract

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With the shift from defined-benefit to defined-contribution pension plans, good portfolio management becomes crucial for sustaining financial well-being in retirement. Using the Vanguard Research Initiative (VRI), a novel linked survey-administrative dataset, this dissertation examines various aspects of older households' portfolio choices.

The first chapter investigates the effect of late-in-life risks on the portfolio choices of older households. Older households face health-related risks, including risk of being in need of long-term care and mortality risk. Portfolio choice depends on the interaction between these health-related risks and household preferences for long-term care and bequests. Using the VRI, this chapter finds that the desire to have enough resources for long-term care and bequests are overall strong but also heterogeneous across households. The estimated relationship between actual stock share of households and the strength of these preferences is qualitatively similar but quantitatively much weaker compared to the predictions from the life-cycle model with the estimated preference heterogeneity.

The second chapter studies the relationship between stock share and expectations and risk preferences. The VRI survey allows individual-level, quantitative estimates of risk tolerance and of the perceived mean and variance of stock returns. Estimated risk tolerance, expected return,

and expected risk have economically and statistically significant explanatory power for the distribution of stock shares across households. The results imply that household portfolio choices respond to individual-level differences in preferences and beliefs proportionately with the predictions of benchmark theories, but that the response of portfolios is substantially attenuated relative to theoretical predictions.

The third chapter discusses what makes the VRI more suitable for answering research questions such as those in the first two chapters of this thesis. First, it has a comprehensive survey measure of wealth, based on an account-by-account approach. The accuracy of this measure is validated by comparison with the administrative records. Second, it has ample observations of older households in a wealth range relevant for research on key financial decision-making issues. To illustrate the value of the VRI, this chapter examines the non-linear relationship between wealth and expected retirement date.

Chapter 1. Portfolio Allocation over Life-Cycle with Multiple Late-in-Life Saving Motives

1.1 Introduction

Older households face multiple risks in retirement. Most importantly, they face health-related risks, including considerable expenditure risk associated with long-term care (LTC) and mortality risk. Given the high cost of LTC, the risk of being in need of LTC effectively increases households' risk aversion, limiting their ability to take additional risks in the financial market for a higher expected return. Mortality risk adds another layer of uncertainty that may further reduce room for risky assets in households' financial portfolio. In household portfolio choice literature, relatively little attention has been given to the implications of these health-related background risks on portfolio choice, in particular on the choice of the share of risky assets. Instead, most research on household portfolio choice has focused on the effects of labor income uncertainty (see Benzoni, Collin-Dufresne, and Goldstein, 2007; Bodie, Merton, and Samuelson, 1992; Cocco, Gomes, and Maenhout, 2005; and Viceira, 2001, among others), which is not a major source of background risk for households that are near or in retirement. This study addresses this gap in the literature by examining how these health-related background risks affect portfolio allocation over the life-cycle.

Health-related risks have complex effects on decisionmaking of households because they likely affect preferences directly. Hence, how they affect asset accumulation, portfolio choices, and spending will depend on preferences about related expenditures. For example, for households who have a preference for high-quality, expensive service when they need LTC, the same probability of being in need of LTC implies effectively a much larger expenditure risk.

Similarly, two households with equal mortality risk may choose different portfolios depending on the strength of the bequest motive. Moreover, the paper will show that there are complicated and subtle interactions of preferences over LTC and bequests with health-related risks.

This paper uses distinctive modeling approach and measurement infrastructure to study the financial decisionmaking of households facing these late-in-life risks. The approach uses novel survey instruments to identify preferences relevant to late-in-life portfolio choices. It uses survey responses to quantify the distribution of these preferences in the population and then to relate these preferences to choices and outcomes in a new dataset—the Vanguard Research Initiative (VRI)—that combines survey and administrative account information on a large population of older Americans who have sufficient financial assets to make these portfolio choices highly relevant.

Specifically, I first estimate households' preferences for expenditures in the LTC state and bequests using responses to hypothetical survey questions. Estimated utility functions for LTC expenditures and bequests not only show the strength of the precautionary saving motive for LTC and the bequest motive over the life-cycle, but also govern households' exposure to health-related background risks for a given amount of resources. I then investigate the empirical relationship between the estimated strength of these two saving motives and actual stock share of households to see whether households' actual portfolio choice responds to health-related background risks. I also study how the optimal stock share should respond to the strength of these saving motives using a life-cycle portfolio choice model with the estimated preference heterogeneity. Lastly, I contrast the findings from the empirical and theoretical analyses to derive implications for a better design of financial advice and financial products.

I begin by finding empirical evidence that the preferences for LTC expenditures and bequests are both strong but also heterogeneous among households. For many households, the estimated preference parameters suggest that their life-cycle saving is mainly driven by a precautionary motive associated with LTC or a bequest motive. On the other hand, a non-trivial fraction of households appear to put much larger weight on their consumption in the state of good health than LTC expenditures or bequests.

My analysis using the life-cycle model with the estimated preference heterogeneity suggests that both a stronger preference for LTC expenditures and a stronger bequest motive imply lower optimal stock share. The more households care about expenditures in the LTC state, the more painful a combination of a negative stock return shock and an LTC shock is. The impact of the LTC preference is limited for households with fewer resources, because for them publicly-funded nursing home functions as a partial insurance against negative stock return shocks. The mechanism behind the effect of the bequest motive is more subtle. On one hand, most households consider bequest as a luxury good, which effectively makes households who put more weight on bequests than consumption less risk averse. On the other hand, the existence of retirement income and LTC risk under the presence of mortality risk makes households with a stronger bequest motive more reluctant to take risks in the financial market, compared to households who mainly care about own consumption. I show that the latter effect dominates the former in my calibrated model, so a stronger bequest motive lowers the optimal stock share.

I find that the relationship between observed actual household portfolio choice and estimated preferences is qualitatively similar but quantitatively weaker than suggested by the life-cycle model. To be specific, a stronger preference for LTC expenditure is associated with lower stock share, though the size of the estimated effect is overall much smaller than the predictions from the model. I do not find a significant relationship between the preference for bequests and actual stock share. The discrepancy between the empirical results and the theoretical results might indicate that what households actually do is different from what they should do, which, in turn, suggests a necessity for better design of financial instruments (Campbell, 2006). Using simulated life-cycle profiles from the model solutions, I show that financial instruments need to incorporate implications of the estimated preference heterogeneity not only in determining the initial level of stock market exposure but also in the adjustment of stock share over the life-cycle.

The structure of the rest of the paper is as follows. Section 1.2 discusses the related literature. Section 1.3 presents a stylized two-period model to explain the mechanism behind the effect of the health-related risks and the health-state-dependent preferences on the portfolio choice. Section 1.4 describes the VRI. In Section 1.5, I explain my methodology of structural preference parameter estimation and present the estimation results. The empirical relationship between household stock share and the preference parameters is discussed in Section 1.6. In Section 1.7, I derive the theoretical effects of preference heterogeneity on portfolio choices using a life-cycle model. I discuss the implications of the gap between empirical and theoretical findings in Section 1.8.

1.2 Literature

The preference parameter estimation in this paper is based on the methodology of Barsky, Juster, Kimball, and Shapiro (1997, hereafter BJKS) and Kimball, Sahm, and Shapiro (2008, hereafter KSS). They estimate the distribution of risk preference parameter using survey responses and allowing for survey response errors. KSS also construct individual cardinal proxies for the risk preference parameters using the estimates from the structural model, which can be used as a right-hand side variable in a linear regression without concerns about an attenuation bias. This paper extends their methodology to the case with multiple preference parameters.

This paper is also related to the literature on the estimation of health-state-dependent and bequest utility functions. De Nardi, French, and Jones (2010), Ameriks, Caplin, Laufer, and van Nieuwerburgh (2011), Lockwood (2014) and Ameriks, Briggs, Caplin, Shapiro, and Tonetti (2015a) estimate preference parameters for a health-state-dependent utility function and/or bequest utility function by either using a structural model only or combining a structural model with SSQs, but they do not allow for heterogeneity in these preferences. Ameriks, Briggs, Caplin, Shapiro, and Tonetti (2015b) estimate heterogeneity in risk preference, precautionary saving motive for LTC, and bequest motive using the SSQs from the VRI. This study differs from theirs in that I examine the impact of preferences on portfolio allocations, while they examine the impact of preferences on demand for LTC insurance as well as annuities. In addition, I estimate the population distribution of the preference parameters following the method outlined in KSS, while Ameriks, Briggs, Caplin, Shapiro, and Tonetti (2015b) estimate their parameters at the individual level. In Appendix 1-D, I provide a detailed comparison of the two estimation methodologies. Finally, my study addresses Finkelstein, Luttmer, and Notowidigdo's (2009) conclusion that using the observed demand for assets with state-dependent returns is the most promising approach in estimating health-state-dependent utility. The SSQs allow us to use this approach in this study.

This paper also adds to the literature that empirically analyzes the effects of health-related risks and bequest motives on households' stock share by distinguishing the role played by preference heterogeneity from that due to other channels. There is a large body of research, including Rosen and Wu (2004), Berkowitz and Qiu (2006), Fan and Zhao (2009), Love and Smith (2010), and Goldman and Maestas (2013), that studies how actual changes in health status (or expected health-related expenditures) affect the stock holdings of households. The literature suggests either no effect or a small negative effect. There is not as much work on the effect of bequest motives on stock share. Hurd (2002) finds no evidence that intended bequests have an effect on stock share, while Spaenjers and Spira (2014) find that households with children tend to have a higher stock share. In most of these empirical studies, the main explanatory variables are remote proxies for (expected) health expenditures and bequests. The remote nature of these proxies makes it challenging to identify the channel behind any observed effect. This paper clearly identifies the effects of preference heterogeneity, controlling for other channels such as effects of different economic and demographic conditions, using responses to the SSQs.

Finally, this paper contributes to the theoretical life-cycle portfolio choice literature by investigating the implications of heterogeneous saving motives. Bodie, Merton, and Samuelson (1992), Viceira (2001), Cocco, Gomes, and Maenhout (2005) and Benzoni, Collin-Dufresne, and Goldstein (2007) use a life-cycle portfolio choice model to analyze the effect of labor income on the optimal stock share. In these papers, retirement is simply considered to be a period without background risk. By contrast, my study provides a more precise understanding of older households by examining how health-expenditure and mortality risk impact portfolio choices. Ding, Kingston, and Purcal (2014) investigate the effect of a bequest motive on the optimal stock share in the absence of health expenditure shocks and income flow. Pang and Warshawsky (2010) and Reichling and Smetters (2015) study annuity demand using a life-cycle model with exogenous health expenditure risk and bequest motives. This paper solves for the optimal stock share under a life-cycle model that features realistically-calibrated processes for health and income, options for LTC service, and, most importantly, preference heterogeneity estimated from the VRI data.

1.3 A Stylized Two-Period Model

This section presents a stylized two-period model to intuitively illustrate the mechanism behind the effect of health-related risks and health-state-dependent preferences on the portfolio choice of households. In particular, I focus on why households who care to have more resources in an LTC state might want to invest a smaller share of their wealth in the stock market.

Let us assume that the household cares only about the consumption in the second period (C_2). Let W denote the amount of wealth that the household has in the first period. The household invests either in a safe asset, which guarantees gross return of R, or a risky asset, of which return is $R+\mu+\eta$ where μ is the risk premium and η is the uncertain part of the return. For simplicity, let us assume that η takes value of either ξ or $-\xi$, with a fifty-fifty chance.

The households may or may not need an LTC service in the second period. If it does not need an LTC service, its utility is determined by a log-utility function $(\log(C_2))$; if it does need an LTC service, the utility function becomes $\theta_{LTC}\log(C_2+\kappa_{LTC})$, where $\kappa_{LTC}<0$ determines the overall strength of the preference for LTC expenditures compared to that for expenditures in the good-health state. Note that this is a special case of a more general LTC-state utility function that will be introduced in the next section.[1]

Let π be the chance that the household needs an LTC service in the second period. If π is 0, then the household solves:

[1] The qualitative results in this section do not depend on the additional assumptions made on the form of utility function in this section. Those assumptions only facilitate deriving a closed form solution.

$$
\begin{aligned}
&Max_{\alpha} E_1 \log(C_2) \\
&\quad s.t.\ C_2 = (1-\alpha)WR + \alpha W(R+\mu+\eta)
\end{aligned}
\tag{1.1}
$$

where α is the share of wealth invested in the risky assets. Then the optimal share of wealth invested in the risky assets, α_O, is determined as:

$$
\alpha_O = \frac{2\mu R}{(\xi+\mu)(\xi-\mu)}. \tag{1.2}
$$

If π is 1, then the household solves the problem that is the same as (1.1), except for that the LTC-state utility function is used instead of the healthy-state utility function. To simplify the algebra, let us further assume that $\kappa_{LTC} = -mW$. The solution in this case, α_{LTC}, is determined as:

$$
\alpha_{LTC} = \frac{2\mu(R-m)}{(\xi+\mu)(\xi-\mu)}, \tag{1.3}
$$

which is apparently smaller than α_O. When *m* is larger, the gap between α_O and α_{LTC} gets larger.

Now, suppose $\pi \in (0,1)$. The household solves the same problem as (1), except for that the objective function is now $(1-\pi)\log(C_2) + \pi\theta_{LTC}\log(C_2+\kappa_{LTC})$. The first order condition of this maximization problem becomes:

$$
\begin{aligned}
&(1-\pi)\{\frac{1}{2}\frac{\mu+\xi}{R+\alpha(\mu+\xi)} + \frac{1}{2}\frac{\mu-\xi}{R+\alpha(\mu-\xi)}\} \\
&+\pi\theta_{LTC}\{\frac{1}{2}\frac{\mu+\xi}{R+\alpha(\mu+\xi)-m} + \frac{1}{2}\frac{\mu-\xi}{R+\alpha(\mu-\xi)-m}\} = 0.
\end{aligned}
\tag{1.4}
$$

It is straightforward to show that α_O makes the first term of the LHS zero, while the second term becomes positive. Similarly, α_{LTC} makes the second term zero, while the first term becomes negative. Given that the LHS of (1.4) is continuous and monotonic in α, the solution for this problem, α^*, is between α_O and α_{LTC}. Finally, as π or θ_{LTC} becomes larger, α^* gets closer to α_{LTC}, because the household puts a larger weight on the first order condition derived from the LTC state.

The above example shows that a higher level of minimum expenditure in the LTC state leads the household to reduce its exposure to financial risk. The effect of the same minimum expenditure becomes stronger when the household puts a larger weight on the utility from the LTC state compared to that from the healthy state. Hence, to fully understand how a household would react to the risk of being in need of LTC in terms of their portfolio choice, we need to estimate relevant elements in its preferences. I begin to discuss how one can estimate these elements using survey responses starting from the next section.

1.4 Data

The paper uses the Vanguard Research Initiative (VRI) to estimate the distribution of the structural preference parameters as well as the empirical relationship between households' stock share and heterogeneous preferences for LTC expenditures and bequests. The VRI is a linked survey-administrative dataset on more than 9,000 Vanguard account holders who are at least 55 years old. The VRI is an Internet survey. There have been three surveys to date on different subject areas. The administrative account data provides both the sample frame and monthly account balance data.

This dataset is appropriate for the research question of this paper for several reasons. First, it contains ample observations of wealthholders, for whom LTC precautionary saving motives and bequest motives are operative. Second, the Strategic Survey Question responses from the VRI survey allow us to estimate preference parameters using survey responses. Finally, it includes comprehensive and accurate measures of wealth and stock shares for the account holders. In the following, I discuss each of these features in greater detail.[2]

1.4.1 Sample Composition: Ample Observations of Wealthholders

By design, the VRI collects data on households with non-negligible wealth that are facing key financial decisions in retirement such as annuitization, the purchase of long-term care insurance, or portfolio allocation choices. In contrast, the Health and Retirement Study (HRS), the leading representative survey of older Americans, has a large fraction of households with not enough financial wealth to face such decisions (Poterba, Venti, and Wise, 2011).

The goal of obtaining ample observations of wealthholders is achieved as the VRI is roughly representative of top 50 percent of households in the wealth distribution. The sampling screen that is used to target wealthholders—the requirement that they have at least $10,000 in their Vanguard accounts—made the VRI sample wealthier by its construction than the more representative samples, such as the HRS and Survey of Consumer Finances (SCF). Ameriks, Caplin, Lee, Shapiro, and Tonetti (2014) show that the VRI is broadly representative of the top half of the wealth distribution and with the similar sampling screens HRS and SCF respondents have similar characteristics as the VRI. In addition, about half of the VRI sample between the ages of 55 and 64 is composed of those who have only employer-sponsored accounts at Vanguard. For this group the selection would be less an issue, and Ameriks, Caplin, Lee, Shapiro, and Tonetti (2014) actually show that their characteristics are even closer to those of the comparable subsets of the HRS and SCF.

[2] See Ameriks, Caplin, Lee, Shapiro, and Tonetti (2014) for complete description.

1.4.2 Strategic Survey Questions

In its second survey (conducted in winter 2014), the VRI implemented Strategic Survey Questions (SSQs) to elicit information regarding preferences about risk, expenditures on LTC, and bequests. In the following I briefly introduce aspects of the SSQs that are relevant for this paper (see Ameriks, Briggs, Caplin, Shapiro, and Tonetti, 2015b for a thorough description of these SSQs).

SSQs put respondents in hypothetical situations so that cross-sectional differences in responses can be interpreted as signals of preference heterogeneity. Under hypothetical situations that are not related to their actual financial situations and demographics (including age and health conditions), respondents are asked to choose between hypothetical financial products.

This paper uses three types of SSQs:

- A gamble on consumption to elicit risk preference (SSQ1)
- A trade-off between expenditures in a state of good health versus those in the LTC state, to elicit state-dependent preference for LTC (SSQ2)
- A trade-off between expenditures in the LTC state and bequests to measure the strength of the bequest motive (SSQ3)

The responses to SSQs can be used to identify the preference parameters in the three utility functions, one for expenditures in the healthy state, one for expenditures in the LTC state, and one for bequests. To do so, I use the fully parametric functional forms:

$$
\begin{aligned}
U(X) &= \frac{(X+\kappa)^{1-1/\gamma}}{1-1/\gamma}, \\
U_{LTC}(X) &= \theta_{LTC}\frac{(X+\kappa_{LTC})^{1-1/\gamma}}{1-1/\gamma}, \\
U_{Beq}(X) &= \theta_{Beq}\frac{(X+\kappa_{Beq})^{1-1/\gamma}}{1-1/\gamma},
\end{aligned}
\tag{1.5}
$$

where the X is expenditure in each health state, i.e., good health, LTC state, and bequest/death. γ is risk tolerance parameter, θ is a utility multiplier governing the strengths of the precautionary LTC saving and bequest motives, and κ is a necessity parameter for each utility function, determining whether the expenditures are considered necessities or luxuries (κ being negative means the expenditures are necessaries, while it being positive means they are luxuries). The functional form for the LTC state and bequest utility functions are the same as those in Ameriks, Briggs, Caplin, Shapiro, and Tonetti (2015a, 2015b). For reasons that will be clear, this paper includes a necessity parameter κ in the healthy state utility function to explain the increase in risk aversion with lower resources found in SSQ1.

In the following, I describe key aspects of setups of each SSQ and distribution of responses. (Table 1-A1 in Appendix 1-A shows the exact setups and wording for each SSQ.) I will also discuss which moment of the SSQ response distributions mainly identifies each preference parameter. I defer more detailed explanation on the modeling of preference heterogeneity, the modeling of survey response errors and the preference parameter estimation procedure to Section 1.5.

In SSQ1, the key elements of the hypothetical situation are as following. Respondents are at age 65; they live alone and rent their home; it is assumed that they will be healthy for the following year. Respondents have to choose between Plan A and Plan B, where Plan A guarantees a fixed level of consumption (\$$W$) while Plan B has a 50 percent chance of doubling it (\$$2W$) and a 50 percent chance of reducing it by x percent (\$ $(1-0.01x)W$) for the following year. Since the question is asked for a sequence of values of x where the sequence depends on the respondent's previous responses, it provides a risk range ($[x_{\min}, x_{\max}]$) which encapsulates the respondent's indifference point.[3]

Figure 1.1(a) shows two noticeable patterns in the distribution of responses to the SSQ1. The vast majority of respondents are not willing to take more than 33 percent of risk to have a chance to double their consumption, implying they are overall quite risk intolerant. In addition, when the same question is asked with a relatively lower initial consumption level ($50,000 instead of $100,000), the results show that respondents tend to be more risk averse. This phenomenon is inconsistent with a homothetic utility function under which we should observe the same response distribution regardless of initial consumption level, motivating the necessity parameter in the healthy-state utility function. In terms of mapping to the preference parameters in the healthy-state utility function, the overall level of risk a respondent is willing to take in SSQ1 identifies γ while how much she become more risk averse with a lower initial consumption level identifies κ.

In SSQ2, it is assumed that respondents will need a LTC service with probability π in the coming year. There is no publicly-funded LTC service and no one can take care of the respondent for free. They have to allocate the given resources ($\$W$) between Plan C and Plan D, where Plan C pays the respondent $\$(1/\pi)$ for every $1 of investment only if the respondent needs an LTC service and Plan D pays $1 for every $1 of investment only if the respondent is healthy in the coming year. In the LTC state, respondents need to finance both their LTC expenditures and their other consumption needs out of returns from Plan C. Responses to SSQ2 are measured as the amount of money they choose to invest in Plan C.

[3] The setup of SSQ1 draws on the hypothetical question used in BJKS and KSS, with a difference that the question used in their papers is about a gamble on income not consumption.

Figure 1.1(b) shows that, in SSQ2, the median respondent allocates resources in such a way that they secure more resources in the LTC state than in the healthy state. For example, when respondents are given $W = \$100,000$ with an LTC probability of $\pi = 1/4$, to have the same amount of resources across two states, they should invest $20,000 in Plan C. That is indeed close to one of two modal allocations in the distribution, but the majority of respondents invest more than that. This implies level of θ_{LTC} greater than one. How much the share allocated to Plan C changes across different values of W and π identifies κ_{LTC}.

Lastly, in SSQ3, respondents are assumed to be in the last year of their lives and in need of an LTC service for the entire year. Again there is no publicly-funded LTC service and no informal care. Respondents need to allocate the given resources ($\$W$) between Plan E and Plan F, where money in Plan E will be used to finance their own needs while that in Plan F will be bequeathed. Responses to SSQ3 are measured as the amount of money they choose to put in Plan E.

Figure 1.1(c) shows that, in SSQ3, when the given resources (W) is $100,000, many respondents choose not to leave a bequest, but the number of respondents choosing to leave a bequest increases as W increases. This suggests that bequests may be perceived as luxury goods rather than necessary expenditures (hence κ_{Beq} is positive). Among those who leave bequests, many leave sizeable bequests, implying that once the bequest motive becomes active (i.e., once they have enough resources) it tends to be strong (hence θ_{Beq} is greater than one).

The SSQs have the following common features for eliciting preferences. Each type of SSQ is asked multiple times with different amounts of given initial resources ($\$W$) and/or with the likelihood of relevant events (π). In addition to identifying preference parameters as just discussed, this test-retest feature enables us to separately identify the distribution of survey response errors. The SSQ scenarios are also stationary questions embedded in a life-cycle setting. Except for SSQ3 (where it is assumed that respondents die at the end of the following year), it is assumed that the same situation repeats at the end of the following year. Respondents do not have any other resources than what is given in the assumed situations; they are not allowed to either borrow from future or save for future. By shutting down borrowing and lending, responses to SSQs can be interpreted as solutions of single-period maximization problems.[4]

The VRI survey takes a number of steps to make the SSQ scenarios more understandable. In the administration of the survey, respondents are provided with the scenario-specific rules prior to making their decisions. They are also allowed to refer back to the rules via a hover button at any point in the decision process. The survey also tests understanding of scenarios before asking SSQs. A majority of respondents were able to give correct answers to more than 80 percent of the verification questions.

Since the survey is conducted on the Internet, it takes advantage of the ability to visualize the trade-offs of the SSQs. In SSQ2 and SSQ3, participants are asked to make their choices using a novel slider interface (see Figure 1-A1 in Appendix 1-A). This interface dynamically informs participants of the resources they will have in each state as a result of the current allocation.[5]

[4] Note that with constant amount of resources, the life-cycle solution will not involve much borrowing or lending unless the interest rate is different from time discount rate, so the assumption of no borrowing and lending is not drastically counterfactual.

[5] See Ameriks, Briggs, Caplin, Shapiro, and Tonetti (2015b) for more detail about verification of rule understanding, the slider interface, and the other mechanisms used for the SSQs. They also show that the SSQ responses are coherent both internally (i.e., there is a strong positive correlation among answers within each SSQ type) and externally (i.e., characteristics that might affect relevant preferences do have predictive power on responses).

1.4.3. Wealth and Stock Share Measurement

The wealth and stock share measures are from the first survey of the VRI (conducted in fall 2013). The measures cover the entire financial portfolio and housing wealth of the households.

The wealth and stock share measures of the VRI are based on a comprehensive account-by-account approach. Respondents are asked about the types of accounts they have (e.g., IRAs, savings, mutual funds), the number of accounts of each type, and the balance and stock share of each account. This account-by-account format matches the way respondents keep track of their own wealth and does not require them to sum balances across accounts to provide total figures for asset categories that are familiar to economists but not necessarily to survey respondents.

The accuracy of the wealth and stock measures is validated by comparing them to the Vanguard administrative account records for those accounts they indicate are held at Vanguard. The comparison shows that the survey measure of wealth is very accurate: the median percentage difference between the survey and administrative measures of total assets held at Vanguard is essentially zero while the length of the interquartile range is only several percentage points.[6]

This paper uses the stock share of households' entire financial portfolio measured from the survey as the main dependent variable in the empirical analysis.

1.4.4. Characteristics of the Sample

In addition to the SSQ responses and wealth measures, I use information on household demographics as well as subjective probability measures regarding their longevity and future need for a LTC service. Table 1.1 presents the distribution of the variables used in this study beyond the SSQs.

[6] See Ameriks, Caplin, Lee, Shapiro, and Tonetti (2014) for more details on the wealth measurement in the VRI.

Almost everyone in the VRI is a stock holder, which is not surprising given that the sample is composed of Vanguard clients. Therefore, the identification of any effect on stock holding comes through the intensive margin rather than through the extensive margin, so the interpretation of results of this paper is free from participation cost issues (see Vissing-Jorgensen, 2002). The demographic composition of the VRI sample is as follows. About two-thirds are coupled and two-thirds are male. By design, the VRI respondents are evenly distributed across the following age bins: [55, 59], [60, 64], ……, and 75+. Furthermore, again by design, about half of those below age 65 are from the employer-sponsored sample. Most 401(k) participants roll over to an IRA when they retire, so there are few employer-sponsored accounts for those aged over 65. As a result, about 20 percent of the entire sample are from the employer-sponsored sample. In terms of health, the vast majority of the sample report that their health is better than or equal to good (using a five-point scale *excellent*, *very good*, *good*, *fair*, and *poor*). About 40 percent have a post college degree while another 33 percent have a college degree. Finally, the median (mean) household annual income and financial wealth are $83,443 ($126,132) and $723,665 ($1,101,468).

As another measure of heterogeneity in household health, the VRI survey asks each participant to estimate her probability of needing at least one year of LTC service as well as his prediction of how likely it is that he will reach a certain age. The results for the VRI sample show that 45 percent expect to require at least one year of LTC service, with remarkable heterogeneity across responses (the interquartile range is [15%, 75%]). The subjective probability questions about reaching certain ages are asked for a set of ages determined as $(\{75,\ 85,\ 95\} \cap \{t \mid t \geq current\ age + 5\})$. The median response for the lowest age asked (the measure used in this study) is 85 percent.

Finally, to control for the heterogeneous exposure to LTC expenditure risk caused by LTC insurance, I include the indicator variable of having LTC insurance. Twenty-three percent of the respondents have a LTC insurance policy.

1.5. Estimation of Structural Preference Parameters

In this section I estimate distributions of the structural preference parameters that govern the preferences for LTC expenditures and bequests, based on the methodology of Barsky, Juster, Kimball, and Shapiro (1997, hereafter BJKS) and Kimball, Sahm, and Shapiro (2008, hereafter KSS). The estimates obtained in this section are used to construct the regressors in the empirical analysis in Section 1.6 and to calibrate the life-cycle model in Section 1.7.

1.5.1. Methodology

I extend the methodology of BJKS and KSS to estimate joint distribution of multiple preference parameters. I model the respective strengths of the preference for LTC expenditure and that for bequests using a utility multiplier and a necessity parameter for the utility function representing each motivation. Using MLE, I jointly estimate the distributions of these parameters as well as that of the risk preference parameter. Having multiple observations for each type of SSQ enables us also to identify the distribution of the survey response errors.[7] Cardinal proxies for the preference parameters are calculated as the conditional expectations using the estimated distributions. In the following, I explain each element of the estimation methodology in detail.

Utility functions As I previewed in Section 1.4, I assume three utility functions, one for expenditures in the healthy state, one for expenditures in the LTC state, and one for bequests:

[7] To be more specific, to identify distributions of N parameters in addition to survey response errors, we need at least N+1 observed responses per individual. In other words, the distribution of SSQ responses should have at least one more degree of freedom than can be explained solely by the distributions of the true preference parameters, to allow room for survey response errors.

$$U_i(X) = \frac{(X+\kappa)^{1-1/\gamma_i}}{1-1/\gamma_i},$$
$$U_{LTC,i}(X) = \theta_{LTC,i}\frac{(X+\kappa_{LTC,i})^{1-1/\gamma_i}}{1-1/\gamma_i}, \tag{1.6}$$
$$U_{Beq,i}(X) = \theta_{Beq,i}\frac{(X+\kappa_{Beq,i})^{1-1/\gamma_i}}{1-1/\gamma_i},$$

where subscript *i* denotes each individual.

The necessity parameter (κ) in the healthy-state utility function has important implications for portfolio choice. Merton (1971) shows that, in a continuous-time model with stock return risk (modeled as an i.i.d. process) as the only uncertainty, for a household with the utility function I assume for the state of good health, the optimal stock share is determined as:

$$\pi = \frac{\mu_s}{\sigma_\eta^2}\gamma(1+\frac{(Y+\kappa)(1-e^{r(t-T)})}{rW}) \tag{1.7}$$

where μ_s is the risk premium, σ_η is the standard deviation of the stock return, Y is the income flow without uncertainty, t is the current time, T is the end of the investment horizon, and W is current wealth. The role of κ is obtained through the ratio between income plus κ and wealth ($\frac{Y+\kappa}{W}$). Intuitively, we expect that a higher income-to-wealth ratio should imply a higher optimal stock share, as the present value of the income flow (human capital) becomes a close substitute for a risk-free asset in the absence of income uncertainty.[8] According to (2), what is compared to wealth is not the gross level of income but rather the income net of the subsistence level of consumption (negative of κ).[9]

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[8] This intuition holds even with income uncertainty as long as income shocks are not highly correlated with stock return shocks (Viceira, 2001; Cocco, Gomes, and Maenhout, 2005).
[9] It should be noted that a negative κ (-κ) can also be interpreted as (slow-moving) habit in consumption. Habit formation has been used to explain macroeconomic phenomena such as a high risk premium (Campbell and Cochrane, 1999). Both Gomes and Michaelides (2003) and Polkovnichenko (2007)

Identification Here I briefly review which moment of the SSQ response distribution mainly identifies each preference parameter.[10] The risk tolerance parameter (γ) is mainly identified by the level of risk that respondents are willing to take in SSQ1. The necessity parameter in the healthy state utility function (κ) is identified by the effect of the initial resource level on the responses in SSQ1. It should be noted that since SSQ1 consists of only two questions, we cannot estimate the distributions of both σ and κ and identify survey response errors at the same time. Therefore, I assume that there is heterogeneity only in γ (hence no subscript i for κ in (1.6)).[11] The utility multipliers for LTC state expenditure (θ_{LTC}) and bequest (θ_{Beq}) are mainly identified by the average share of resources that respondents allocate for LTC expenditures and bequests in SSQ2 and SSQ3. The necessity parameters for those two utility functions ($\kappa_{LTC}, \kappa_{Beq}$) are mainly identified by how the level of given resources affects responses in SSQ2 and SSQ3.

Modeling heterogeneity in preference parameters Following KSS, I model the cross-person heterogeneity of preference parameter as draws from probability distributions. I assume the distribution of the risk tolerance parameter and those of the utility multipliers on LTC

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examine the effect of habit formation on household portfolio choices, while Brunnermeier and Nagel (2008) test the microeconomic implications of habit formation. Although I do not explicitly model (the negative of) κ as a time-varying habit, this study provides empirical evidence for this necessity parameter. In a related paper, Wachter and Yogo (2010) explain why more affluent households have a higher stock share using a two-good—basic and luxury—model, where households are less risk averse over luxury good consumption. κ can be considered to be a reduced form representation of this two-good model, since both models generate lower risk aversion for households with larger wealth.

[10] The full relationship between survey responses and preference parameters is complex and non-linear, in particular under the presence of survey response errors. Later in this section, I provide detailed explanations regarding how I model preference heterogeneity and the survey response process.

[11] When I estimate the distributions of the parameters conditional on the covariates used in the stock share regression, I assume that κ is homogenous conditional on the covariates (i.e., κ is a deterministic function of these covariates). The motivation for estimating the distributions conditional on the covariates is explained in Section 1.6.

expenditure and bequest to be log-normal, while those of the necessity parameters for LTC expenditure and bequest to be normal:

$$\log(\gamma_i) \sim N(\mu_\gamma, \sigma_\gamma^2) \tag{1.8}$$

$$\log(\theta_{LTC,i}) \sim N(\mu_{LTC}, \sigma_{LTC}^2) \tag{1.9}$$

$$\log(\theta_{Beq,i}) \sim N(\mu_{Beq}, \sigma_{Beq}^2) \tag{1.10}$$

$$\kappa_{LTC,i} \sim N(\mu_{\kappa,LTC}, \sigma_{\kappa,LTC}^2) \tag{1.11}$$

$$\kappa_{Beq,i} \sim N(\mu_{\kappa,Beq}, \sigma_{\kappa,Beq}^2). \tag{1.12}$$

Log-normality assumption prevents the risk preference parameter and utility multipliers from being negative. These functional form assumptions are also consistent with shape of survey responses distributions shown in Figure 1.1. I also assume that the preference parameters are statistically independent, except for potential dependence through observed covariates.[12]

Modeling of survey responses I model the survey responses as the sum of the solutions of the underlying optimization problems for the SSQs and "trembling-hand" type survey response errors, where "trembling-hand" means that error terms are added to the survey responses (instead of preference parameters). Given the realizations of the preference parameters from (1.8)–(1.12), we can determine the solutions of the optimization problems underlying the SSQs. I assume that survey response errors are independent across questions and normally distributed with a mean of zero:

$$\varepsilon_{i,kj} \sim N(0, \sigma_{\varepsilon,kj}), \tag{1.13}$$

[12] As will be explained below, in one version of estimation I model the mean (μ) parameter of each of these distributions as a linear function of all the covariates used in the stock share regression. Hence I do allow for correlations between preference parameters through these covariates.

where kj denotes the j^{th} question of SSQ type k.

In the following, I show how to map the SSQ responses to the solutions of the corresponding optimization problems under the presence of the survey response errors.

1) SSQ1: Let W_{1j} be the amount of consumption given in the j^{th} question in SSQ1. Given γ_i and κ, the level of risk (in terms of the percentage loss associated with the risky gamble) at which individual i becomes indifferent between the risky gamble and the guaranteed consumption can be determined as $x^*_{i,1j}$,[13] such that:

$$\frac{(W_{1j}+\kappa)^{1-1/\gamma_i}}{1-1/\gamma_i}=0.5\frac{(2W_{1j}+\kappa)^{1-1/\gamma_i}}{1-1/\gamma_i}+0.5\frac{((1-x^*_{i,1j})W_{1j}+\kappa)^{1-1/\gamma_i}}{1-1/\gamma_i}. \tag{1.14}$$

The indifference point that is actually used in answering the survey question, $x_{i,1j}$, is determined as:

$$x_{i,1j}=x^*_{i,1j}+\varepsilon_{i,1j}. \tag{1.15}$$

This determines the risk range within which the observed response falls.

2) SSQ2: The underlying optimization problem for the j-th question of SSQ2 is:

$$\begin{aligned}&Max_x(1-\pi_{2j})\frac{(W_{2j}-x_{i,2j}+\kappa)^{1-1/\gamma_i}}{1-1/\gamma_i}+\pi_{2j}\theta_{LTC,i}\frac{(\frac{1}{\pi_{2j}}x+\kappa_{LTC,i})^{1-1/\gamma_i}}{1-1/\gamma_i}\\&s.t.\quad 0\le x_{i,2j}\le W_{2j},\end{aligned} \tag{1.16}$$

where $x_{i,2j}$ is the amount invested in Plan C that pays the respondent when she needs a LTC service and π_{2j} is the likelihood of being in need of a LTC service for in following year. Let $x^*_{i,2j}$ denote the individual i's solution for (1.16). We can then denote the observed response as:

[13] Note that the unit of x is share, not percentage.

$R_{i,2j}^{br} = \min(\max(0, x_{i,2j}^{*} + \varepsilon_{i,2j}), W_{2j})$, which is the sum of the optimal solution and a survey response error subject to the boundary conditions, where *br* indicates the response is before rounding. Rounding responses is prevalent in SSQ2 and SSQ3, so in the estimation procedure I need to address the issue of rounding in the estimation procedure. I explain how I do so after introducing the model for SSQ3.

3) SSQ3: The structure for the optimization problem for SSQ3 is similar to that of SSQ2. The underlying maximization problem for the *j*-th question of SSQ3 is:

$$\begin{aligned} &Max_x \theta_{Beq,i} \frac{(W_{3j} - x_{i,3j} + \kappa_{Beq,i})^{1-1/\gamma_i}}{1-1/\gamma_i} + \theta_{LTC,i} \frac{(x_{i,3j} + \kappa_{LTC,i})^{1-1/\gamma_i}}{1-1/\gamma_i} \quad . \\ &s.t. \quad 0 \le x_{i,3j} \le W_{3j} \end{aligned} \tag{1.17}$$

The observed response, before rounding, is assumed to be generated through $R_{i,3j}^{br} = \min(\max(x_{i,3j}^{*} + \varepsilon_{i,3j}, 0), W_{3j})$, where $x_{i,3j}^{*}$ is the solution for (1.17).

4) Rounding of responses: The distribution of SSQ responses suggests that participants round their answers. For example, Figure 1.1 shows a bunching of responses at $100,000 in the second question of SSQ3. This bunching likely reflects rounding since the number of these responses is too high to be generated from smooth distributions of the underlying parameters and survey response errors.

To address this issue, I follow Manski and Molinari (2010) and define the degree of rounding for each respondent using the highest level of precision the respondent provides, separately for SSQ2 and SSQ3. For SSQ2, I set three levels of precision: rounding to multiples of $25K, rounding to multiples of $10K, and no rounding. For example, if all of a respondent's answers are multiples of $25K, then I determine that this is her level of rounding. Then, for this respondent, $R_{i,2j} = \$50K$ would imply that $R_{i,2j}^{br} = [\$50K - \$12.5K, \$50K + \$12.5K]$, with the latter interval used to calculate the likelihood function. If a respondent gives an answer that is neither a multiple of \$25K nor of \$10K, then I assume that she does not round her responses. Using this procedure, I find that 7 percent of respondents round to multiples of \$25K and 8 percent round to multiples of \$10K for SSQ2. For SSQ3, I apply the same logic but allow a higher level of rounding to multiples of \$50K. Doing so, I find that 20 percent of respondents round to multiples of \$50K, 9 percent to multiples of \$25K, and 19 percent to multiples of \$10K.

Maximum likelihood estimation algorithm Let $R_{i,mj}$ be the response observed for the *j*-th question of SSQ type *m*, for individual *i* ($m \in \{1,2,3\}$ and $j \in \{1,2,3\}$ ($j \in \{1,2\}$ for $m=1$)). Given the parameter values governing the distribution of the preference parameters and survey response errors, $\Theta \equiv \{\mu_\gamma, \sigma_\gamma, \kappa, \mu_{LTC}, \sigma_{LTC}, \mu_{\kappa,LTC}, \sigma_{\kappa,LTC}, \mu_{Beq}, \sigma_{Beq}, \mu_{\kappa,Beq}, \sigma_{\kappa,Beq}, \{\sigma_{\varepsilon mj}\}_{m,j}\}$, I can calculate the likelihood of having the observed responses in the data. I estimate Θ by maximum likelihood estimation. The following summarizes the algorithm.

1. Guess initial values for Θ.[14]

2. Given Θ, generate *K* nodes $\{\gamma^k, \theta^k_{LTC}, \theta^k_{Beq}, \kappa^k_{LTC}, \kappa^k_{Beq}\}_{k=1}^K$ in the preference parameter distribution and corresponding probabilities $\{\pi_k\}_{k=1}^K$ such that $\sum_{k=1}^K \pi_k = 1$, using Gaussian Quadrature.

3. For each node *k* and individual *i*, calculate $\{\varepsilon^*_{i,mj,k}\}_{mj}$ such that these realizations of the survey response error support the observed responses under $\{\gamma^k, \theta^k_{LTC}, \theta^k_{Beq}, \kappa^k_{LTC}, \kappa^k_{Beq}\}_{k=1}^K$.[15]

[14] I tried various sets of values for initial guesses and found that the estimation results are robust with respect to the initial guess.

[15] In SSQ2 and SSQ3, if the respondent provides an internal response and we determine that she does not round her responses, the corresponding survey response error takes a single value. For all the other cases, including all the cases for SSQ1, the survey response error takes values in an interval.

4. Calculate the joint likelihood of the realization of the error terms in step 3. If $\pi^{\varepsilon}_{i,k}$ denotes this joint likelihood, then:

$$\pi^{\varepsilon}_{i,k} = \Pi_{m,j} \pi^{\varepsilon}_{i,mj,k}, \tag{1.18}$$

where $\pi^{\varepsilon}_{i,mj,k}$ is the likelihood of drawing $\varepsilon^{*}_{i,mj,k}$.[16]

5. Calculate the likelihood function for individual i as:

$$L_i = \sum_{k=1}^{K} \pi^{\varepsilon}_{i,k} \pi_k . \tag{1.19}$$

Then the likelihood function for the entire set of observations is calculated as $L = \Pi_i L_i$.

6. Using the Berndt-Hall-Hall-Hausman algorithm (Berndt, Hall, Hall, and Hausman, 1974), update the guess for Θ. If the new guess is sufficiently close to values assumed in step 1, stop. Otherwise go back to step 2 with the updated values.

Construction of the Cardinal Proxies for the Preference Parameters Once I obtain the estimates $\hat{\Theta}$, I then calculate the cardinal proxies for the preference parameters conditional on observed responses using Bayes's rule:

[16] SSQ1 has two questions while SSQ2 and SSQ3 have three questions. Hence, I weight the likelihood from SSQ1, i.e., I use $(\pi^{\varepsilon}_{i,mj,1})^{3/2}$ in place of $\pi^{\varepsilon}_{i,mj,1}$. Then the likelihood function evenly represents the information contained in each type of SSQ. Intuitively, this weighting scheme is equivalent to assuming that there is a third question in SSQ1 that contains exactly the same information as in the first two questions of SSQ1. Note that the weighting does not have any direct effect on the estimation of parameters related to LTC or bequest preferences, because SSQ1 does not involve these parameters (although it can indirectly affect the estimation of these parameters through the estimation of the SSQ1-related parameters). Without weighting, the estimate for κ is not in line with the pattern we observe in SSQ1, though the identification of that parameter should mainly come from SSQ1. One alternative to weighting is to estimate κ using SSQ1 only, and impose this estimate in the joint estimation. The results for the stock share regression based on this approach are fairly similar to those obtained from the estimation based on weighting.

$$E[\theta_i \mid R_{i,mj}] = \frac{\sum_{k=1}^{K} \theta^k \pi_k \pi_{i,k}^{\varepsilon}}{L_i} \quad (1.20)$$

for $\theta \in \{\log\gamma, \log\theta_{LTC}, \log\theta_{Beq}, \kappa_{LTC}, \kappa_{Beq}\}$.[17] Note that when I estimate the distributions conditional on the covariates used in the stock-share regression, the same algorithm applies, but the means of the preference parameter distributions $\{\mu_\gamma, \mu_{LTC}, \mu_{\kappa,LTC}, \mu_{Beq}, \mu_{\kappa,Beq}\}$ and κ are modeled as linear functions of those covariates.

1.5.2. Estimation Results

In this section, I present the results of the estimation. The results in Table 1.2 show the estimated distributions of the preference parameters and survey response errors. (Appendix 1-B shows the estimates conditional on the covariates.) Panel (a) of Table 1.2 shows the estimated moments of the distributions while Panel (b) shows the distributions of the preference parameters implied by these moments.

The necessity parameter for the healthy-state utility function, κ, is estimated to be $-\$10.82K$, implying that \$10.82K per year is the subsistence level of consumption. The interquartile range for the risk tolerance parameter is [0.17, 0.43], which can be translated into a relative risk aversion of [0.15, 0.37] ([0.13, 0.33]) under the estimated κ and an income level of \$100K (\$50K). Although this range is slightly higher than the interquartile range from the KSS estimates ([0.10, 0.26]) that are obtained from the entire HRS sample, the difference is small.

The fact that the VRI and HRS have similar distribution of risk preference has the following two important implications. First, it suggests that low stock holdings in the HRS is mainly due to low wealth level or other economic factor, not different risk preference than found

[17] For parameters that I assume to be log-normally distributed, I use log of the parameters in the empirical analysis in Section 1.6. In calculating cardinal proxies for these cases, I use $\log\theta^k$ instead of θ^k in (15).

in the VRI. Second, it suggests that the findings from the VRI sample can be extrapolated to the population because risk preference is similar to that found in a representative population despite the higher wealth and education of the VRI population.

Furthermore, we see from the estimation results that there is a substantial heterogeneity in each of the utility multipliers. At the 10th percentiles, respondents do not put much weight on LTC expenditures/bequests (θ_{LTC} = 0.19, θ_{Beq} = 0.12) compared to expenditure in the healthy state. By contrast, at the 90th percentiles, respondents place great weight on these expenditures (θ_{LTC} =70.91, θ_{Beq} = 1134.69). For respondents with these preference parameter values, the importance of expenditure in the healthy state is dwarfed by the importance of these expenditures.

For the necessity parameters of LTC-state and bequest utility functions (κ_{LTC} and κ_{Beq}), the mean of the former is smaller than κ and that for the latter is larger than κ , implying that the average respondent considers LTC expenditures as a necessity and bequests as a luxury in comparison to spending in the state of good health. But there are also strong heterogeneities in both of these parameters. The interquartile ranges are [-52.61K, -19.33K] for κ_{LTC} and [8.32K, 69.16K] for κ_{Beq} . There are also some households that consider expenditures in the LTC state as a luxury good compared to spending in the state of good health (i.e., $\kappa_{LTC} \geq \kappa$), as well as some households that consider bequests as a necessity compared to spending in the healthy state (i.e., $\kappa_{Beq} \leq \kappa$).

Given that both the utility multipliers and the necessity parameters govern the respective strengths of the saving motivations, just looking at the distribution of each parameter separately is not enough to understand the degree of heterogeneities in these motivations. To show the implications of the estimated distributions of the parameters more clearly, in Appendix 1-C I solve a static optimization problem for a one-year period where each household allocates its given wealth into expenditures in the healthy state, expenditures in the LTC state, and bequest and present the distribution of these allocations.

1.6 The Empirical Relationship between Stock Share and Saving Motives

How does the estimated strong heterogeneity in preferences relate to the actual portfolio choices of households? In this section I answer this question by relating stock share to SSQ responses, both using the raw SSQ responses as a reduced form analysis and the cardinal proxies for the preference parameters as a structural analysis.

1.6.1. Analysis Using Raw SSQ Responses

For the reduced form analysis, I define the SSQ1 regressor based on categories of how much risk the respondent is willing to take to have a 50 percent chance of doubling her income, with $W_1 = \$100K$ (the most risk averse category, i.e., 0–10%, is the omitted category). For SSQ2, I use the fraction of wealth that the respondent allocates to the LTC state (averaged over three questions). Finally, for SSQ3, I use the share of wealth bequeathed (averaged over three questions).

The results in Table 1.3 show a statistically significant relationship between the proportion of stock in a household's portfolio and the raw responses to SSQ1 and SSQ2. Specifically, I find that risk tolerance is positively related to the stock share. Willingness to take the risk of losing 33–50% of income, compared to 0–10%, increases the stock share by 6 percentage points (5 percentage points after controlling for the covariates). I also find that the willingness to allocate more resources to LTC expenditures, proxied by SSQ2, is negatively related to the stock share; this result becomes only marginally significant at the 10% level when I control for covariates. Giving 10% more of wealth to the LTC state in SSQ2 is associated with an approximate 0.5 percentage point (0.3 when using the covariates) decrease in the stock share. Finally, I find no significant relation between the willingness to bequeath, proxied by SSQ3, and the stock share, with point estimates close to zero.

While these results are indicative of the effect of preference heterogeneity on stock share of households, the use of raw responses limits analysis due to attenuation bias caused by survey response errors as well as the difficulty in quantitatively interpreting the regression results without mapping the SSQ responses to the structural preference parameters. For these reasons, I turn to analyses using the cardinal proxies for the preference parameters.

1.6.2. Analysis Using Cardinal Proxies

The cardinal proxies are generated regressors. Nonetheless, we can still obtain unbiased estimates using them. If the difference between a generated regressor and the true variable is a classical measurement error then using the generated regressor instead of the true variable yields an attenuation bias. The cardinal proxies for the preference parameters constructed under the estimation methodology of this paper, however, are free from this issue. They are calculated as conditional expectations, so by construction, the difference between the latent variables and the proxies is uncorrelated with the proxies. Appendix 1-D extends this discussion.

Table 1.4 shows the results from analyses using the cardinal proxies for the preference parameters. Specification 1 includes only the cardinal proxies while Specification 2 also includes the control variables. For Specification 2, I use the cardinal proxies from the structural preference parameter estimations conditional on these same controls. As stressed by KSS, when the preference parameter proxies are to be included as a regressor in an equation of interest, the proxies must be constructed conditional on all the covariates in the question of interest.

Otherwise, deviation of the proxy from its true value will be correlated with covariates, which biases the coefficient estimates in the equation of interest.

These analyses yield qualitatively similar results to those using the raw responses. That is, I again find that risk tolerance is positively correlated with the stock share while the utility multiplier for the LTC state is negatively correlated with the stock share. The relation between risk tolerance and the stock share is similar to what theoretical models predict (see (1.7) for example). For LTC expenditures, given the same probability of being in need of a LTC service, a larger θ_{LTC} is related to the larger effective size of the expenditure shock associated with this health shock. Finally, I find that neither the necessity parameter for the LTC state (κ_{LTC}) nor the multiplier (θ_{Beq}) or necessity parameter (κ_{Beq}) for the bequest utility has an effect on portfolio composition.

Since the coefficients in Table 1.4 do not clearly show the quantitative implications of preference heterogeneity on portfolio composition, I calculate the implied change in the stock share when each cardinal proxy is increased by two standard deviations and present the results in Table 1.5. Two-standard-deviation increase in γ increases the stock share by about 3.7 percentage points. The increase yields a slightly larger effect for θ_{LTC} , decreasing the stock share by about 4.6 percentage points. The other parameters yield smaller effects.

In this section I showed how actual stock share responds to the preference heterogeneity in the VRI sample. In the following section I will investigate the theoretical implication of the preference heterogeneity and then compare those findings with the empirical findings.

1.7 Life-cycle Portfolio Choice Model with Multiple Late-in-Life Saving Motives

To investigate the theoretical implications of heterogeneous saving motives on the optimal stock share of a household's portfolio, I build a life-cycle portfolio choice model featuring the preference heterogeneity estimated from the VRI. Overall, the results from the model are qualitatively in line with the empirical results. But I also find that the theoretical model predicts larger quantitative effects of the heterogeneous saving motives on portfolio choices than those found in the empirical analysis.

1.7.1. Model

In the life-cycle portfolio choice model, households are subject to aggregate stock market return risk as well as idiosyncratic health, mortality and labor income risks. In each period in the model, households must determine how much to save and consume and how much of their savings to be invested in stocks. Households in an LTC state must also determine whether to use a private LTC service after paying costs out of pocket or a means-tested, publically-funded LTC service after forfeiting the entire wealth. The amount of LTC expenditures in the case of using a private LTC service is endogenously determined, based on the utility function for the LTC state. Any wealth remaining at the end of life is assumed to be bequeathed. To assess the effect of heterogeneous saving motives on the optimal stock share, I compare the policy functions across individuals who differ only in their preference parameters.

Health transitions and preferences In this model, a household is composed of a single member.[18] The model starts from age 55, which is the lowest age observed in the VRI, and the household can live up to age 110. Each period, the health status (s) of a household takes one value from the set $\{G, B, LTC, D\}$, where each state means good health, bad health, LTC state,

[18] This is to avoid complications arising from modeling joint survival probabilities and spousal benefits for Social Security and defined benefit pension plans. The estimated relationship between the stock share and preference parameters is not appreciably different between single households and coupled households.

and death, respectively. The health state evolves following a first-order Markov process with the transition matrix $\pi_{ss'}$ where D is an absorbent state. The transition matrix $\pi_{ss'}$ is also a function of age (t) and gender (g). Households discount the next period utility by the time discount factor β.

In this model, the utility function depends on the health state, as specified in (1.5). When $s = G$ or B, the utility function is U_i, while with $s = LTC$ it becomes $U_{LTC,i}$. In the LTC state, the (subjective) minimum required LTC expenditure is captured in the negative of the necessity parameter $(-\kappa_{LTC,i})$. The amount a household chooses to spend on LTC service in addition to $-\kappa_{LTC,i}$ depends on other parameter values, in particular $\theta_{LTC,i}$.[19] In the LTC state, a household also has the option of using a publicly-funded LTC service after forfeiting all of its wealth. In this case, the value of the public LTC service expressed in the expenditure equivalence is parameterized as PC, so that the corresponding utility becomes $U_{LTC,i}(PC)$.[20] When a household draws $s = D$ for the first time, it leaves all its wealth as bequests, with the utility determined by $U_{Beq,i}$ and no utility obtained in subsequent periods.

The labor income process The model assumes that a household retires at age 65. Until then, its labor income is exogenously determined as:

$$\log(Y_{it}) = \log(\bar{y}_i) + \nu_{it}, \ \ \nu_{it} \sim N(0, \sigma_\nu^2) \text{ for } t < 65, \tag{1.21}$$

where ν_{it} is a temporary shock. Given that households have only 10 years until retirement in this model, I abstract from permanent income shocks. After retirement, a household receives a

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[19] Other than $-\kappa_{LTC,i}$ and $-\kappa$, I do not explicitly model mandatory and uninsured health cost.

[20] I do not explicitly model welfare in the other health states given that the sample is affluent enough to finance expenditures of at least $-\kappa$ every period. In the model, the lowest support for the income process is set to be larger than $-\kappa$ for all the ages considered.

retirement income that captures both Social Security income and a defined benefit pension income and hence comes with no uncertainty. This annuity income is modeled as a fraction (λ) of the mean income before retirement:

$$\log(Y_{it}) = \log(\lambda) + \log(\bar{y}_i) \text{ for } t \geq 65. \tag{1.22}$$

Financial assets Households can invest in two different assets: a riskless asset and a risky asset, where the latter represents stocks.[21] The gross real return on the risk-free asset is set as the constant $\bar{R}_f$. The distribution of the real gross return on the risky asset, R_t , is modeled as:

$$R_t = \mu_s + \bar{R}_f + \eta_t,\ \ \eta_t \sim N(0, \sigma_\eta^2) \tag{1.23}$$

where μ_s is the risk premium and η_t is an i.i.d. stock return shock. Following Cocco, Gomes, and Maenhout (2005), I assume that the aggregate stock return shock is uncorrelated with the idiosyncratic labor income shock.

Optimization problem of households To specify the optimization problem, I begin by letting W_{it} represent the beginning-of-period financial wealth of a household, and α_{it} be the share of savings invested in stocks, with Gov_{it} indicating whether a household chooses to use a publicly-funded LTC service in the LTC state ($Gov_{it} = 1$ means it uses a publicly funded LTC service, while $Gov_{it} = 0$ means it purchases a private service). The optimization problem, omitting the subscripts *i* and *t*, can then be written as:

[21] I abstract from housing wealth in this model.

$$
\begin{aligned}
V(W,t,s,g) = \max_{X,W',\alpha,Gov}\ & \mathrm{I}_{s=LTC}(1-Gov)\{U_{LTC}(X)+\beta E[\textstyle\sum_{s'=G,B,LTC}\pi_{ss'}(t,g)V(W',t+1,s',g)+\pi_{sD}U_{Beq}(W')]\} \\
& +\mathrm{I}_{s=LTC}Gov\{U_{LTC}(PC)+\beta E[\textstyle\sum_{s'=G,B,LTC}\pi_{ss'}(t,g)V(W',t+1,s',g)+\pi_{sD}U_{Beq}(W')]\} \\
& +\mathrm{I}_{s=G,B}\{U(X)+\beta E[\textstyle\sum_{s'=G,B,LTC}\pi_{ss'}(t,g)V(W',t+1,s',g)+\pi_{sD}U_{Beq}(W')]\} \\
s.t.\ \ & \mathrm{W}'=(1-Gov)[(W-X)((1-\alpha)\bar{R}_f+\alpha R_s)]+y' \\
& \mathrm{X}\le W \\
& \alpha\in[0,1].
\end{aligned}
$$

Note that I do not allow borrowing or the short-sale of stocks; hence the last constraint is imposed.

Computation I solve for the optimal policy function numerically using backward induction. Since the last period maximization problem is static the value function is trivially obtained. This value function is used as a continuation value for the maximization problem of the penultimate period. I repeat this until the maximization problem at the first period is solved.

For the choice over continuous spaces (i.e., over X and α), the optimization is done using a grid search. Normal distributions for labor income and stock return risks are approximated as discrete processes using a Gaussian quadrature.

Calibration To understand the effects of heterogeneous preferences on the optimal stock share of a household's portfolio, I solve the model for various sets of preference parameter values that reflect the range of estimates in the VRI. I focus on the effect of being one standard deviation away (both up and down) from the mean of each preference parameter distribution, so that I can compare the effect of two-standard-deviation difference in each preference parameter to the results in Table 1.5. The necessity parameter for the ordinary utility function (κ) is fixed at the value estimated from the VRI (-10.82K). The time discount factor (β) is set at 0.96, a value typically used in the literature for annual models. I calibrate the value of a publicly-funded nursing home to be equivalent to that of spending slightly more than the subjective minimum expenditure on a private LTC service ($PC = -\kappa_{LTC} + 10K$).[22]

The health transition Markov process matrix $\pi_{ss'}$ is estimated from the HRS (1994–2010). I first estimate a multinomial logit model for the biannual transition process conditional on age, gender, and current health status, and then transform the estimated biannual transition matrix into annual one. See Appendix E for a detailed explanation of this estimation process.

The calibration of asset returns is mainly based on Cocco, Gomes, and Maenhout (2005). A risk-free return ($\bar{R}_f$) is set at 1.02. The standard deviation of the risky asset return (σ_η) is set at 0.17. Since the focus of this paper is to analyze the effects of different saving motives at the intensive margin rather than solving the risk premium puzzle, I set the risk premium (μ_s) to be lower (0.02) than the 0.04 used in Cocco, Gomes, and Maenhout (2005).[23,24] With this risk premium, the stock share in the model around the median level of financial wealth observed in the VRI (about $700K) is close to the mean value in the VRI (about 0.55).

I use three values for the mean annual income before retirement ($\bar{y}$): $45K, $90K, and $120K. These values are the median and the interquartile income distribution range in the VRI. To calibrate the replacement rate after retirement (λ), I calculate the ratio between the expected

---

[22] Note that, at the median of κ_{LTC}, this value of *PC* becomes close to what Ameriks, Briggs, Caplin, Shapiro, and Tonetti (2015b) estimate using a SSQ not used in this paper.

[23] When $\mu_s = 0.04$, for the range of the risk preference parameter estimated from the VRI, households choose to invest their entire savings in stocks, not allowing variations at the intensive margin. Cocco, Gomes, and Maenhout (2005) still obtain an interior solution with this risk premium by calibrating the relative risk aversion at 10. However, this value is out of the range supported by the VRI estimates.

[24] A lower risk premium can be considered a reduced form representation of ambiguity aversion among households with respect to the mean of stock return distribution. In addition to the risk modeled in (18), if there is additional uncertainty (ambiguity) about the value of μ_s, and if respondents have aversions to this ambiguity, their portfolio choice should resemble that of those who believe μ_s to be low without ambiguity (see Klibanoff, Marinacci, and Mukerji, 2005).

annuity income (Social Security income plus the defined benefit pension income) and the current household income. The parameter is calibrated to the mean of the distribution of this ratio, 0.5. Finally, the transitory income shock variance (σ_{ν}^{2}) is set at 0.07, close to the value used in Cocco, Gomes, and Maenhout (2005).[25]

Table 1.6 outlines the parameter calibration. Panel A summarizes the values used for the heterogeneous preference parameters while Panel B shows the other parameter values.

1.7.2. Results

By comparing policy functions across households with different preference parameters, I first find that both a stronger precautionary saving motive for LTC and a stronger bequest motive lower the optimal stock share. I then investigate the mechanism behind these effects by shutting off some risks in the model. I also find that the slope of the life-cycle profile of stock share depends on the strength of each saving motivation.

1.7.2.1. Effect of Preference Heterogeneity on the Optimal Stock Share

To put the results in the context of the literature, I first investigate how the optimal stock share changes over income, wealth, and age for households with the median values for all the preference parameters. Figure 1.2 shows the stock share policy functions for males in good health with median preferences. Panel (a) is for age 55, while (b) is for age 80.

The main driving force behind the differences in the optimal stock share in this figure is the ratio between a household's financial wealth and the value of human capital, where the latter is a present value sum of labor and retirement income. When there is no risk in retirement income, and when labor income risk is not correlated with stock returns—human capital

[25] They estimate this to be 0.058 for college graduates. I set it slightly higher here given that my model does not have permanent income shocks.

functions as a close substitute for risk-free assets.[26] In this case, a household with more human capital should have a higher optimal stock share in its financial portfolio. Hence, higher wealth should be associated with a lower stock share given income levels, while higher income and a younger age should be associated with a higher stock share given wealth levels. This is the mechanism that Cocco, Gomes, and Maenhout (2005) and Viceira (2001) focus on.

Now I investigate the effects of the preference heterogeneity. Figure 1.3 shows how the optimal stock share changes when we increase risk tolerance and decrease the strength of each saving motive (i.e., decrease each utility multiplier and increase each necessity parameter), for age 55 and selected combinations of wealth and income. When I analyze the effect of one preference parameter, the other parameters are set at the median values. The changes reflect the effects of two-standard-deviation changes in the preference parameters for ease in comparing them to the empirical estimates in Table 1.5.

Qualitatively, the results for the effect of the risk tolerance and the precautionary saving motive for LTC are similar to what I find from the empirical analysis. Being more risk tolerant increases the optimal stock share, while having a higher θ_{LTC} implies a lower stock share, as in the empirical analysis. For the other parameters, I find patterns that are not found in the empirical analysis. A lower κ_{LTC} has an effect similar to a higher θ_{LTC}: when the subjective minimum requirement expenditure in the LTC state is higher, the optimal stock share is lower. The effects of both θ_{Beq} and κ_{Beq} show that a stronger bequest motive is associated with a lower stock share.

[26] Viceira (2001) shows that this is still the case even with moderate correlation between labor income and stock return processes.

For all the parameters, the model predicts greater effects than found in the actual behavior of the VRI sample. Increasing risk tolerance by two standard deviations in the model is associated with a more than 40 percentage point increase in the stock share across wealth and income levels, compared to the 3.2 percentage point increase found in the empirical analysis in Section 1.6. The heterogeneity in the other parameters have smaller but still substantial effects. For example, heterogeneity in precautionary saving motives for LTC, expressed as differences in θ_{LTC}, creates about a 7 percentage point difference in the stock share for many wealth and income levels, while the difference can be as large as 15 percentage points.[27] The corresponding numbers for κ_{LTC} are much larger—10 percentage points for many wealth-income combinations and more than 20 percentage points for some cases. Note that the numbers from the empirical analysis were similar (though somewhat smaller) in the case of θ_{LTC} (4.1 percentage points), while negligible for κ_{LTC} (1.7 percentage points). Finally, the effects of heterogeneity in θ_{Beq} and κ_{Beq} are smaller compared to that of θ_{LTC} and κ_{LTC}, but in many cases they are still larger than the numbers from the empirical analysis and the direction is actually opposite to what the point estimates from the empirical analysis suggest.

I find almost the same pattern for age 80 (Figure 1.4). Overall, the size of the effect is reduced in terms of percentage point differences, but this is mainly due to that older households have a lower stock share than younger households because of the reduced value of human capital (see Figure 1.2(b)). In terms of percent difference (not percentage point difference) in stock

[27] When the income level is high and the wealth level is low, the effect is zero, since for these households, under the range of values of θ_{LTC} used in this analysis, the optimal stock share is 100 percent. Large effect of heterogeneity in θ_{LTC} for these households will be obtained if I allow for leveraging. The same caveat applies to the analyses for the other preference parameters.

share, the effects have similar magnitudes. Notice that the chance of having a negative health shock increases with age, but at the same time the chance of having a long sequence of LTC shock (which is the most catastrophic event) decreases due to increased mortality risk. Given that an LTC shock plays an important role in the negative effect of both of the saving motives, as will be explained below, the similar results for the age 55 and age 80 groups may reflect these factors canceling each other out for the older group.

1.7.2.2 Mechanisms Behind the Effects

Negative impact of a stronger LTC precautionary motive on the optimal stock share A higher θ_{LTC} or lower κ_{LTC} means that households face larger background risk, since an endogenously-determined LTC expenditure is larger when households are hit by an LTC shock. Therefore, those with higher θ_{LTC} or lower κ_{LTC} want to reduce their exposure to financial market risk.

For those who do not have enough resources, the availability of publicly-funded LTC service reduces this effect. This fact is well demonstrated in the effect of κ_{LTC} at age 80. For the low-wealth and low-income combination, larger required expenditures in the LTC state (i.e., lower κ_{LTC}) is associated with a higher optimal stock share (see Figure 1.4(e)). When both the wealth and income levels are low, and if they are going to spend significant money on LTC service when they are hit by a LTC shock, it is more likely that they will end up using the option of a public LTC service. Consequently, this household would be less affected by the combination of a negative stock return shock and an LTC shock since it would forfeit its wealth anyway upon choosing to use the public LTC service.

Negative impact of a stronger bequest motive on the optimal stock share The negative effect of a stronger bequest motive on the optimal stock share, in particular that of θ_{Beq}, may seem puzzling given that the medium value of κ_{Beq} is positive. Since a bequest is a luxury good, higher weight on the bequest motive should imply lower effective risk aversion. Ding, Kingston, and Purcal (2014) have a similar finding in an environment without health and mortality risks and income.

The negative effect comes from the two elements of the model: the existence of retirement income and LTC risk under the presence of mortality risk. First, to understand the role played by the retirement income, suppose that a household that invested its entire wealth in stocks experiences a negative ten percent stock return. If that household has mainly been saving to finance its own consumption rather than to bequeath its wealth, this loss of stock value will not translate into a ten percent reduction in permanent consumption as long as the household has significant retirement income from either Social Security or defined benefit pensions, which is not affected by the stock market performance. If that household has mainly saved to leave bequests, however, the loss in stock value can be translated into about a ten percent reduction in bequests, in particular when the household dies soon after that, because unrealized retirement income cannot be bequeathed. In short, the existence of unrealized retirement income and mortality risk can increase the effective risk of a negative stock market return for those with stronger bequest motives.[28]

Second, the effective risk of the same LTC shock is larger for a household with larger θ_{Beq} because when a household is hit by a LTC shock, the amount of wealth that can be bequeathed is dramatically reduced and, at the same time, mortality risk is increased. They would not have enough time to accumulate their wealth again until they die. For those who

[28] It is clear that the size of this effect should depend on the replacement rate (λ) of retirement income. Hence, we can predict that the transition from a DB-pension to a DC-pension system should reduce the effect of this channel.

mainly care about their own consumption (i.e., those with lower θ_{Beq}), however, the fact that an LTC shock accompanies the increase mortality risk is functioning as an insurance since the chance that they will outlive their resources is reduced with the higher mortality risk.

To measure the effect of an LTC shock on bequests, I ran 10,000 simulations for each value of θ_{Beq} and calculated the average bequest conditional on the age at death, θ_{Beq}, and also on whether the household ever had an LTC shock in its lifetime or not (see Section 1.7.2.3 for details on the setup of the simulations). Figure 1.5(a) shows the result. (Figure 1.5(b) plots the survival rate up to each age to show the likelihoods of dying at different ages.) Having an LTC shock in their lives reduces bequests on average about \$100K for all the θ_{Beq} values and for most of ages at death, while the effect gets larger for those whose age at death is higher than 95. In terms of proportion rather than absolute value, the size of the shock on bequest gets larger as they die at higher ages. And this shock is more painful to those with high θ_{Beq} values.

To test the strength of these channels, I shut off LTC and bequest risks and revisit the effect of θ_{Beq} (Figure 1.5(c)). In the absence of these risks, we see that the stronger bequest motive implies higher stock share, as in Ding, Kingston, and Purcal (2014), though the effect is generally very small.

Small effect of bequest motive Though a strong bequest motive lowers the optimal stock share, overall the size of the effect is not large. To investigate the reason for this small effect, in Figure 1.6 I separately calculate the effect of one-standard-deviation differences of θ_{Beq} in its lower range (low θ_{Beq} - medium θ_{Beq}) and higher range (medium θ_{Beq} - high θ_{Beq}). The figure shows that the effect of θ_{Beq} is non-linear: the effect is almost null until it becomes large enough.

Almost the entire effects of two-standard-deviation differences in θ_{Beq} are from the one-standard deviation differences in its higher range. Since the median LTC precautionary saving motive is already strong enough to leave sizeable accidental bequests as long as they do not live up to very high ages and/or they are not hit by a long sequence of LTC shocks, when the bequest motive is not strong, it is already saturated with these accidental bequests. This can be seen from the fact that one-standard-deviation difference in θ_{Beq} in its lower range does not affect the accumulation of wealth and hence in the amount of accidental bequests (Figure 1.5(a)). Once θ_{Beq} is large enough, it starts to affect both wealth accumulation and portfolio allocation.

1.7.2.3 Life-Cycle Profile of Stock Share

To summarize the effect of the preference heterogeneity on stock share of households over life-cycle, I generate life-cycle profiles of stock share by simulating the model to investigate the model's implications for the design of life-cycle financial advice. For each combination of parameter values considered in Figure 1.3 and 1.4, I simulate 10,000 households using the policy functions for saving and portfolio choices and then take the average to obtain the profiles. The simulation starts from age 55 with a wealth level of \$700K. I set $\bar{y}$ to be \$90,000. In Figure 1.6, I show profiles across different θ_{LTC} (Panel (a) and (b)) and θ_{Beq} (Panel (c) and (d)).

In Panel (a) I first show the average wealth profile since different preference parameter values affect wealth-to-income ratio and the latter, in turn, affects the optimal stock share. Households accumulate wealth before retirement (age 65) and then decumulate afterward. With a stronger precautionary saving motive associated with LTC (i.e. higher θ_{LTC}), the accumulation rate is faster while the decumulation rate is slower, leading to an overall higher wealth level.

Accumulation of wealth and approaching retirement together can explain the downward sloping stock share profile before retirement depicted in Panel (b). In this phase, the slope is the same across different values of θ_{LTC}. Furthermore, the profile in this phase is fairly close to the often-mentioned rule of thumb for life-cycle funds, which says that stock share in terms of percentage should be determined by subtracting one's age from 100.

After retirement, however, the slope depends on the strength of the precautionary saving motive. At the median preference, the slope becomes flat after retirement. With a strong precautionary saving motive for LTC, the slope is negative; the opposite is true when this saving motive is weak. Differences in the slopes, again, mainly reflect differences in the wealth-to-human-capital ratio across different groups. Those with a stronger precautionary saving motive for LTC save more, and an increased wealth-to-human-capital ratio implies a lower stock share.

Panel (c) and (d) show that I obtain similar results over θ_{Beq}. One noticeable difference is that until θ_{Beq} becomes large enough, the effect of that preference parameter on both wealth accumulation and portfolio allocation is limited, given the strength of the median precautionary saving motive for LTC.

This exercise shows that there is no uniform rule for stock share adjustment over the life-cycle that can be applied to every household. The rules, on the one hand, should consider differences in optimal stock share, given wealth level, across households with different motivations for saving (reflected in different initial levels of stock share profiles in Figure 1.7(b) and 1.7(d)), and on the other hand, the rules should also consider different wealth-to-human capital ratios that result from the heterogeneity in motivations for saving (reflected in different slopes of stock share profiles in Figure 1.7(b) and 1.7(d)).

1.8 Conclusion

I find evidence that both the preferences for LTC expenditures and bequests are overall strong but also heterogeneous across households. The former implies that older households are on average substantially exposed to health-related risks including LTC risk and mortality risk, while the latter implies that there is large heterogeneity in their exposures to these risks. The life-cycle portfolio choice model with the estimated preference heterogeneity predicts that the optimal stock share is lower for a household with either a stronger LTC precautionary saving motive or a stronger bequest motive. I find a qualitatively similar pattern in the relationship between the households' actual stock share and the estimated preference parameters. The size of the response, however, turns out to be much smaller than the prediction from the model.

This paper has three broad findings concerning LTC risk. First, the interaction of LTC risk and health-dependent utility substantially affects portfolio choice and wealth accumulation in an otherwise standard life-cycle model. Second, there is substantial heterogeneity in preferences for spending in the LTC state. Put together, these findings imply that household portfolio choices should be strongly affected by these preferences and should vary across households in accordance with their preferences. The third finding, however, is that in a large sample of households with sufficient financial resources where these choices and risks should be highly relevant, the actual response of portfolios to preference heterogeneity is in the direction implied by the life-cycle model, but substantially attenuated relative to the predictions from the model. One possible reason for this low-powered response of choices to the stated preference is that financial advice does not sufficiently take into account of LTC risk. This risk can take the form either of high probability of needing LTC or, as this paper emphasizes, preference for large spending should LTC be needed. The theoretical findings of this paper imply that portfolio advice should be conditioned on these preferences and risks. The paper, by documenting the heterogeneity in preferences and by showing its implications for portfolios for households in different circumstances, provides a roadmap for improving the financial advice to and financial products for households who need to manage financial assets during retirement while facing multiple risks.

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Table 1.1. Summary Statistics

	Mean	Percentiles				
		10	25	50	75	90
Stock Share	0.548	0.189	0.378	0.553	0.743	0.905
Coupled	0.673					
Male	0.647					
Age	68.0	58	62	67	73	78
Employer-sponsored sample	0.219					
Health (≥ Good)	0.948					
Education (Post college)	0.404					
Education (College)	0.330					
Income ($)	126,132	28,740	50,000	83,443	125,000	250,000
Financial Wealth($)	1,101,468	153,000	344,000	723,665	1,356,211	2,399,317
Prob. need LTC[a]	0.430	0.05	0.15	0.45	0.75	0.85
Prob. live approx. 10 more years[b]	0.753	0.45	0.65	0.85	0.95	0.95
Having LTC insurance	0.234					

Note: The tabulation is conditioned on having responses to all the variables used in this paper (all the SSQs in addition to the variables in this table). N=5,471

[a] The subjective probability of being in need of a LTC service at least for 1 year in the remaining life.

[b] The subjective probability of living up to at least age $\min(\{75,\ 85,\ 95\} \cap \{t \mid t \geq age+5\})$. For example, for a respondent whose age is 75, it is the probability of living up to age 85.

Table 1.2. Estimated Distributions of the Preference Parameters and Survey Response Errors

(a) Estimated distribution parameters

Parameter	Estimate	S.E.
μ_{γ}	-1.322	(0.013)
σ_{γ}	0.691	(0.007)
κ	-10.82K	(0.43K)
μ_{LTC}	1.292	(0.034)
σ_{LTC}	2.317	(0.029)
$\mu_{\kappa,LTC}$	-35.97K	(0.64K)
$\sigma_{\kappa,LTC}$	24.67K	(0.29K)
μ_{Beq}	2.487	(0.042)
σ_{Beq}	3.548	(0.047)
$\mu_{\kappa,Beq}$	38.74K	(1.11K)
$\sigma_{\kappa,Beq}$	45.10K	(0.69K)
$\sigma_{\varepsilon 11}$	0.177	(0.002)
$\sigma_{\varepsilon 12}$	0.109	(0.001)
$\sigma_{\varepsilon 21}$	14.98K	(0.14K)
$\sigma_{\varepsilon 22}$	11.98K	(0.15K)
$\sigma_{\varepsilon 23}$	8.11K	(0.09K)
$\sigma_{\varepsilon 31}$	15.24K	(0.14K)
$\sigma_{\varepsilon 32}$	9.84K	(0.17K)
$\sigma_{\varepsilon 33}$	19.33K	(0.25K)
N	5,471	
Log-likelihood	-125,903	

(b) Implied distributions of preference parameters

	Percentiles					
Parameter	10	25	50	75	90	Mean
γ_i	0.11	0.17	0.27	0.43	0.65	0.34
$\theta_{LTC,i}$	0.19	0.76	3.64	17.37	70.91	53.32
$\theta_{Beq,i}$	0.12	1.10	12.03	131.65	1134.69	6510.37
κ_{LTC}	-67.59K	-52.61K	-35.97K	-19.33K	-4.35K	-35.97K
κ_{Beq}	-19.06K	8.32K	38.74K	69.16K	96.54K	38.74K

Table 1.3. Stock Share Regression: Using Raw Responses to SSQs

	1	2
SSQ1 (10-20%)	0.028***	0.016
	(0.010)	(0.010)
SSQ1 (20-33%)	0.048***	0.034***
	(0.010)	(0.010)
SSQ1 (33-50%)	0.059***	0.046***
	(0.012)	(0.012)
SSQ1 (50-75%)	0.081***	0.070***
	(0.013)	(0.013)
SSQ1 (75-100%)	0.037	0.037
	(0.026)	(0.026)
SSQ2	-0.048**	-0.034*
(Share of wealth for LTC)	(0.020)	(0.020)
SSQ3	0.008	0.015
(Share of wealth for bequest)	(0.015)	(0.015)
Coupled		-0.017**
		(0.008)
Male		0.024***
		(0.008)
Age		-0.000
		(0.001)
Employer-sponsored		-0.046***
		(0.009)
Health (≥Good)		-0.020
		(0.016)
Post college degree		0.034**
		(0.015)
College degree		0.027*
		(0.014)
Log income		0.014***
		(0.005)
Log wealth		0.015***
		(0.004)
LTC prob.		-0.023**
		(0.012)
Longevity prob.		0.044***
		(0.017)
LTCI		-0.013
		(0.008)
N	5471	5471
R^2	0.011	0.031

Note: For SSQ1, the most risk averse category (i.e., willing to risk 0–10% of their income to have a 50% chance of doubling income) is the omitted category. For SSQ2 the raw response is defined as the share of wealth the respondent allots for the LTC state, averaged over the three questions. For SSQ3, it is the share of wealth bequeathed, averaged over the three questions. For a description of the controls, see the note to Table 1.1.

*= p<0.1, **=p<0.05, ***=p<0.01

Table 1.4. Stock Share Regression: Using Estimated Preference Parameters (Cardinal Proxies)

	1	2
$\log \gamma$	0.027***	0.023***
	(0.006)	(0.006)
$\log \theta_{LTC}$	-0.010***	-0.009***
	(0.002)	(0.002)
$\log \theta_{Beq}$	0.002	0.001
	(0.002)	(0.002)
κ_{LTC}	0.034	0.038
(in $100K)	(0.023)	(0.023)
κ_{Beq}	-0.029*	-0.010
(in $100K)	(0.015)	(0.016)
Coupled		-0.016
		(0.010)
Male		0.014
		(0.011)
Age		-0.000
		(0.001)
Employer-sponsored		-0.036**
		(0.015)
Health (≥Good)		-0.011
		(0.020)
Post college degree		0.020
		(0.018)
College degree		0.020
		(0.016)
Log income		0.012*
		(0.007)
Log wealth		0.015***
		(0.005)
LTC prob.		-0.032***
		(0.010)
Longevity prob.		0.035*
		(0.019)
LTCI		-0.011
		(0.008)
N	5471	5471
R^2	0.009	0.029

Note: See Section 1.5 for construction of the cardinal proxies. For a description of the controls, see the note to Table 1.1. Standard errors are bootstrapped, with 100 repetitions.

*= p<0.1, **=p<0.05, ***=p<0.01

Table 1.5. Implied Change in Stock Share by a Two-standard-deviation Increase in Each Preference Parameters

	1 (without control)	2 (with control)
$\log \gamma$	0.037	0.032
$\log \theta_{LTC}$	-0.046	-0.041
$\log \theta_{Beq}$	0.012	0.011
κ_{LTC}	0.017	0.019
κ_{Beq}	-0.026	-0.009

Table 1.6. Calibration of Parameters for Baseline Model

A. Heterogeneous preference parameters

Parameters		Value
γ	High	0.53
	Medium	0.27
	Low	0.13
θ_{LTC}	High	36.93
	Medium	3.64
	Low	0.36
θ_{Beq}	High	418.80
	Medium	12.03
	Low	0.34
κ_{LTC}	High	-11.30K
	Medium	-35.97K
	Low	-60.64K
κ_{Beq}	High	83.84K
	Medium	38.74K
	Low	-6.36K

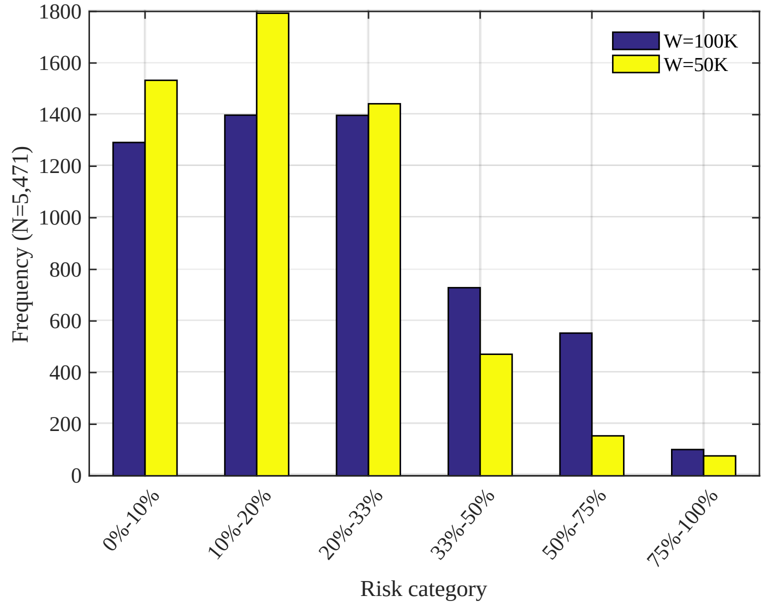
Note: For each parameter, medium value is the mean value of the distribution (exponential of mean if the distribution of the parameter is log-normal) while high (low) value is the mean plus (minus) one standard deviation (again exponential of those values if the distribution of the parameters is log-normal).

B. Other parameters

Parameters	Value	Target/Source
κ	-10.82K	VRI estimation
β	0.96	Standard
PC	$-\kappa_{LTC}+10K$	Ameriks et al. (2015b)
$\pi_{ss'}$		HRS estimation
$\bar{R}_f$	1.02	Cocco et al. (2005)
σ_η	0.17	Cocco et al. (2005)
μ_s	0.02	VRI stock share level
$\bar{y}$	{$45K, $90K, $120K}	VRI data
λ	0.5	VRI data
σ_v^2	0.07	Cocco et al. (2005)

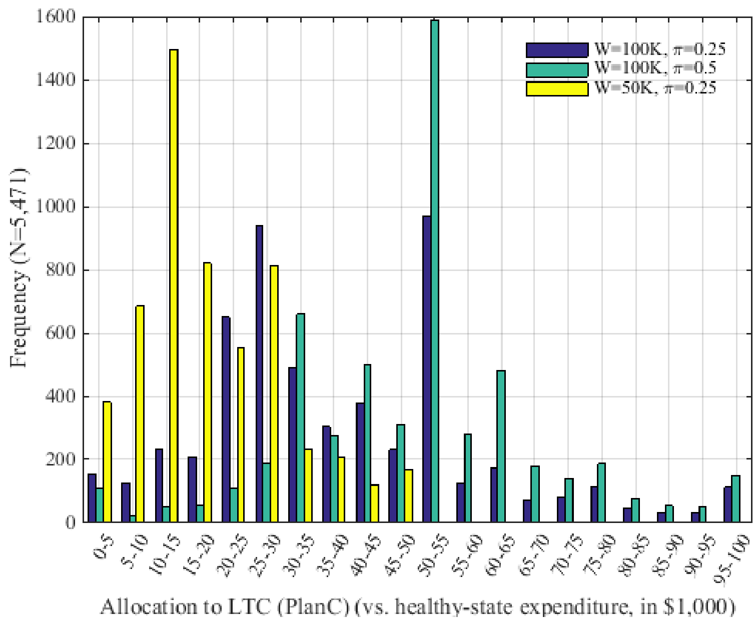
Figure 1.1. Distribution of Responses to SSQs (N=5,471)

(a) SSQ1

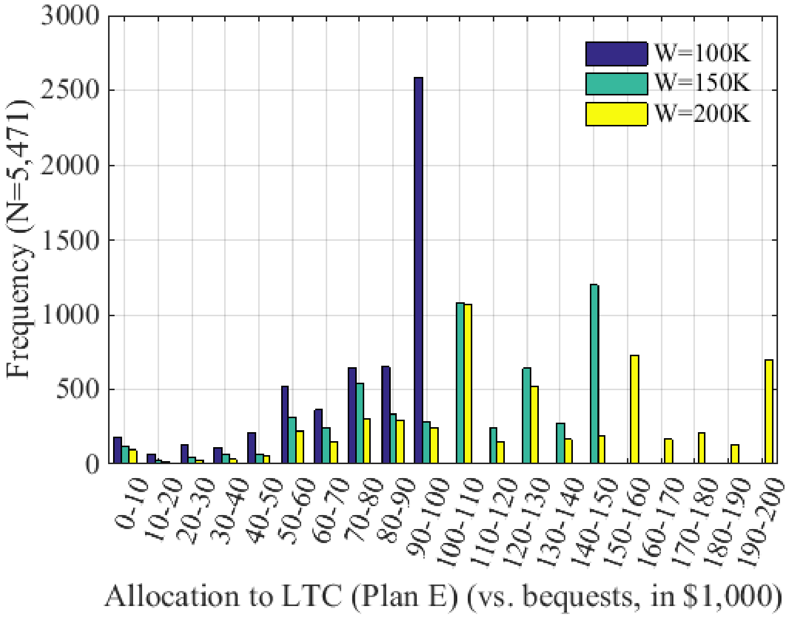


Note: Risk categories show the downside risk that is accepted for a 50 percent chance of doubling income. 0–10% is the most risk averse group while 75–100% is the most risk tolerant one.

(b) SSQ2



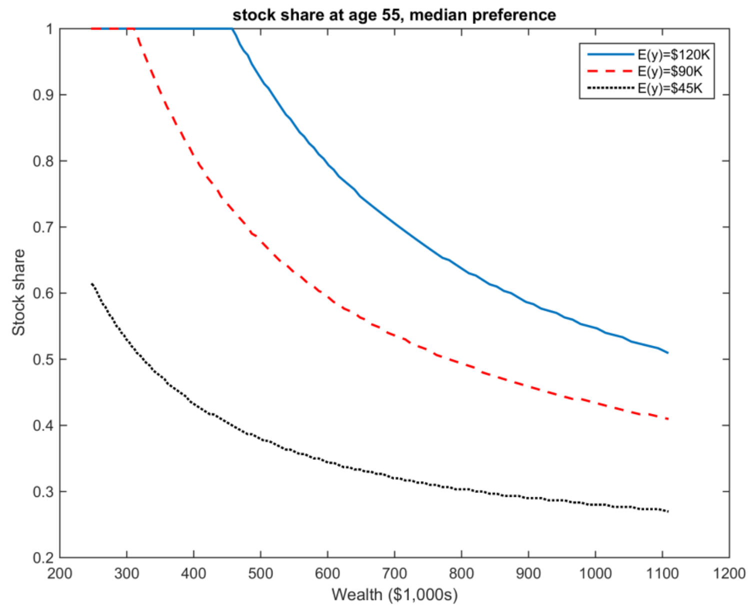
(c) SSQ3



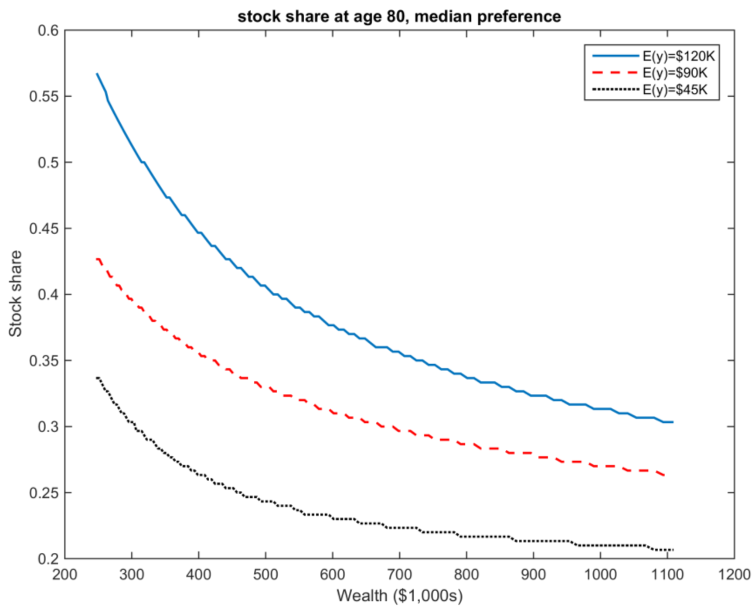
W=100K
W=150K
W=200K
Frequency (N=5,471)
3000
2500
2000
1500
1000
500
0
0-10
10-20
20-30
30-40
40-50
50-60
60-70
70-80
80-90
90-100
100-110
110-120
120-130
130-140
140-150
150-160
160-170
170-180
180-190
190-200
Allocation to LTC (Plan E) (vs. bequests, in $1,000)

Figure 1.2. Stock Share Policy Functions (with the median preference parameters)

(a) Age 55



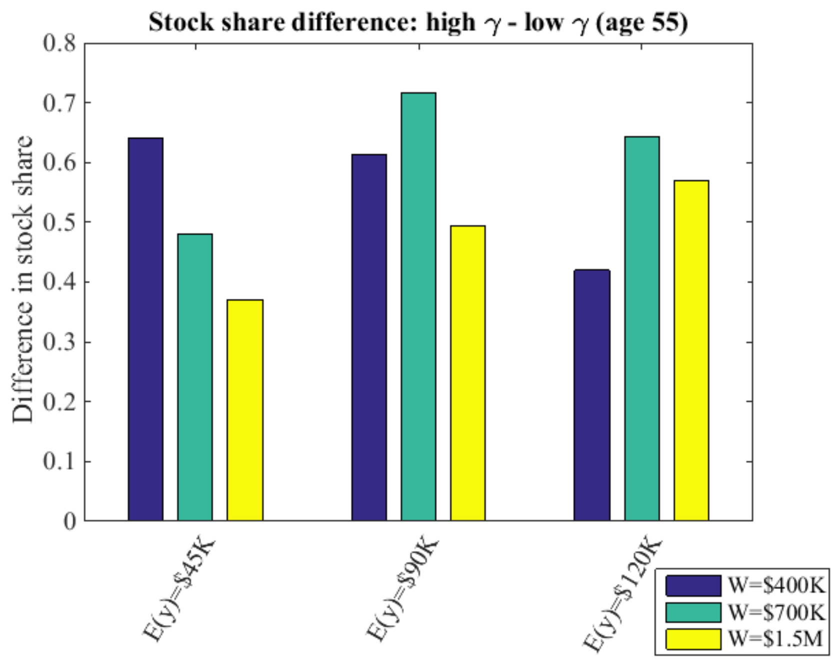
(b) Age 80



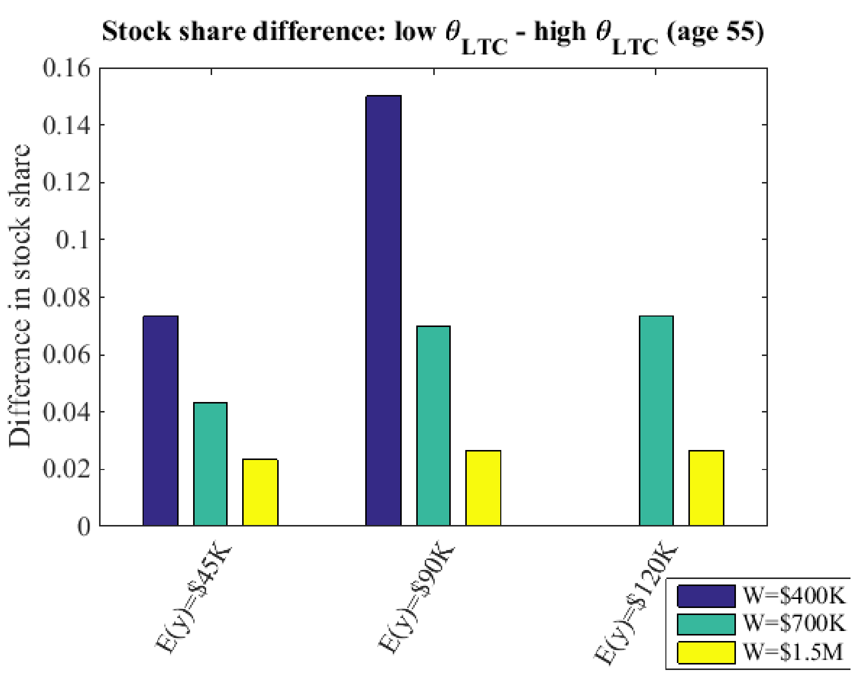
Note: Figure shows the optimal stock share policy function for healthy males, under various values of average income and median preferences. The horizontal axis is financial wealth at the beginning of the period (in $1,000s), and the vertical axis is the optimal stock share.

Figure 1.3. Effects of heterogeneous preference parameters on optimal stock share (age 55, healthy, male)

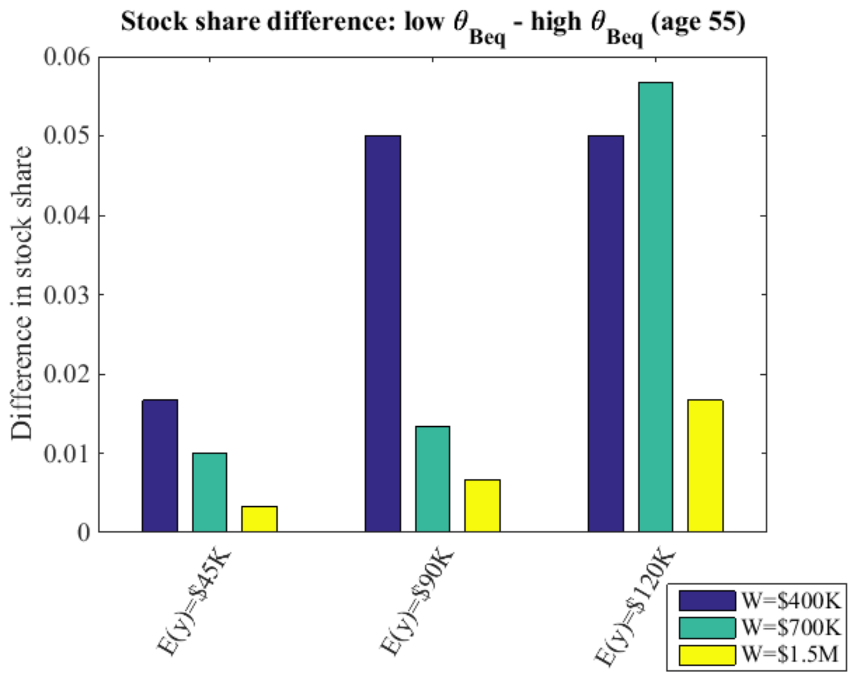
(a) Effect of γ



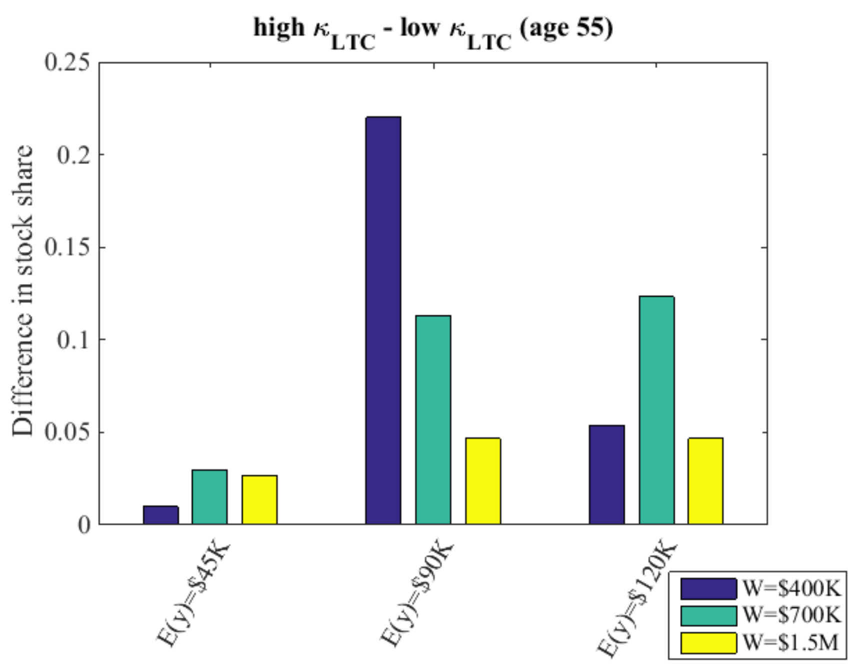
(b) Effect of θ_{LTC}



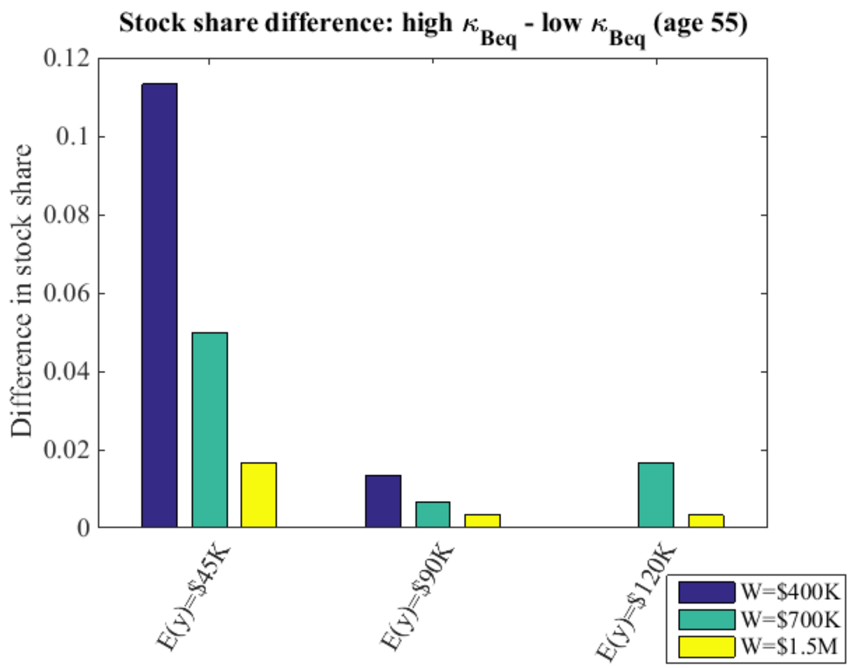
(c) Effect of θ_{Beq}



(d) Effect of κ_{LTC}



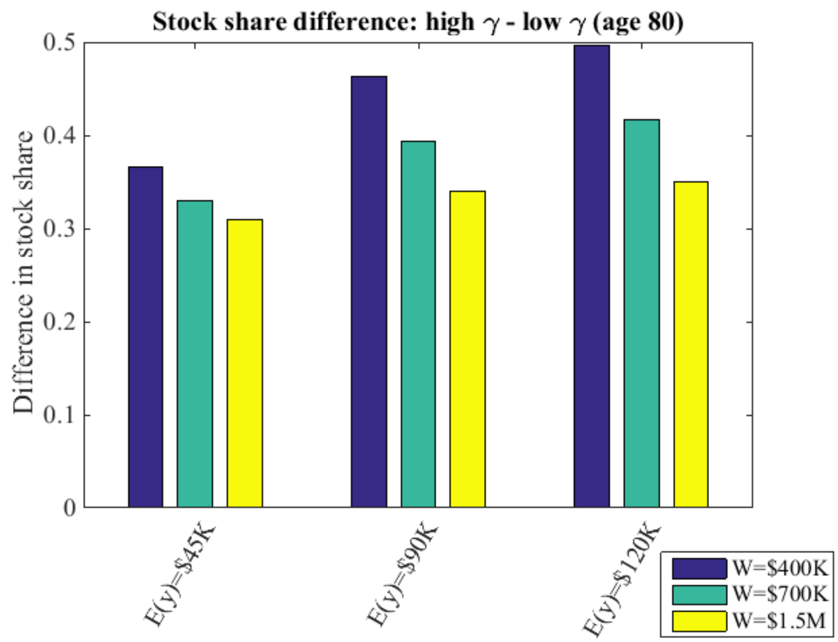
(e) Effect of κ_{Beq}



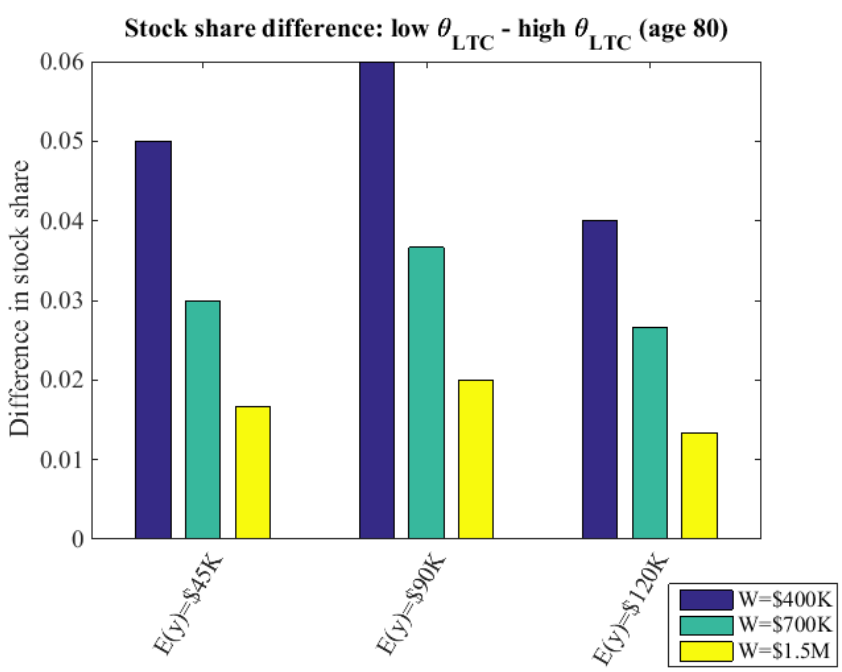
Note: Figure shows the difference in the optimal stock share across different values for preference parameters, under various wealth and mean income levels, at age 55 for healthy males.

Figure 1.4. Effects of heterogeneous preference parameters on optimal stock share (age 80, healthy, male)

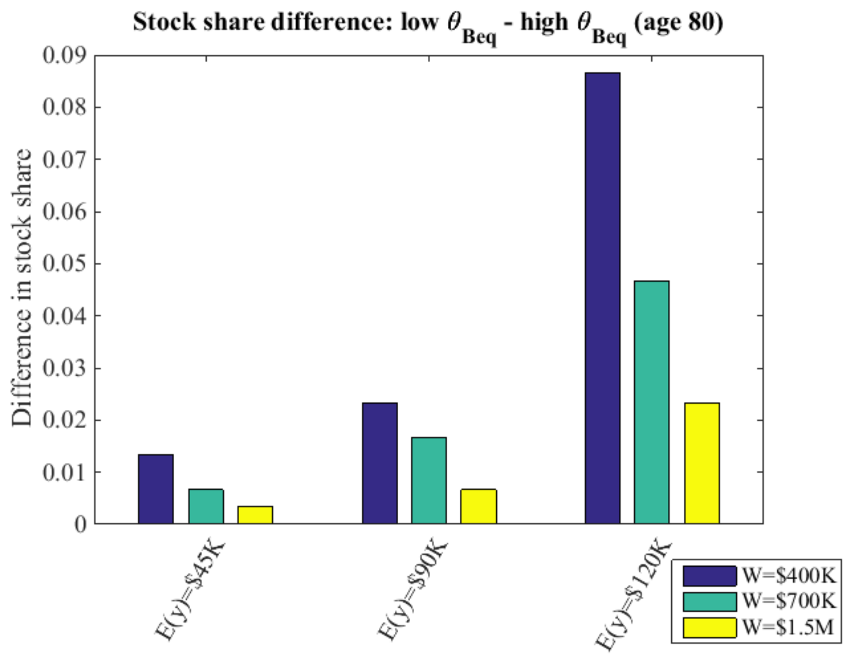
(a) Effect of γ



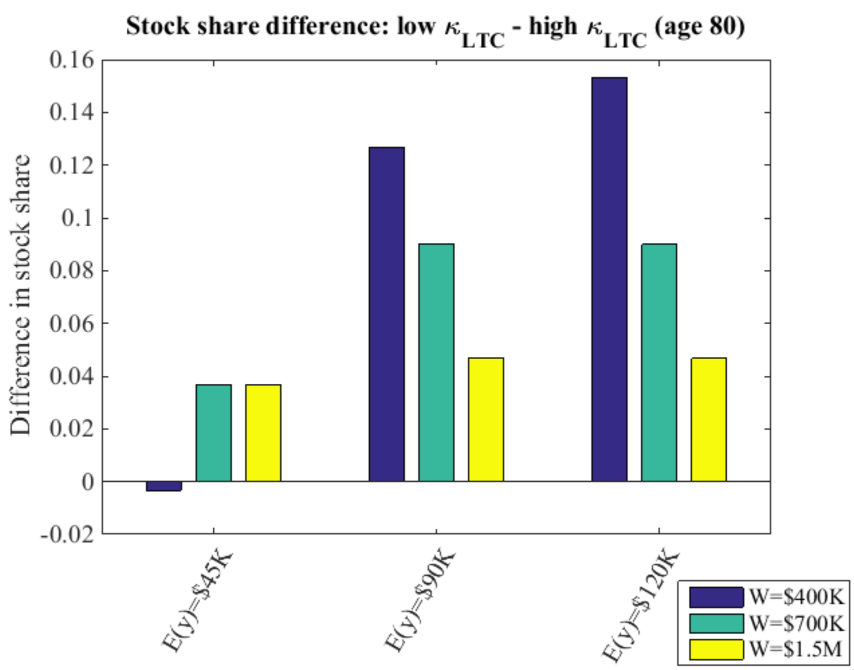
(b) Effect of θ_{LTC}



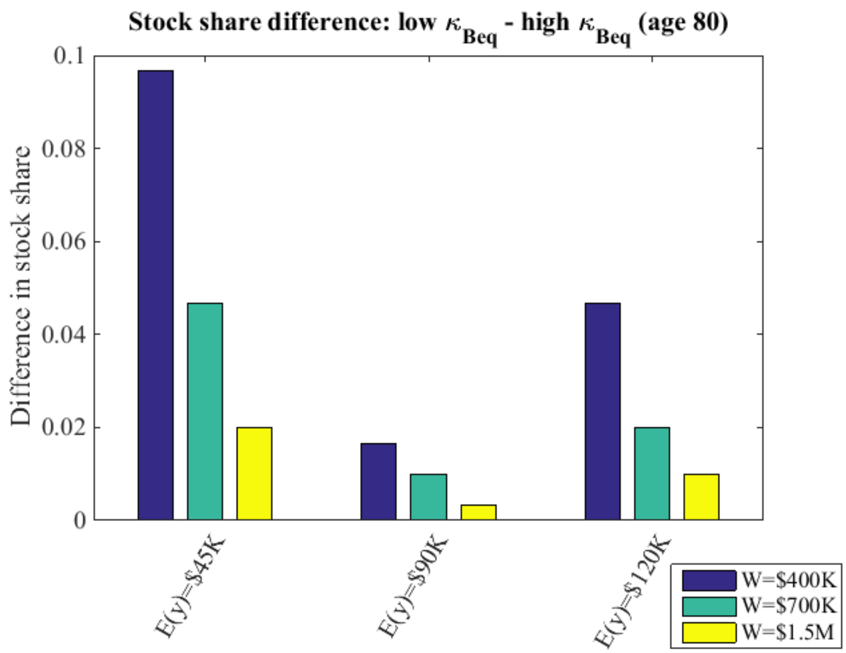
(c) Effect of θ_{Beq}



(d) Effect of κ_{LTC}



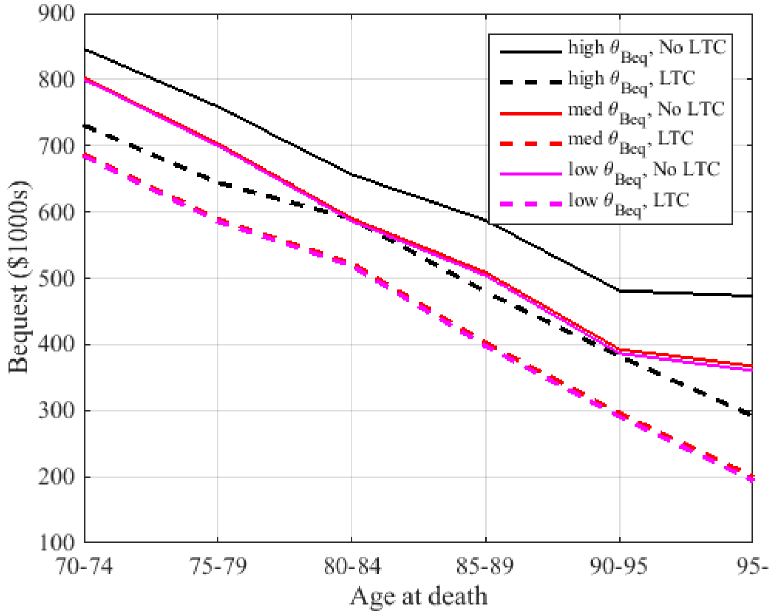
(e) Effect of κ_{Beq}



Note: Figure shows the difference in the optimal stock share across different values for preference parameters, under various wealth and mean income levels, at age 80 for healthy males.

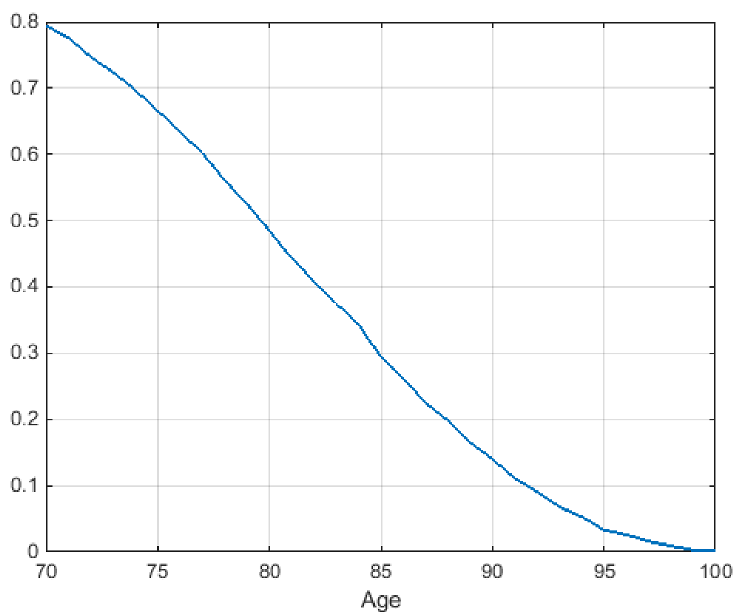
Figure 1.5. Mechanism behind the effect of θ_{Beq}

(a) Effect of LTC shock on bequests

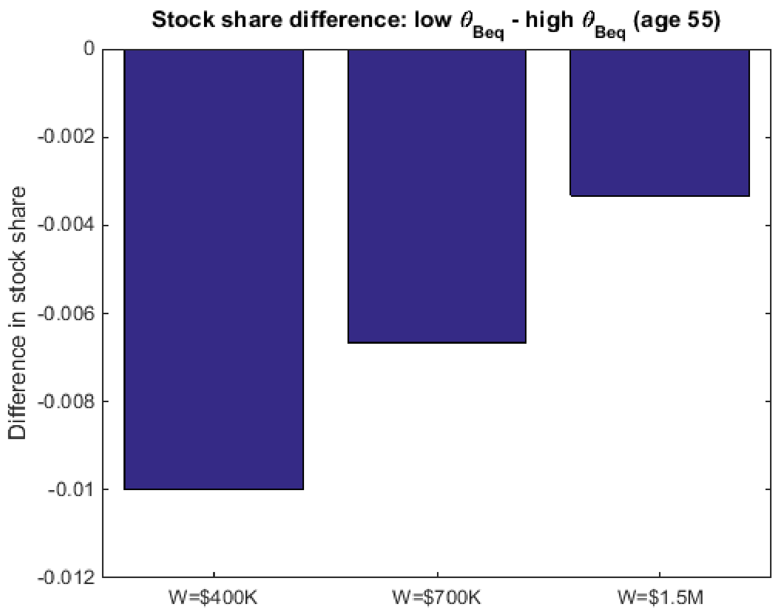


Note: Figure shows the average amount of bequest conditional on age at death, θ_{Beq}, and whether the household ever had LTC shock during its lifetime. Averages are calculated from 10,000 simulations for each θ_{Beq} value. Each simulation starts with wealth of $700,000 and $\bar{y} = \$90,000$.

(b) Survival rate



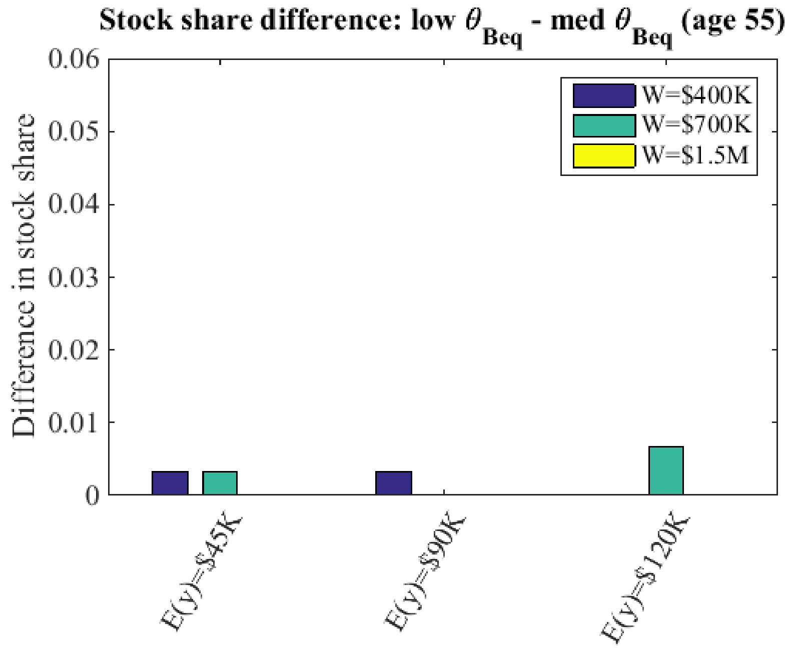
(c) Effect of θ_{Beq} under no health-related risks



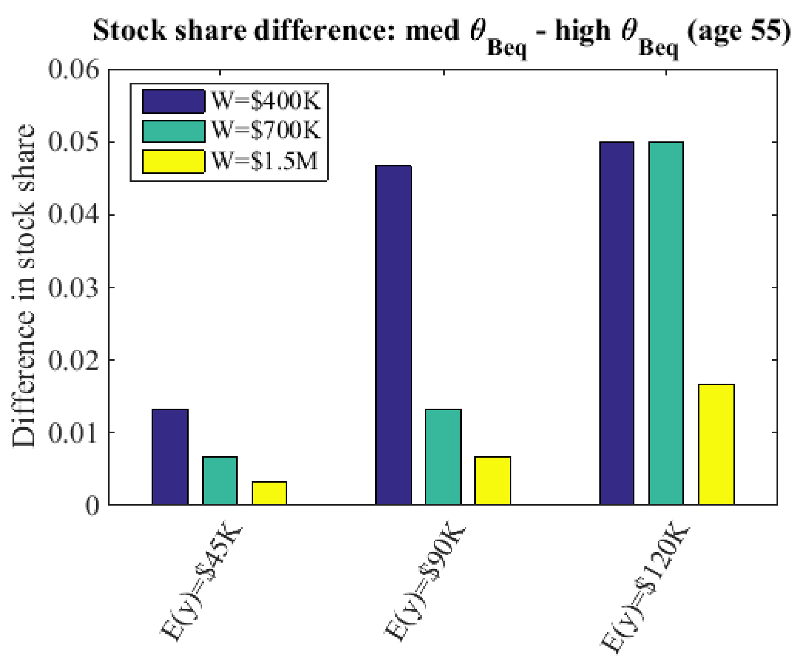
Note: Figure shows the difference in the optimal stock share across different values θ_{Beq} under no LTC risk and mortality risk. A household lives up to age 110 and then dies with probability one. The figure is drawn for healthy males at age 55, with $\bar{y} = \$90{,}000$, under various wealth levels.

Figure 1.6. Effect of one-standard-deviation difference in θ_{Beq}

(a) Limited effects in the lower range of θ_{Beq}



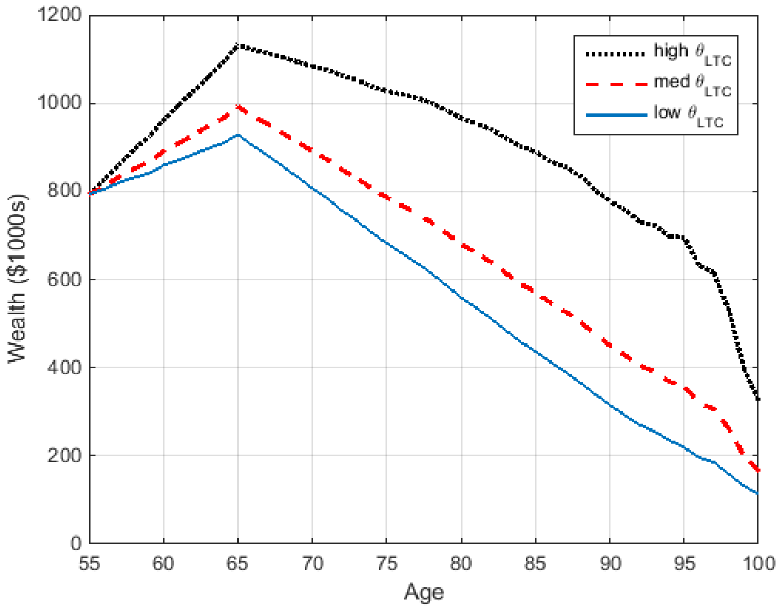
(b) Larger effects at the higher range of θ_{Beq}



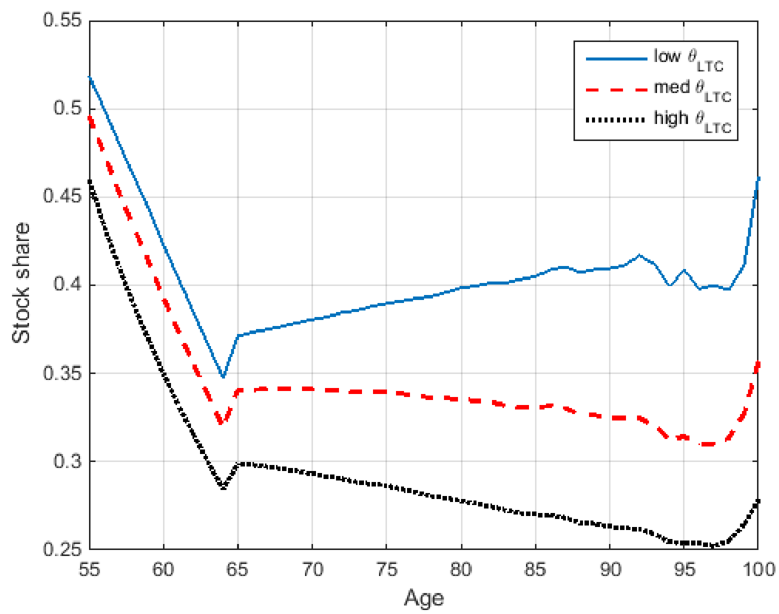
Note: Figure is constructed in the same way as in Figure 1.5(c), but in this Figure I calculate the effect of one-standard-deviation differences in θ_{Beq} .

Figure 1.7. Life-cycle profiles for wealth and stock share under various θ_{LTC} and θ_{Beq}

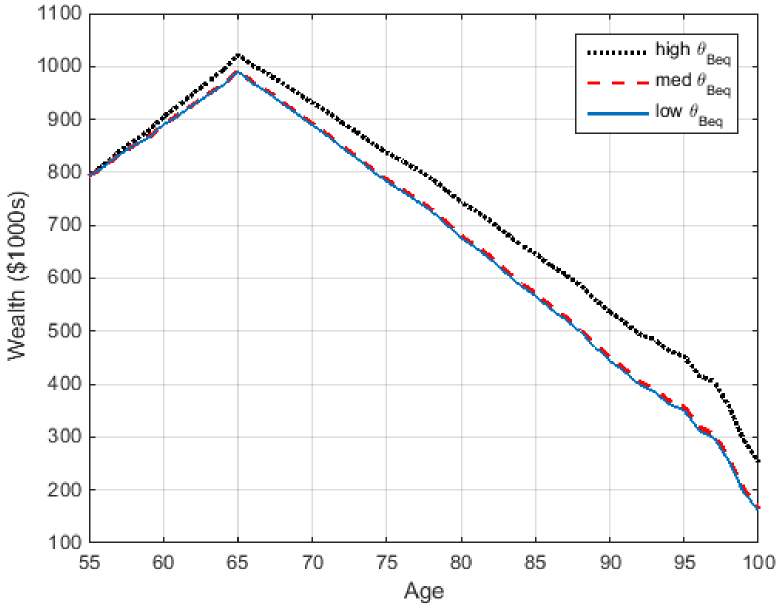
(a) Wealth with various θ_{LTC}



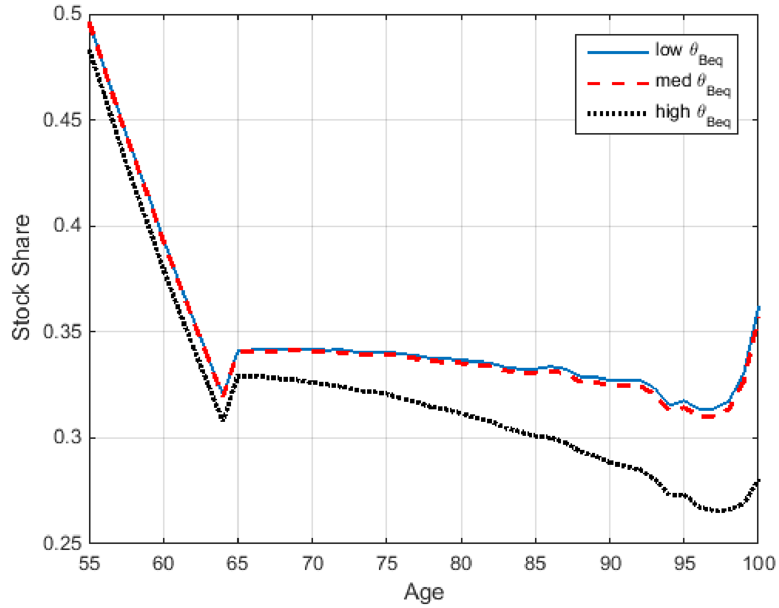
(b) Stock share with various θ_{LTC}



(c) Wealth with various θ_{Beq}



(d) Stock share with various θ_{Beq}



Note: Figure shows the life-cycle profiles of wealth and stock share under various values of θ_{LTC}. Profiles are calculated from 1,000 simulations for each parameter value. Each simulation starts with wealth of \$700,000 and $\bar{y} = \$90,000$.

Life-Cycle Portfolio Allocation with Multiple Late-in-Life Saving Motives

Appendix

1-A. Details on Strategic Survey Questions (SSQs)

Table 1-A1 shows the exact wordings and parameter values used for each type of SSQ. Each type is asked multiple times with different amounts of given resources (W) and/or different likelihoods of relevant events (π).

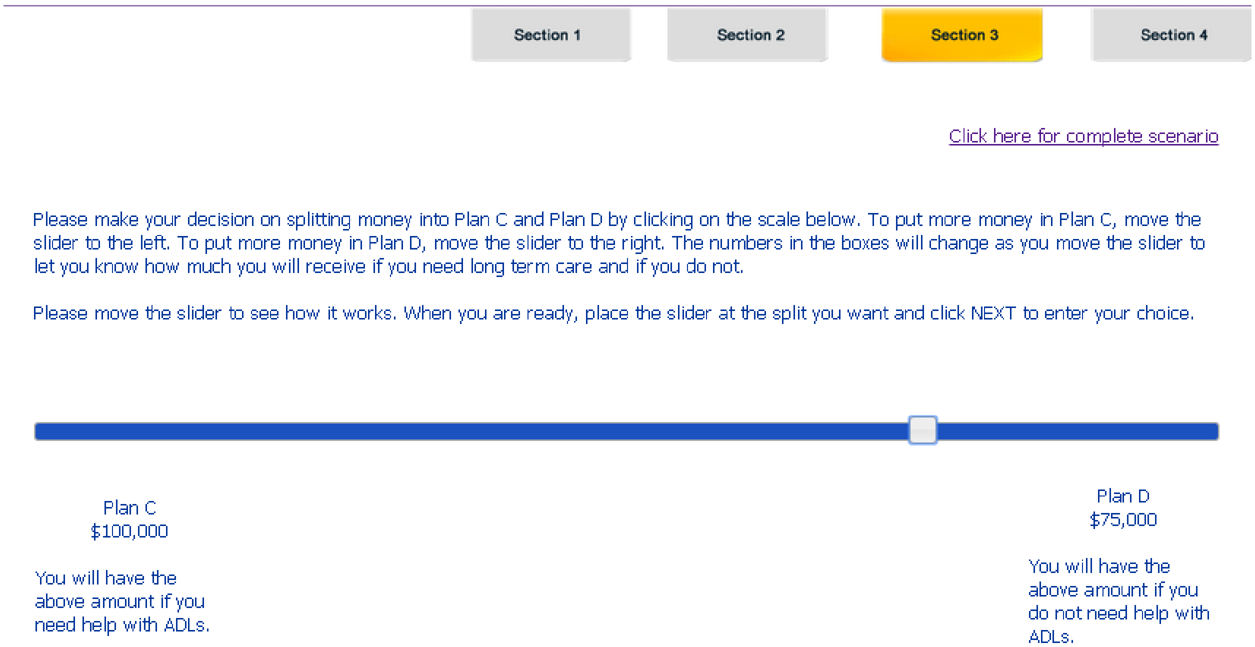
Figure 1-A1 shows an example of the interface—a bar with a slider—that is used in SSQ2 and SSQ3 to help respondents understand the underlying trade-off in allocating their resources. In this figure, a respondent is answering the first question of SSQ2 (allocating $100,000 between Plan C and Plan D, where the chance of needing a LTC service in the next year is 25%). When the respondent first sees this screen, it does not have a slider and there is only an empty bar. Once the respondent clicks on the bar, the slider appears where she clicked. The purpose of this design is to prevent any anchoring effect of an arbitrarily-chosen initial location. After the initial click, the respondent can move the slider to the left and right to adjust the allocation. Whenever the slider is moved, the numbers below the bar, which show the amount of resources available for each state under the current allocation, automatically update. In this way, the respondent can see the consequence of her decision without needing to make complex calculations.

Table 1-A1. Strategic Survey Questions

SSQ1 (Risk tolerance)	
Set up	Suppose you are 80 years old. Suppose, further, that for the next year: • You live alone, rent your home, and pay all your own bills. • You are in good health and will remain in good health. • You will have no medical bills or other unexpected expenses. • You do not work.
Hypothetical financial products	• Plan A guarantees that you will have \$W for spending next year. • Plan B will possibly provide you with more money, but is less certain. There is a 50% chance that Plan B would double your money, leaving you with \$2W, and a 50% chance that it would cut it by x%, leaving you with \$ $(1-0.01\times x)W$.
Rules	• You have no other assets or income, and so the only money you have available for all your spending next year is from either Plan A or Plan B. • Any money that is not spent at the end of next year cannot be saved for the future. • You cannot give any money away or leave it as a bequest. • If you need anything next year, you have to pay for it. No one else can buy anything for you. • At the end of next year you will be offered the same choice with another \$W for following year.
Parameters asked	$W = 100,000$ and 50,000.
SSQ2 (LTC-state utility function)	
Set up	• You are 80 years old, live alone, rent your home, and pay all your own bills. • There is a π chance that you will need help with ADLs for all of next year. • There is a (1- π) chance that you will not need any help at all with ADLs for all of next year. • You have \$W to divide between two plans for the next year. • At the end of next year you will be offered the same choice with another \$W for following year.
Hypothetical financial products	• Plan C is hypothetical ADL insurance that gives you \$(1/ π) for each dollar invested if you do need help with ADLs. • Plan D gives you \$1 for each dollar invested only if you do not need help with ADLs.
Rules	• You can only spend money from Plan C or Plan D next year. You do not have any other money. • Any money that is not spent at the end of next year cannot be saved for the future, given away, or left as a bequest. • Regardless of whether or not you need help with ADLs, your hospital,

	doctor bills, and medications are completely paid by insurance. • Other than Plan C, you have no other resources available to help with your long-term care. You have to pay for any long-term care you may need from Plan C. • There is no public-care option or Medicaid if you do not have enough money to pay for a nursing home or other long-term care. • An impartial third party that you trust will verify whether or not you need help with ADLs immediately, impartially, and with complete accuracy.
Parameters asked	(W, π) = (100,000, 25%), (100,000, 50%) and (50,000, 25%).
SSQ3 (Bequest utility function)	
Set up	• You are 85 years old, live alone, rent your home, and pay all your own bills. • You know with certainty that you will live for only 12 more months and that you will need help with ADLs for the entire 12 months. • You have $W to split into the following two plans.
Hypothetical financial products	• Plan E is reserved for your spending. From Plan E, you will need to pay all of your expenses, including long-term care and any other wants, needs, and discretionary purchases. • Plan F is an irrevocable bequest.
Rules	• You have no money other than $W. • No one—including friends or family—can take care of you for free. Long-term care must be purchased at market rates. • Any money in Plan E that you do not spend cannot be given away or left as a bequest. • Bequests from Plan F are not subject to any taxation. • You have full insurance that covers all of your hospital, doctor, and medications, but you have no long-term care insurance. • There is no public-care option or Medicaid if you do not have enough money to pay for a nursing home or other long-term care.
Parameters asked	W = 100,000, 150,000 and 200,000.

Figure 1-A1. Example of the SSQ Interface



1-B. Estimation of Preference Parameter Distribution Conditional on Covariates

Table 1-B1 shows the results from the estimation conditional on the covariates. For most of the covariates, they have offsetting effects on the multiplier and the necessity parameter so their effect on each saving motivation is ambiguous. For example, for more educated respondents, the utility multiplier for the LTC state tends to be smaller while the corresponding necessity parameter tends to be more negative (i.e., the minimum expenditure in the LTC state increases).

The following variables have unambiguous effects on the saving motives. Older respondents tend to be more risk averse. They also have a stronger precautionary saving motive for LTC and a stronger bequest motive. The strength of the bequest motive is also associated with a more pessimistic expectation regarding their own health (both LTC and longevity expectations) and a lower income level.

Table 1-B1. Estimated Distributions of the Preference Parameters and Survey Response Errors, Conditional on Covariates

	Preference parameters					
	μ_{σ}	κ	μ_{LTC}	$\mu_{\kappa,LTC}$	μ_{Beq}	$\mu_{\kappa,Beq}$
Constant	-1.147***	-12.473*	2.693***	-16.710	4.140***	16.937
	(0.214)	(7.192)	(0.558)	(10.242)	(0.761)	(16.451)
Coupled	-0.025	2.594***	0.077	2.704**	0.641***	1.498
	(0.025)	(0.883)	(0.072)	(1.210)	(0.088)	(1.678)
Male	0.239***	-1.475*	-0.798***	-9.527***	-0.579***	-15.097***
	(0.023)	(0.849)	(0.071)	(1.238)	(0.091)	(1.731)
Age	-0.003*	-0.118*	0.033***	-0.099	0.032***	-0.352***
	(0.002)	(0.061)	(0.005)	(0.079)	(0.006)	(0.122)
Employer-sponsored	-0.108***	6.624***	0.496***	12.407***	0.424***	0.596
	(0.030)	(1.147)	(0.077)	(2.077)	(0.097)	(2.127)
Health (≥Good)	-0.219***	8.963***	0.489***	14.679***	1.238***	18.509***
	(0.049)	(1.491)	(0.162)	(2.077)	(0.200)	(2.607)
Post college degree	0.205***	-9.270***	-0.778***	-15.812***	-0.741***	-10.092***
	(0.037)	(1.543)	(0.114)	(2.192)	(0.152)	(3.443)
College degree	0.085**	-5.000***	-0.558***	-7.088***	-0.558***	-7.771**
	(0.034)	(1.497)	(0.103)	(2.102)	(0.145)	(3.300)
Log income	0.015	-0.589	-0.261***	-2.211**	-0.277**	0.209
	(0.014)	(0.494)	(0.029)	(0.734)	(0.054)	(1.263)
Log wealth	-0.028***	0.113	0.027	1.851***	-0.084**	-5.913***
	(0.011)	(0.400)	(0.025)	(0.560)	(0.034)	(0.795)
LTC prob.	0.061*	-1.726	-0.296**	-12.479***	0.409***	-7.569***
	(0.034)	(1.177)	(0.102)	(1.674)	(0.122)	(2.344)
Longevity prob.	0.316***	-7.851***	-0.650***	-11.733***	-0.861***	3.876
	(0.046)	(1.728)	(0.143)	(2.383)	(0.174)	(3.680)
LTCI	-0.119***	3.590***	-0.199**	-2.340*	-0.173*	-2.961
	(0.025)	(0.952)	(0.089)	(1.314)	(0.105)	(1.910)
Heterogeneity						
σ	0.679***	n/a	2.286***	24.599***	3.530***	43.332***
	(0.007)		(0.029)	(0.405)	(0.046)	(0.674)
Measurement error						
σ_{e11}			0.176***			
			(0.002)			
σ_{e12}			0.109***			
			(0.001)			
σ_{e21}			14.660***			

	(0.138)
σ_{e22}	11.834***
	(0.147)
σ_{e23}	7.994***
	(0.091)
σ_{e31}	15.081***
	(0.147)
σ_{e32}	9.703***
	(0.164)
σ_{e33}	19.204***
	(0.234)
Log-likelihood	-125,659

1-C. Distribution of Expenditure Shares from a Static Problem

To show the implications of the estimated parameter distributions more clearly, following Ameriks, Briggs, Caplin, Shapiro, and Tonetti (2015a), I conduct the following exercise. I assume the following maximization problem:

$$Max_{x1,x2} \frac{(x_1-\kappa)^{1-1/\gamma_i}}{1-1/\gamma_i} + \theta_{LTC,i} \frac{(x_2-\kappa_{LTC,i})^{1-1/\gamma_i}}{1-1/\gamma_i} + \theta_{Beq,i} \frac{(W-x_1-x_2-\kappa_{Beq,i})^{1-1/\gamma_i}}{1-1/\gamma_i} \qquad (1\text{-C.1})$$
$$s.t. \quad 0 \le x_1, x_2 \le W$$

which is a static problem with no uncertainty. The household should divide the given resource W into three expenditures: expenditures in the healthy state (x_1), expenditures in the LTC state (x_2), and bequests ($W-x_1-x_2$). Although this problem is unrealistic, the solution can demonstrate the strength of each saving motivation under the estimated parameters. For each individual, I solve (1-C.1) under W=$400K and $1M and the proxy values of the preference parameters.[29]

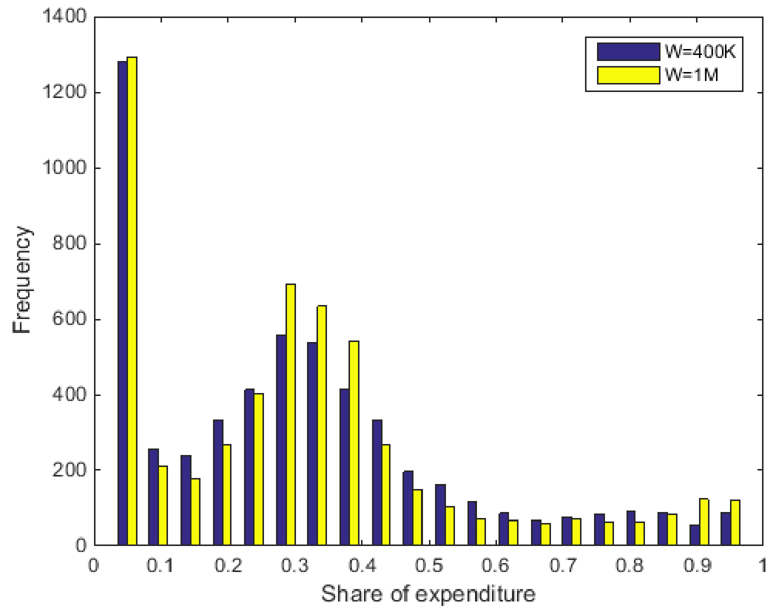
In Figure 1-C1, I show the distribution of expenditure shares. Under W=$400K, many respondents spend more than 40 percent of their wealth for expenditure in the LTC state. About

[29] For the parameters that are assumed to have log-normal distribution, I take the expectation of log of the parameters and take the exponential of it, to avoid Jensen's inequality. The proxy calculated in this way matches the median of the estimated distribution, though it misses the mean, in terms of the level of the parameter. Furthermore, since the proxies are calculated as conditional expectations, it has mean reversion compared to the estimated distribution. Hence plugging these proxies directly into (1-C.1) would yield less heterogeneity in saving motives compared to what the estimated distributions imply. To correct this problem, in the case of log-normally distributed parameters, before I take exponential of the conditional expectation of the log of the parameter, I convert it by $\log h' = \log h + (\log h - \mu_\theta)\frac{\sigma_\theta}{\sigma_h}$ where $\log h$ is the expected value of the log of the parameter, μ_θ is the estimated mean of the log-normal distribution, σ_h is the standard deviation of $\log h$ and σ_θ is the estimated standard deviation of the log-normal distribution. Then I take the exponential of $\log h'$ to calculate cardinal proxies for this exercise. For normally distributed parameters, I apply the same procedure except for that log operators are dropped in the above formula and do not take exponential at the end.

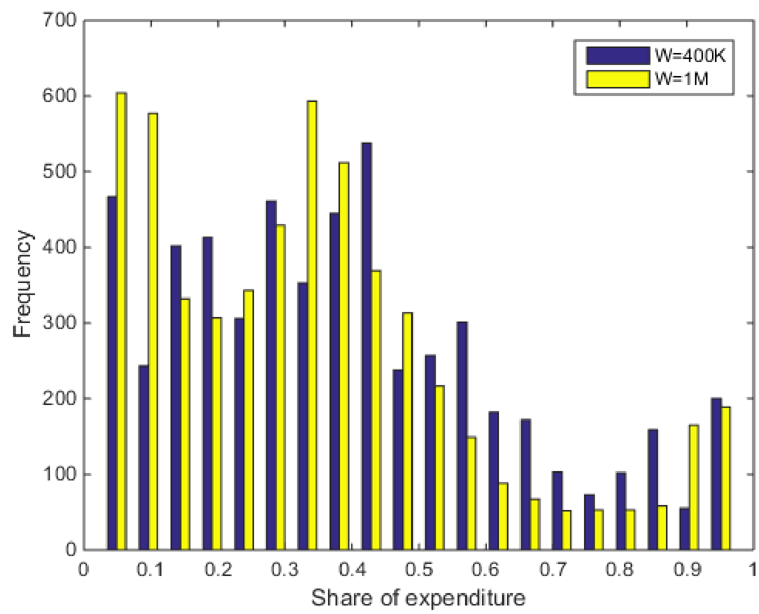
30 percent of respondents do not leave any bequests. Not many respondents spend a large fraction of their resources in the healthy state. When they have more resources (W=$1M), the share of expenditure in the LTC state tends to go down while the share of bequest tends to go up. These changes are driven by the differences in the necessity parameters, which make—on average—bequests luxury goods, and expenditures in the LTC state necessary goods.

Figure 1-C1. Distribution of Expenditure Share in the Static Problem (N=5,471)

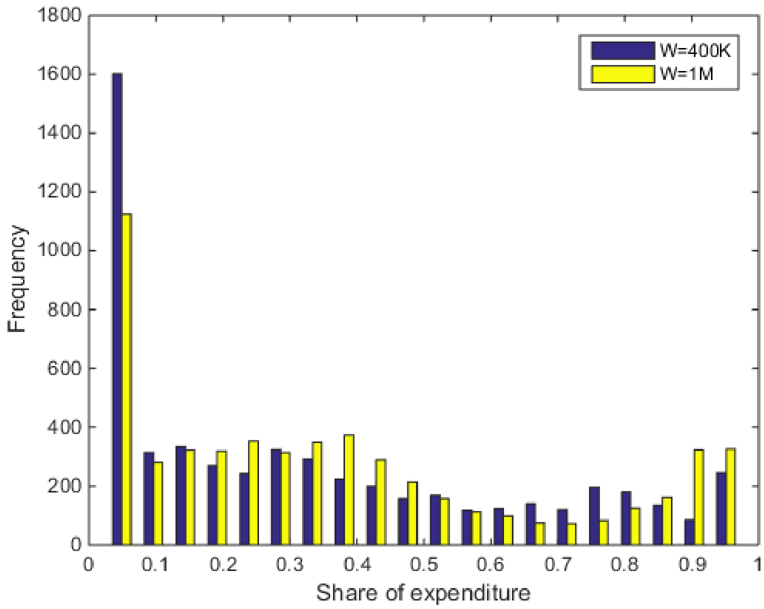
(a) Share of expenditure in the healthy state



(b) Share of expenditure in the LTC state



(c) Share of bequest



1-D. Properties of the cardinal proxies constructed based on the KSS approach

In this appendix I explain how using cardinal proxies, constructed under the KSS approach, in place of the true preference parameters can yield unbiased estimates in a linear regression.[30] I also compare the KSS method used in this paper and the individual-level estimation used in Ameriks, Briggs, Caplin, Shapiro, and Tonetti (2015b).

Let θ denote the true preference parameter. When θ is observable, we can run the following regression:

$$y = \beta\theta + \varepsilon \tag{1-D.1}$$

to estimate the relationship between dependent variable of interest (y) and θ. In this paper, I cannot observe θ, so instead I use the proxy $h = E[\theta \mid R]$ where R represents responses to the survey questions. Let $u \equiv \theta - h$. Then the actual regression I am running is:

$$y = \beta h + \nu \tag{1-D.2}$$

where $\nu = \beta u + \varepsilon$. If u is a classical measurement error such that it is correlated with h, then h is positively correlated with ν so the regression yields an attenuation bias. One important virtue of the KSS approach—estimating the population distribution of the parameters first and then calculating cardinal proxies as conditional expectations—is that the resulting cardinal proxy h is uncorrelated with u by construction because h is the result of projection and u is the error term in that projection. Instead, u is correlated with the true preference parameter θ.

To show this property visually, I run the following simulation. I assume that the true preference parameter is distributed as $\log(\theta_i) \sim N(\mu, \sigma^2)$. I do not observe this parameter, but I

[30] This discussion is based on Kimball, Sahm, and Shapiro (2008).

observe a survey response generated as $R_i = \theta_i + \varepsilon_i,\ \varepsilon_i \sim N(0, \sigma_\varepsilon^2)$. I assume that μ, σ^2 are unknown while σ_ε^2 is known. I estimate the unknown parameters using the KSS method and then construct the cardinal proxy h for θ. Figure 1-D1(a) shows the scatter plot of h and θ. Given any level of h, distribution of observations is symmetric across the 45-degree line, showing that there is no correlation between h and u. It is also clear that u is correlated with θ: for large values of θ the observations are much more likely to be below the 45-degree line, while the opposite is true for small values of θ.[31] This is because of mean reversion in h, which comes from the fact that h is calculated as a conditional expectation. A downside of the KSS method is that, due to this mean reversion, the proxy values should not be directly used to calibrate parameters at the individual level in a heterogeneous agent model. The degree of heterogeneity in h is much smaller than the estimated heterogeneity in the population distribution.

An alternative approach is the individual-level estimation used in Ameriks, Briggs, Caplin, Shapiro, and Tonetti (2015b). The underlying model—utility functions and survey response generation processes—is almost the same as that used in this paper. The main difference is that, instead of estimating the population distribution of the parameters, it directly estimates preference parameters at the individual level, using the responses of each individual only. The likelihood function is maximized over individual preference parameters, not over moments of population distribution of the parameters. The parameters estimated in this way can

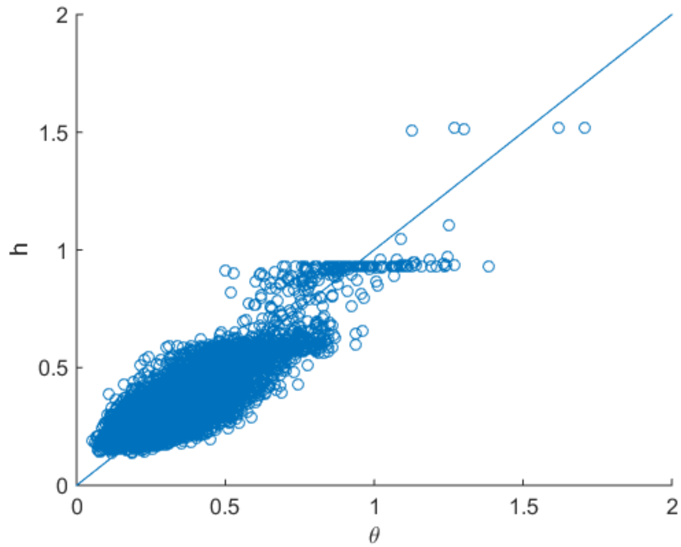
[31] Note that in a linear regression that also has other covariates in the RHS, u can be correlated with those controls through θ, resulting in biased estimates. To correct this, I can make the mean of the parameter distributions (μ) a linear function of the controls that will be included in the second stage regression. This would enable us to obtain unbiased estimates in that u would not be correlated with any of the controls or with the proxy.

also be considered as the cardinal proxies (h) for the parameters for each individual. One advantage of this approach is that it does not make any functional form assumption for the population distribution. Also, there is no mean reversion in h since h is not calculated as conditional expectation anymore. The absence of mean reversion makes the estimates attractive for calibrating a heterogeneous agent model at the individual level as in Ameriks, Briggs, Caplin, Shapiro, and Tonetti (2015b). One main disadvantage is that now h is positively correlated with u, since survey response error directly affects both the point estimate (and hence the proxy) for each individual and the difference between the proxy and the true parameter. The correlation between h and u makes the estimates improper as regressors in a linear regression. Figure 1-D1(b) shows the scatter plot between h and u under the individual-level estimation, in the same exercise as in 1-D1(a). (In 1-D1(b), h is nothing but R.) Under this method, u is uncorrelated with θ: given any level of θ, the distribution of observations is symmetrical with respect to the 45-degree line. In contrast, this distribution is correlated with h: for a large value of h the observations are more likely to be above the 45-degree line and the opposite is true for a small value of h.

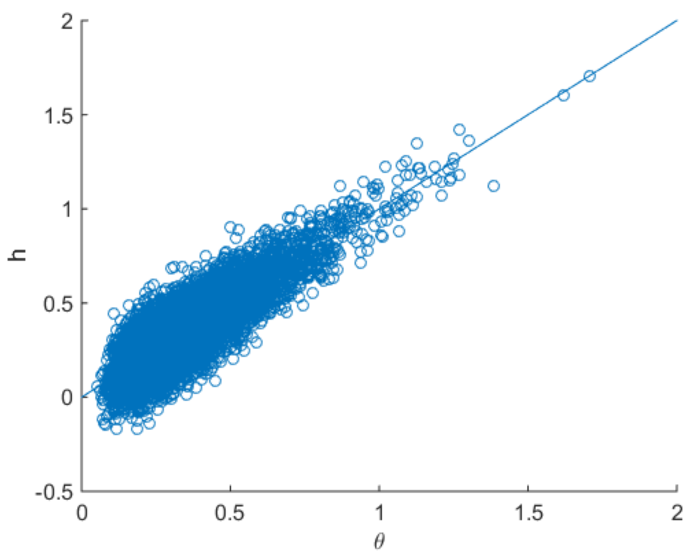
This discussion shows that the choice of the estimation method should be based on how estimates will be used in the analysis.

Figure 1-D1. Scatter plot of true parameter (θ) and cardinal proxy (h)

(a) KSS method



(b) Individual-level estimation



1-E. Estimation of Health State Transition Matrix using the HRS

I use an approach similar to that in De Nardi, French, and Jones (2013). To define health status, I use the self-reported subjective health data from the HRS: $s = G$ corresponds to {*Excellent*, *Very Good*, *Good}* in the subjective health report and $s = B$ to {*Fair*, *Poor*}. As long as a respondent reports that she requires help for at least one activity of daily living (ADL), then she is classified as $s = LTC$.[32] The transition to death ($s = D$) is identified with the exit report in the HRS.

Let *x* be a vector that includes a constant, age, gender, and square of age and interactions of these variables, as well as indicators for previous health status and previous health interacted with age. I estimate a multinomial logit model, such that for $i = \{G, B, LTC\}$ and $j = \{G, B, LTC, D\}$,

$$\begin{aligned}\pi_{ij} &= \Pr(s' = j \mid s = i) \\ &= \gamma_{ij} / \sum_{k \in \{G,B,LTC,D\}} \gamma_{ik} \\ \gamma_{iD} &\equiv 1,\ \forall i \\ \gamma_{ik} &\equiv \exp(x\beta_k),\ \forall \text{i},\ k \in \{G, B, LTC\}\end{aligned} \tag{1-E.1}$$

where $\{\beta_k\}_{k\in\{G.B,LTC\}}$ are sets of coefficient vectors and of course $\Pr(s' = D \mid s = D) = 1$.

Note that what I need is an annual transition matrix while the HRS data have information on biannual transitions. These two transition processes are linked, however, by:

$$\begin{aligned}\Pr(s'' = j \mid s = i) &= \sum_k \Pr(s'' = j \mid s' = k) \Pr(s' = k \mid s = i) \\ &= \sum_k \pi_{kj,t+1} \pi_{ik,t}\end{aligned} \tag{1-E.2}$$

[32] This definition of the LTC state is the closest to that in the VRI survey.

where the subscript t shows that the transition probability is a function of age (which is part of x). (1-E.1) and (1-E.2) allow us to estimate $\{\beta_k\}_{k\in\{G.B,LTC\}}$ directly from the data using maximum likelihood estimation. The transition matrix is built on the estimated coefficients.

Chapter 2. Heterogeneity in Expectations, Risk Tolerance, and Household Stock Shares

2.1 Introduction

The source of heterogeneity in portfolio choices is an important question in household finance (Campbell, 2006). Theories, such as consumption CAPM, predict that the share of risky assets should be positively related to their expected returns, negatively related to their risk, and positively related to investors' risk tolerance. Heterogeneity in preferences and beliefs are therefore natural candidates for explaining heterogeneity in household portfolios.

The existing literature addresses various aspects of heterogeneity. Differences in experience can cause different portfolio choices of households (Malmendier and Nagel, 2011; Seru, Shumway and Stoffman, 2010) as well as professional investors (Vissing-Jorgensen, 2003; Greenwood and Nagel, 2009). These effects may operate through preferences and beliefs as experience can influence both.[1] The association of portfolio allocation with wealth, and individual heterogeneity in that association, may also be driven, at least in part, by expectations and preferences (Calvet and Sodini, 2014). The recent literature has established the role of risk preference and beliefs about future returns in the stock share of household portfolios, although most papers examined stock ownership, that is, the extensive margin, because there are frequently so many households with no stock holdings in the data. The focus on the extensive margin makes quantitative comparisons against benchmark portfolio choice models difficult

[1] See, for example, Vissing-Jorgensen (2003), Glaser and Weber (2005), Hurd, van Rooij and Winter (2011), Hudomiet, Kezdi and Willis (2011), Amromin and Sharpe (2012), Hoffman, Post and Pennings (2013), and Guiso, Sapienza and Zingales (2014). Heterogeneity in expectations is also important in other contexts, for example, for the housing market (see Piazzesi and Schneider, 2009) and for inflation (see Malmendier and Nagel, forthcoming; Armantier et al., 2013; Bruine de Bruin et al., 2011).

because their predictions largely concern the magnitude of the intensive margin response of portfolio shares to preferences and beliefs.[2] Indeed, explaining heterogeneity at the intensive margin, that is, the share of stocks in the portfolio of stock market participants, has remained rather elusive (Brunnermeier and Nagel, 2008). An important reason behind the scarcity of empirical results is the lack of appropriate data. Good data on portfolio composition are needed for a large enough sample of stockholding households, complemented with appropriate measures of preferences and beliefs.

This paper takes a comprehensive approach to examining heterogeneity in portfolio choice by using a distinctive data set created by the Vanguard Research Initiative (VRI) that combines administrative account data and survey responses for a large sample of Vanguard account holders. The VRI has multiple features that make it especially well-suited for examination of heterogeneity in stock holdings.

First, it is a large sample of stock holders. Moreover, despite being drawn from the account holders of a single company, the characteristics of the sample are broadly representative of the targeted population of households with non-negligible financial assets. Hence, unlike

[2] In papers that examine the extensive margin, Barsky, Juster, Kimball and Shapiro (1997), Dohmen, Falk, Huffman and Sunde (2010) and Guiso, Sapienza and Zingales (2014) show that more risk tolerant individuals are more likely to hold stocks, while Dominitz and Manski (2007) and Hurd, Rooij and Winter (2011) show that individuals with higher levels of stock market expectations and lower perceived risk are more likely to hold stocks. Kimball, Sahm and Shapiro (2008) model the intensive margin. Kezdi and Willis (2011) and Dimmock, Kouwenberg, Mitchell and Peijnenburg (2013) combine the extensive and intensive margins in Tobit-type models and establish associations with risk tolerance, expectations and ambiguity aversion, respectively. Vissing-Jorgensen (2003) and Amromin and Sharpe (2012) show that expectations are related to the share of stocks among stockholders but they do not consider risk tolerance. Weber, Weber and Nosic (2013) show that individual measures of risk tolerance and expectations predict the share of stocks respondents invest in a hypothetical financial portfolio. Hoffmann, Post and Pennings (2013) and Merkle and Weber (2011) analyze the role of expectations and risk tolerance in trading behavior of individual investors rather than the share of stocks in household portfolios.

most studies that focus on the extensive margin for stock holdings, this sample will allow for meaningful inferences about the intensive margin of portfolio choice.

Second, the VRI survey includes batteries of questions that we purposely designed to produce estimates of preference and belief parameters that should help to explain the cross-distribution of portfolio choices. These survey questions yield *quantitative* estimates of individual-level moments of subjective returns distribution and of individual-level values of preference parameters. These estimates can then be related to portfolio decisions in ways that are quantitatively interpretable relative to benchmark economic models.

Third, the design of the VRI allows careful consideration of response errors along a variety of dimensions. These include errors in measuring stock shares in both survey and administrative data and errors in eliciting preferences and expectations from survey responses.

These features—a large, broadly representative sample of stockholders together with quantitative measurements of the potential sources of heterogeneity in stockholding—make the VRI a unique platform for understanding why different households make different portfolio choices.

Section 2.2 describes the VRI sample and the measurements of stock share. It addresses the relationship between Vanguard assets and households' overall assets. It also compares administrative and survey measures of portfolio shares. Section 2.3 describes how we measure preferences and beliefs. To get individual-specific estimates of preference parameters, we use a modification of the Barsky, Juster, Kimball, and Shapiro (1997) approach of eliciting risk tolerance from hypothetical gambles over permanent income. To get individual-specific estimates of the moments of the perceived distribution of returns, we use both the Manski (2004) approach of eliciting points in the CDF of perceived returns together with individuals' estimates of expected returns. We use a unified procedure accounting for response error to produce unbiased estimates of the subjective variables for both preferences and beliefs. Section 2.4 combines these estimates to explain the cross-section of stock shares. We find that the stock share is positively related to the individuals' perceived expected stock returns, is negatively related to their perceived standard deviation of the returns, and is positively related to their risk tolerance. These relationships are economically and statistically significant, they are robust across many specifications, and they are substantially less attenuated than corresponding estimates that do not take care of measurement error in the survey answers. The relative magnitude of the importance of expected returns, standard deviation of returns, and risk tolerance for explaining portfolio shares is quite close to the predictions of benchmark theory, though the absolute magnitudes are much smaller than theory would predict. Additional results suggest that the selected nature of our sample is unlikely to explain this attenuation.

Hence, though the results show that it is possible to use survey responses about economically-relevant subjective variables to explain meaningful features of stock holding, the actual distribution of stockholding varies less with the subjective variables than theory would predict given the measured heterogeneity in subjective variables. We call the finding that portfolio shares have a damped response to preferences and beliefs the "attenuation puzzle." The paper uses two benchmark models of portfolio choice to assess the relationship between *quantitative* measures of preferences and beliefs—the classic Merton model and a richer lifecycle model that makes more realistic assumptions about the environment for portfolio choice. The paper's contributions to the measurement of preferences and beliefs address head-on potential explanations for the attenuation puzzle based on the measurement and modeling of preferences and beliefs:

- First, in contrast to measures of risk tolerance and expected returns based on loose or vague attitudinal scales, this paper presents quantitative estimates of the preference and belief parameters that theory mandates should determine portfolio choice.
- Second, this paper uses a statistical approach where the estimated individual-specific preference and belief parameters are by construction uncorrelated with the measurement errors that arise from the response errors that are inherent in eliciting subjective responses from individuals.

Hence, the estimated relationships presented in the paper are not subject to the attenuation biases that arise from having regressors that are only loose proxies for the variables of interest or that are subject to classical errors in variables. Consequently, our findings imply that the attenuation puzzle is a feature of investor behavior that is not well-captured by benchmark models.

2.2 VRI Data and Stock Share Measurement

2.2.1 VRI sample

The Vanguard Research Initiative (VRI) consists of linked survey and administrative data of account holders who have non-negligible financial assets at Vanguard, are at least 55 years old, and use the Internet to access their Vanguard accounts. This last requirement is necessary because the VRI is an Internet survey. The VRI is an individual level survey, but it includes questions about household-level wealth and income as well as questions about spouses' or partners' demographics and labor supply. The survey oversampled older account holders and singles. The VRI draws respondents from two lines of business—individual account holders and employer-sponsored account holders.[3]

We use responses to three VRI surveys, conducted in the fall of 2013, winter of 2014 and summer of 2014.[4] The main focus of the first survey was to inventory income, wealth and portfolio of households as well as to gather basis demographics. The second survey implemented Strategic Survey Questions (SSQs), which ask respondents to make choices under hypothetical situations designed to elicit meaningful preference data. This paper uses the questions about risk preference. The third survey includes the questions about beliefs about returns used for this paper, and also covers a number of issues not related to this paper. 4,730 respondents completed all the three surveys. The item non-response rate of the VRI is remarkably low. Our analysis includes the 4,414 respondents with non-missing observations for all the variables used in the analysis.

The VRI sample frame is based on administrative account data for Vanguard. Having such data to create a sample is an important element of the VRI design. Additionally, administrative data are composed of monthly history of Vanguard assets, with information on types, balances and stock shares of the accounts linked to the survey measures. This paper uses both survey and administrative measures of assets and their composition. The survey measure covers all assets, not just those held at Vanguard. See Ameriks, Caplin, Lee, Shapiro and Tonetti

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[3] The employer-sponsored are enrolled at Vanguard through 401(k) or similar defined-contribution accounts. While both individual and employer-sponsored account holders are selected via ownership of a Vanguard account, the selection into individual and employer-sponsored accounts is presumably quite different. We will present separate estimates to get a sense of whether selection matters for results.

[4] The plan is to implement the VRI as a panel. These three surveys, however, cover distinctive topics with little longitudinal content. They were broken into three surveys of 40 to 60 minutes for the practical reason of not overwhelming respondents.

(2014a, 2014b) for a detailed discussion of the design of the VRI including sampling and response rates, and of the VRI's approach to wealth measurement.

Details of the measurement and distributions of stock shares, preference parameters, and stock market expectations will be discussed in the next sections. Here we briefly describe the measurement of wealth and other variables that are used in the analysis: marital status, gender, age, education, earnings, annuity income, expectations about longevity and long-term care use..

The VRI survey measure of wealth is based on a comprehensive account-by-account approach. The survey first asked about types of accounts respondents have (e.g. IRA, checking, money market funds) and the number each type of account held by the respondent or her spouse. For each account they indicated owning, the respondents were asked to provide the balance as well as the share of stock-market assets. When finished with all accounts, respondents were presented a summary table consolidating their responses and were invited to make corrections, if any.

Measuring wealth and stock shares account by account matches the way respondents keep track of their own wealth, and it does not require them to sum balances across accounts to provide total figures for asset categories that are familiar to economists but less so to survey respondents. In contrast, the Health and Retirement Study (HRS) and the Survey of Consumer Finances (SCF)—other leading surveys with state of the art wealth measurement—use account-by-account approaches but only for selected sets of account types. Item non-response in the wealth section of the VRI affects less than 1 percent of the observations.[5]

[5] Summary statistics of the wealth measures are shown in Table 2-A1 in the Appendix. Table 2-A2 in the Appendix shows the summary statistics of the variables we use as controls in our analysis, together with the definition of those variables.

Table 2.1 compares the VRI sample to the HRS and SCF.[6] The HRS and SCF are nationally representative samples (of those above age 50 in the case of the HRS). Table 2.1 compares the VRI sample to the subsample of the HRS and SCF after imposing restrictions similar to VRI eligibility: being at least 55 years old, having access to Internet at home, and having at least $10,000 financial wealth. The table shows the number of households, the number of stock holding households, average financial wealth and total wealth, average stock shares, and some demographic characteristics of the individuals responding each survey.

The number of respondents who completed Survey 1 is substantially larger than the VRI-eligible subsample of the HRS and the SCF. The difference in the number of respondent in stock holder households is even larger: while the parallel sample has slightly over 1,000 stock-holding households in the SCF and slightly over 2,000 in the HRS, the entire VRI sample has more than 8,000 stock holders and the sample used in our analysis has more than 4,000.

The demographic composition of the VRI sample is very similar to the parallel subsamples of the HRS and the SCF. Average total wealth and average financial wealth in the VRI are remarkably close to corresponding estimates from the SCF; the HRS estimates are lower. The average stock share in financial wealth among stock holders is very similar in the VRI and the HRS; the SCF estimates are somewhat smaller. VRI respondents are slightly less likely to be married, and they are somewhat older, more educated and more likely to be retired. The differences in marital status, age and retirement are largely due to the fact that the VRI oversampled older individuals and singles. 65 percent of the VRI sample is male, compared to 79 percent in the SCF and 56 percent in the HRS. While the respondent-level compositions are arbitrary to some degree (account holders in the VRI, financial respondents in the HRS, and

[6] This comparison with the HRS and the SCF draws on Ameriks, Caplin, Lee, Shapiro and Tonetti (2014a). See this for further details about the VRI sample and wealth measurement.

household heads in the SCF), the fact men are overrepresented in all samples reflects that they are more likely to own accounts with substantial wealth. The sample used in our analysis is very similar to the initial VRI sample indicating that attrition between the VRI surveys was close to be random.

2.2.2. Measuring stock shares

Our analysis focuses on the share of stock market-based assets in total financial wealth.[7] The stock share in financial wealth is the weighted average of the stock shares of the accounts as reported by the respondents. Respondents who did not answer all of the account-by-account stock share questions were asked the overall stock share of their financial portfolio. Ninety-five percent of respondents answered all the account-by-account stock share questions; the distribution of stock share is very similar across the two groups.

Besides the overall stock share we also analyze the stock share in wealth held at Vanguard based on administrative data. The monthly history of accounts in the VRI administrative data breaks down the balance of each account into stock, bond and money market holdings. This break-down is not readily available for all accounts, so we imputed stock share when needed using information on the type of fund the account is invested in (e.g., for an account invested in a balanced fund, we assume 60% of stock share). The administrative stock share measure is available both at around the time when the stock expectation questions are asked and also at the time when the survey measure of household portfolio is obtained (the wealth survey took place in the fall of 2013, while expectations were asked in the summer of

[7] Specifying stock share in financial wealth is standard in the literature. Alternative measures may include housing wealth and human capital wealth in the denominator. We include such wealth items as control variables in the analysis and show that their inclusion leads to very similar results for the parameters of interest.

2014). At the same time, the administrative stock share measure corresponds to the subset of financial wealth held at Vanguard.

Figure 2.1 compares the stock share measures based on the survey and the administrative data that will be the main dependent variables for our analysis. The horizontal axis shows the administrative measure of the stock share in assets held at Vanguard at the time we measured expectations in Survey 3, while the vertical axis shows the Survey 1 measure of stock share in total financial assets.[8] The size of the marks on the figure is proportional to the Vanguard financial wealth of the respondents. The figure shows that many observations are near the 45-degree line, so as a practical matter either measure may provide similar inferences for many respondents. At the same time, the two are often different. Indeed, the correlation coefficient is only 0.61.[9] The two measures can be different for three main reasons. First, they are measured at different times, in summer 2014 versus fall 2013. Second, they refer to different sets of assets: Vanguard assets versus all financial assets. Third, they are measured in different ways: using administrative records versus answers to survey questions.

It is important to understand which of these differences matter. Figures 2-2 through 2-4 compare alternative stock share measures broken down by the time of measurement, the accounts covered, and the method of measurement (survey or administrative). First, consider the time dimension. The horizontal axis of Figure 2-2 shows the stock share in assets held at Vanguard at the time of Survey 1 (fall 2013), while the vertical axis shows the same, measured at the time of Survey 3 (summer 2014). Almost all observations are on the 45 degree line, and the correlation is very strong (0.95), implying that the stock share changed little over this time period. As a

[8] Due to the imputation used for the balanced funds, there is bunching at 60 percent according to the administrative measure.

[9] All figures and correlation coefficients are weighted by Vanguard wealth. The unweighted correlation is 0.40, indicating that deviations are somewhat larger if wealth is low.

practical matter, this means that changes in portfolios between administration of the VRI surveys is very small, so that differences in when the various questions were fielded is likely not that important. It is also of substantive interest that portfolio shares are so sticky, something that we see also in much longer intervals of the administrative data.

Second, consider the issue of whether or not the assets are held at Vanguard. Figure 2.3 plots stock share at Vanguard versus overall, both measured as survey responses in Survey 1. There is relatively high correlation in the stock shares (correlation = 0.81), so differences in portfolio shares across providers, though not trivial, is not the main source of the dispersion shown in Figure 2.1. The difference can be small because account holders have most of their assets at Vanguard, or that they have asset compositions that are similar across Vanguard and non-Vanguard providers.

Third, Figure 2.4 shows the stock share at Vanguard at the time of Survey 1. Administrative data are on the horizontal axis and survey data are on the vertical axis. The dispersion is very much as in Figure 2.1 (correlation = 0.64). Hence, it turns out that the main source of the dispersion is the deviation between survey and administrative measurements, not difference in timing or difference arising from Vanguard versus overall portfolios.

Several findings of independent interest emerge. First, based on the administrative data, portfolio shares are quite sticky over time. Second, the deviations of survey and administrative measures of portfolios suggest that individuals perceive different stock exposure than they have at any moment. Both these findings present challenges to standard theories of portfolio choice and therefore affect the interpretation of results relating portfolio choices to preferences and beliefs. We return to these issues after presenting the results.

2.3. Measuring Preferences and Expectations

2.3.3 Measuring risk tolerance

Survey 2 of the VRI included Strategic Survey Questions (SSQs) that ask respondents to make choices between hypothetical financial products under hypothetical situations. By specifying hypothetical situations that are independent from their own economic, health and family conditions, these SSQs enable us to better estimate structural preference parameters. This approach to measurement was pioneered by Barsky, Juster, Kimball, and Shapiro (1997) for measuring risk preference in the HRS and Ameriks, Caplin, Laufer, and Van Nieuwerburgh (2011) for measuring preferences surrounding long-term care. The approach is refined and extended in the VRI (see Ameriks, Briggs, Caplin, Shapiro and Tonetti, 2015a, b). In this paper, we use the VRI's risk tolerance questions that pose gambles over consumption. The VRI risk preference questions ask about preference between having a certain level of consumption and a 50-50 chance of having double that level of consumption versus having it fall by *x*%. It then alters the downside risk *x* to partition respondents into risk tolerance groups.[10] Table 2-A3 in Appendix 2-A gives the exact wording of the risk tolerance question in the VRI.

The question is asked for two different levels of riskless consumption, $100K and $50K per year, and downside risks of 1/10, 1/5, 1/3, 1/2, and 3/4. Table 2.2 shows the distribution of the answers to the two questions. Most respondents have low tolerance for risk. About half of the respondents chose the first two categories, indicating that they would not accept a risk of more than 20% drop in their consumption to take a chance to double their consumption. Only a small fraction chose the last two categories with a risk of more than a 50% drop. Overall, the

[10] The original HRS question has the same structure, but asks about gambles over life-time income rather than consumption.

distribution is similar to the distribution of the answers to a similar question in the HRS except that the fraction of respondents in the two extreme categories (0-10% and 75-100%) is slightly lower in the VRI (see Kimball, Sahm, and Shapiro 2008 for HRS).

The Table 2.1 shows that more respondents fall into the lower risk categories when riskless consumption is $50,000 instead of $100,000. We will handle this increase relative risk tolerance by positing a utility function with a subsistence level of consumption. Following Barsky, Juster, Kimball, and Shapiro (1997) and Kimball, Sahm and Shapiro (2008), we will use the multiple responses to identify the heterogeneity of the preference parameter and survey response errors (see details below).

Estimation of a cardinal risk tolerance parameter requires specifying a utility function. We assume that the flow utility function is a generalization of CRRA with a subsistence level of consumption

$$u_i(c) = \frac{(c+\kappa)^{1-1/\gamma_i}}{1-1/\gamma_i}, \tag{2.1}$$

where subscript i denotes heterogeneity across individuals, c is consumption, the negative of κ is the subsistence level of consumption, assumed to be the same for all individuals, and γ is the parameter of risk tolerance.

For this utility function, relative risk tolerance (RRT_i) is

$$RRT_i = \gamma_i \frac{c+\kappa}{c} < \gamma_i,$$

where the risk tolerance parameter γ_i is relative risk tolerance in the $\kappa = 0$ case. See Figure 1-A1 in the Appendix for the relationship of relative risk tolerance and γ as a function of consumption.

To parameterize the heterogeneity of the risk tolerance parameter, we assume that the parameter is distributed lognormally in the population according to

$$\log(\gamma_i) = \bar{\gamma} + u_{\gamma i},\ u_{\gamma i} \sim N(0, \sigma^2_{u\gamma}). \tag{2.2}$$

We model the measurement error as a log additive term to the parameter, such that

$$\begin{aligned} &\log(\tilde{\gamma}_{ij}) = \log(\gamma_i) + \varepsilon_{\gamma ij} \qquad \text{for } j = 1,2 \\ &\varepsilon_{\gamma ij} \sim N(0, \sigma^2_{\varepsilon\gamma j}) \end{aligned} \tag{2.3}$$

where γ_i is the true risk tolerance parameter for individual *i*, $\varepsilon_{\gamma ij}$ is measurement error, and $\tilde{\gamma}_{ij}$ is the risk tolerance parameter that provides the basis for individual *i'*s response to the j^{th} question. Thus, in answering question *j* given the level of resource *c* and risk *x* that are associated with the risky gamble, the respondent compares

$$\frac{(c+\kappa)^{1-1/\tilde{\gamma}_{ij}}}{1-1/\tilde{\gamma}_{ij}} \ \text{ vs. } 0.5\frac{(2c+\kappa)^{1-1/\tilde{\gamma}_{ij}}}{1-1/\tilde{\gamma}_{ij}} + 0.5\frac{((1-x)c+\kappa)^{1-1/\tilde{\gamma}_{ij}}}{1-1/\tilde{\gamma}_{ij}} \tag{2.4}$$

to determine whether to accept the risky gamble or not. This approach follows Kimball, Sahm, and Shapiro (2008). We carried out the estimation procedure jointly for risk tolerance and stock market expectations, so will defer discussion of estimation until Section 2.3.3 below.

2.3.2. Measuring beliefs about stock returns

Survey 3 of the VRI asked about beliefs about the one-year return of the U.S. stock market, represented by a stock market index such as the Dow Jones Industrial Average (DJIA). Respondents had to answer three questions: the expected return on the stock market in the 12 months following the interview (*m*); the percent chance that the stock market will be higher in 12 months following the interview (*p0*) and the percent chance that it will be at least 20% higher (*p20*). The exact wording of the questions is in Table 1-A4 in the Appendix.[11]

Answers to the expected value questions were constrained to be integers. Answers to the percent chance questions were constrained to be 5 point increments between 0 and 15 and between 85 and 100, and they were constrained to be 10 point increments between 15 and 85 (the set $\{0,5,10,15,25,35,45,55,65,75,85,90,95,100\}$). Answers to percent chance questions tend to be rounded to the nearest ten when they are not constrained, with an especially large fraction answering 50 percent (Hurd, 2009). The constraints in the VRI survey forced people to round to other values; in particular, they don't allow for 50 percent answers. Another constraint on the answers ensured that $p20 \le p0$.[12] No constraints were put on *m* versus *p0* and *p20*.[13]

Table 2.3 shows the summary statistics of the answers to the questions about the distribution of stock market returns. The survey responses for expected returns (*m*) are distributed around the historical average of 4 to 7 percent depending on sample period, and their dispersion is moderate.[14] In contrast, most answers to the probability questions are lower than the historical probabilities, and they have substantial heterogeneity. A non-negligible fraction of the respondents gave a positive number to the expected return question (*m*) and a less than 50 percent chance answer to the probability of a positive return (*p0*). Taken together these answer patterns are consistent with many individuals implicitly applying a positive threshold when they

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[11] Bruine de Bruin et al. (2011) and Armantier et al. (2013) examine the reliability of the percent chance questions for inflation as well as how they relate to questions about point expectations of inflation.
[12] Respondents whose initial answer to *p20* violated this constraint are reminded of the constraint by the survey software and asked for a new reply to either *p*0 or *p*20 (or both).
[13] A randomly selected half of the respondents received the *m* question first, followed by *p*0 and *p*20, while the other half received *p*0 and *p*20 first, followed by *m*. The distribution of the responses is different across the two sequences, but those differences do not affect our main results.
[14] Individuals may use different sample windows for inferring expected returns (see Malmendier and Nagel 2011). The table shows some different windows for realized returns. Average returns are quite variable owing to the well-known problem of estimating the expected return on the market.

answer the *p0* question (by thinking that the stock market goes up only if it goes up by at least some positive amount).[15]

In order to use our data more efficiently and in a way that is more informative from a theoretical point of view we map the three survey responses, *m, p0*, and *p20* into a perceived returns distribution. The procedure closely parallels that for the risk tolerance questions: the survey responses are based on individual beliefs drawn from normal distribution plus survey response error. We assume that individual *i* believes that yearly returns follow a lognormal distribution with individual-specific mean and standard deviation of log stock returns of μ_i and σ_i. Similar to how we handle the cross-sectional distribution of the risk tolerance parameter, these parameters are drawn across individuals as

$$\begin{array}{l}\mu_i = \bar{\mu} + u_{\mu i} \\ \sigma_i = \bar{\sigma} + u_{\sigma i}\end{array}, \quad \begin{pmatrix} u_{\mu i} \\ u_{\sigma i} \end{pmatrix} \sim N\left(\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} \sigma_{u\mu}^2 & \rho_{\mu\sigma}\sigma_{u\mu}\sigma_{u\sigma} \\ . & \sigma_{u\sigma}^2 \end{pmatrix} \right). \tag{2.5}$$

Individuals answer the survey questions *m*, *p*0 and *p*20 based on their beliefs, but their answers contain survey noise, that is, measurement error specific to the survey situation. Using the structure of the survey questions on expected returns and the two points of the probability distribution, applying the assumption of lognormal returns, and adding survey response error yields

$$\tilde{m}_i = \mu_i + \varepsilon_{mi}, \ \varepsilon_{mi} \sim N(0, \sigma_{\varepsilon m}^2) \tag{2.6}$$

[15] Glaser, Langer, Reynders and Weber (2007) document a similar pattern when they compare stock market expectations elicited in terms of returns versus prices. They label the phenomenon as “framing effect,” and our explanation can be viewed as a source of such a framing effect. Note that, although skewed returns could explain the phenomenon we observe, it is an unlikely explanation. The combination m_i>0 and $p0_i$<0.5 would correspond to long positive tails, implying mean above the median and infrequent large gains. This skewedness is the opposite of what one would expect from a “black swan” theory of infrequent stock market crashes.

$$\tilde{p}_{0i} = \Phi(\frac{\mu_i}{\sigma_i} + \varepsilon_{0i}),\ \varepsilon_{0i} \sim N(\psi, \sigma^2_{\varepsilon p}) \quad (2.7)$$

$$\tilde{p}_{20i} = \Phi(\frac{\mu_i - 0.2}{\sigma_i} + \varepsilon_{20i}),\ \varepsilon_{20i} \sim N(0, \sigma^2_{\varepsilon p}) \quad (2.8)$$

where $\tilde{m}_i$, $\tilde{p}_{0i}$, and $\tilde{p}_{20i}$ are the error-ridden variables that determine survey responses. Survey error is assumed to be independent across the three answers, with mean zero except for *p*0 where its mean is ψ , which allows for the documented differences between *m* and *p*0. An interpretation of ψ is that, on average, respondents answer the question about positive returns (*p*0) as if they had some positive threshold in mind instead of zero ($\Phi\left(-\psi / \sigma_i\right)$, $\psi < 0$). The variables $\tilde{m}_i$, $\tilde{p}_{0i}$, and $\tilde{p}_{20i}$ are before rounding. Recall that the VRI probability scale is for rounded responses. Similarly, as discussed above, the risk tolerance questions yield discrete responses. The next section discusses how our estimation procedure handles this issue.

2.3.3. Joint estimation of heterogeneity in stock market expectations and risk tolerance

Given the models of heterogeneity in preferences and beliefs (equations (2.2) and (2.5)), the structural interpretation of the survey questions together with the additive survey response errors ((2.3), (2.4), (2.6), (2.7) and (2.8)), we can now move to estimation of the model. The parameters to be estimated are $\bar{\gamma}, \bar{\mu},\ \bar{\sigma},\ \sigma^2_{u\gamma},\ \sigma^2_{u\mu},\ \sigma^2_{u\sigma},\ \rho_{\mu\sigma},\ \psi,\ \sigma^2_{\varepsilon\gamma 1},\ \sigma^2_{\varepsilon\gamma 2},\ \sigma^2_{\varepsilon m},\ \sigma^2_{\varepsilon p}$. We allow for $\bar{\gamma}$, $\bar{\mu}$, $\bar{\sigma}$, and ψ to vary with covariates. Additionally, we allow the beliefs about returns to depend on risk preference, so the covariates of $\bar{\mu}$ and $\bar{\sigma}$ include the latent γ_i . The estimation method is maximum likelihood. It allows for interval responses to the risk tolerance question and the returns questions. Appendix 2-B shows the likelihood function.

Table 2.4 shows key estimated statistics of the distribution of preferences and beliefs based on the estimated statistical model of preferences, beliefs, and response error. Table 2-A5 in the appendix shows the estimates of the underlying parameters of the model.[16] The subsistence level of consumption ($-\kappa$) is estimated to be \$17,000.[17] The estimated mean of the risk tolerance parameter (γ) implies low risk tolerance on average. A respondent with the mean level of γ and κ has relative risk tolerance 0.34 (relative risk aversion 2.9) when the consumption level is \$100,000. In terms of the SSQ question, she would be indifferent between a fixed consumption of \$100,000 and the 50-50 gamble of doubling that consumption and losing 20 percent. There is a considerable heterogeneity in risk tolerance. At the 25th percentile of risk tolerance parameter, the point of indifference is the downside risk of losing 13 percent; at the 75th percentile the point of indifference is the downside risk of losing 29 percent. These numbers indicate higher levels of risk tolerance than in a representative sample of Americans older than 50 years of age. Kimball, Sahm and Shapiro (2008) estimate the corresponding risk tolerance percentiles (25th, 50th and 75th) to imply indifference to 7, 12 and 20 percent of downside risk, respectively.

Beliefs about mean stock returns are in line with historical mean returns, on average. Beliefs about standard deviation are slightly lower than the historical value of 0.16. Heterogeneity in perceived mean returns (μ) is substantial, with the lowest 25 percent believing expected returns to be 2 percent or less and the top 25 percent believing 12 percent or more. At the same time, estimated heterogeneity in the perceived standard deviation of stock returns (σ) is

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[16] The summary statistics in Table 2.4 are from estimates without covariates. Appendix Table 2-A6 reports the estimates of the statistical model with covariates.
[17] The design of the SSQ does not allow heterogeneity in κ to be readily identified, although it tightly identifies its mean.

small, perhaps because it is easier for people to estimate the second moment of the returns distribution than the first moment, as pointed out by Merton (1980).[18,19]

Based on the estimated distribution summarized in Table 2.4, 17 percent of the population expects negative stock returns. As we will see, this part of the population holds less stock than on average, but still has substantial stock market exposure. Symmetrically, 17 percent expect returns to be larger than 12 percent, rates of return that should make people hold the vast majority of their wealth in stocks given the distribution of risk and risk preferences. Though this part of the population holds more stock than on average, very high stock shares are uncommon. Taken together, these facts suggest that expectations translate into stock shares in an attenuated fashion, a finding that our analysis will verify in the next section.

The Table 2.4 results take into account substantial estimated survey noise. Again, the parameters of the survey noise distributions are presented in Appendix Table 2-A5. To understand the magnitude of noise, consider the differences in terms of the survey responses of individuals with the estimated averages of latent preferences and beliefs, one without measurement error and one with a positive standard deviation unit shock of measurement error. A one standard deviation unit measurement error in the first risk tolerance SSQ would make the survey response imply a point of indifference of a 38% drop of consumption instead of the 20%

[18] According to our estimates heterogeneity in preferences and beliefs are weakly related. More risk tolerant respondents believe that stock returns are slightly higher, but we don't find association of risk tolerance and beliefs about the standard deviation of returns. Beliefs about the mean and the standard deviation of returns are weakly positively correlated.

[19] Preferences and beliefs are significantly related to observable right hand side variables in our sample (Table 2.A5 in the Appendix). However, when interpreting these associations, one has to keep in mind that the VRI sample is selected on wealth and stock ownership. For example, sample selection may explain the negative correlation of wealth and stock market expectations. Almost all households in the VRI sample have nonzero stockholding. With fixed costs of stock market participation wealth should matter at the extensive margin on top of expectations. As a result, we expect wealthier stockholders to have lower expected returns than less wealthy stockholders.

implied by an error-free answer. A one standard deviation unit measurement error in the second risk tolerance SSQ would make the response imply an indifference point of 27% instead of 17%. One standard deviation unit measurement error in the response to the expected stock returns question would result in a response of 14% instead of 6%; one standard deviation unit measurement error in the stock market probability answers would change *p0* responses to 67% from 48% and *p20* responses to 25% from 12%. The estimated bias of the measurement error in the *p0* response (ψ) suggests that, on average, people think of positive gains only when they exceed 4 percent when answering the *p*0 question.[20]

2.3.4. Estimating individual-specific cardinal proxies of risk tolerance and beliefs

In the previous sections, we show how to separately identify the true heterogeneity in preferences and beliefs and the survey response errors in the survey measures of them. In this subsection, we explain how we construct the individual-specific belief and preference parameters based on those estimates that are immune from the standard effects of using generated regressors.

1. *Constructing individual-specific preference and belief parameters*

Using the estimation results we calculate individual-specific proxy variables $\hat{\mu}_i$, $\hat{\sigma}_i$ and $\hat{\gamma}_i$. These proxies are the expected values of the corresponding latent variables: the individual-specific expected value and standard deviation of the distribution of stock market returns perceived by the individual (μ_i, σ_i), and the individual-specific latent parameter of risk tolerance (γ_i). They are expected values conditional on the individual's responses to the survey

[20] Allowing for covariates (Appendix Table 2-A6), ψ is estimated to be substantially less negative among more educated and wealthier people, indicating that their threshold value is closer to the nominal threshold zero.

questions on stock market returns $\left(m_i, p_{0i}, p_{20i}\right)$ and to the SSQ's with the two hypothetical gambles. To get these expected value of the latent individual-specific parameters conditional on the survey response and the statistical model, there are two steps. First, the distribution of the latent variables conditional on the observed responses can be obtained from the likelihood function using Bayes' theorem. Second, integrating out this function yields the individual-specific proxy variables ($\hat{\mu}_i$, $\hat{\sigma}_i$ and $\hat{\gamma}_i$) as the conditional expectations of the latent variables given the observed survey responses. These proxy variables deal with measurement error in survey responses. Appendix 2-B spells out these steps in detail.

2. *Using individual-specific preference and belief parameters in regressions*

Our aim is to use the survey-based estimates of individual-specific parameters to explain heterogeneity in portfolio choice. Note that this proxy error is not conventional errors in variables. Because each proxy is a conditional expectation, which is basically a projection, this measurement error is uncorrelated with the proxy (and correlated with the true latent variable). Hence, it can be included on the right-hand side of a regression without creating an attenuation bias (see Kimball, Sahm and Shapiro, 2008).

When the regressions include other covariates as well the OLS estimates are unbiased if the proxies are estimated conditional on those covariates, too. We therefore estimate two sets of proxies. The first set is conditional on the survey answers to the risk tolerance and the stock market belief questions only. The second set is conditional on other covariates as well. We use the second set of proxy estimates as right-hand-side variables in regressions that also include those covariates. In the next section, we present such regressions to explain portfolio behavior based on our estimates of preferences and beliefs.

2.4 Explaining Heterogeneity in Portfolio Choice

2.4.1. Stock share and answers to survey questions

Before turning to the regressions based on our structural estimates of the latent preferences and beliefs, we investigate the relationship between the stock share of household portfolios and the raw survey responses. Figure 2.5 shows non-parametric regressions of the stock share in total financial assets on the survey answers to expected stock market returns (m_i), the average between the probability that the stock market would go up and that of an increase of 20 percent or more $((p0_i + p20_i)/2)$, the difference between those two ($p0_i - p20_i$), and the answer to the risk tolerance question with income level $100,000. (Figure 2-A2 shows the analogous nonparametric regression results on $p0_i$ and $p20_i$ separately.)

The results indicate a positive relationship between the stock share of household portfolios and expected stock market returns (m_i) and the mean of the two probability responses $((p0_i + p20_i)/2)$. The stock share is also positively related to the difference between the responses to the probability questions ($p0_i - p20_i$), suggesting a negative relationship with perceived risk of stock returns. Finally, the stock share is monotonically positively related to the answers to the risk tolerance question except for the last categories that has relatively few responses, suggesting a monotonic positive relationship with risk tolerance. Hence, the relationship between the raw survey responses and the stock share has the direction benchmark theories of portfolio choice would suggest.

We also estimate linear regressions with survey measure and the administrative measure of stock share as alternative left hand side variables and the same right hand-side variables entered with and without the control variables that include detailed measures of demographics, education, employment, income, wealth, as well as background risks of long-term care and longevity. The results are included in Tables 2-A7 and 2-A8 in the Appendix. The results imply statistically significant relationships of stock share with the survey answers with or without the control variables. The magnitudes of the associations are difficult to interpret because not all measures have a cardinal interpretation and because of the presence of survey noise. These problems are addressed in the next section.

2.4.2. Stock share and cardinal proxies of expectations and risk tolerance

Our more structural analysis has two goals. First, it relates the stock share of household portfolios to cross-sectional heterogeneity in preferences and expectations in a way that is related to portfolio choice theory thus making magnitudes easier to interpret. Second, it aims at incorporating survey noise in the estimation thus reducing its effect on the estimated magnitudes. This is a structural analysis in the sense that it makes use of additional assumptions in order to relate stock shares to heterogeneity in latent preferences and expectations. The analysis is still reduced form in the sense that it aims at uncovering associations without claims for causality. Nonetheless, since the explanatory variables are proxies that have cardinal interpretations relevant for economic theories, they potentially convey much more information than the relationship of raw survey responses to economic outcomes.

Start from a general function of the solution of optimal stock share

$$s_i^* = s^*\left(\mu_i, \sigma_i, \gamma_i, \kappa; x_i, u_i\right) \tag{2.9}$$

where μ_i and σ_i are the beliefs of person i about the mean and the standard deviation of one-year-ahead stock returns, γ_i is the parameter of risk tolerance, x_i is a vector of wealth, demographic variables and other risk factors that are measured in our data, and u_i combines all unobservables. We assume that unobservables are independent of observables.

The relative deviation of s^* *around* its mean value is related to relative deviations of the other variables around their mean values, holding values of x_i constant by

$$\frac{s_i^* - \overline{s^*}}{\overline{s^*}} \approx \beta_0 + \beta_1 \frac{\mu_i - \bar{\mu}}{\bar{\mu}} + \beta_2 \frac{\sigma_i - \bar{\sigma}}{\bar{\sigma}} + \beta_3 \frac{\gamma_i - \bar{\gamma}}{\bar{\gamma}} + \beta_4' x_i + u_i. \tag{2.10}$$

The coefficients approximate the first derivatives of the function around the mean values, with $\beta_1 = \partial \tilde{s}^* / \partial \tilde{\mu}$, $\beta_2 = \partial \tilde{s}^* / \partial \tilde{\sigma}$ and $\beta_3 = \partial \tilde{s}^* / \partial \tilde{\gamma}$, where the tilde denote relative differences from mean values. This approximation is a way of log-linearizing the function that allows observations with nonpositive values of some of the variables, which is relevant for μ_i in our case. We linearize about the risk tolerance parameter rather than relative risk tolerance to avoid the ambiguity that relative risk tolerance depends on the level of consumption.

We estimated (2.10) using the observed stock share s_i to approximate the target stock share s_i^*, and the individual proxies $\hat{\mu}_i$, $\hat{\sigma}_i$ and $\hat{\gamma}_i$ approximating the latent variables μ_i , σ_i and γ_i as described earlier. We estimated the equation by OLS both with and without covariates.[21] When we controlled for covariates in the stock share equation we entered the structural parameters that were estimated conditional on the same covariates. Kimball, Sahm, and Shapiro (2008) show that it is necessary to construct the proxies conditional on the same covariates as included in the main regression to deliver unbiased coefficient estimates. As the proxies are generated regressors, we estimated the standard errors by bootstrapping the entire estimation procedure including the structural estimation of the model underlying the proxies. We estimated two versions of each regression: one with the survey measure of the share of stocks in total financial wealth on the left hand side and one with the administrative measure of stock share in

[21] We do not use a Tobit-type procedure to account for the truncation at 0 and 1 because there are very few observations (less than 2 percent of the sample) at these boundaries.

wealth held at Vanguard. The main results are in Table 2.5. Table 2-A9 in the Appendix shows the detailed results.

The estimates show that the share of stocks is positively related to the perceived mean of stock market returns, negatively related to the perceived standard deviation of stock market returns, and positively related to the risk tolerance parameter. The estimated coefficients are statistically significant with the survey measure of stock shares on the left hand-side, but they are smaller and less significant in the administrative stock share regressions. In both cases the coefficients are very similar whether we enter them with or without the covariates.[22]

According to the point estimates, a one percent higher perceived mean is associated with one twentieth of a percent higher stock share; a one percent higher perceived standard deviation is associated with around one tenth of a percent lower stock share; and a one percent higher risk tolerance parameter is associated with one thirtieth of a percent higher stock share. Converting the relative magnitudes to absolute ones, our estimates imply that for the stock share to be higher by 1 percentage point expected returns need to be higher by 2.1 percentage points, the perceived standard deviation needs to be lower by 2.4 percentage points, or the risk tolerance parameter needs to be higher by 0.24.[23]

[22] Table 2-A9 in the Appendix shows that most of the coefficients on the other covariates are in line with prior expectations: the stock share is smaller in the employer-sponsored subsample and larger for wealthier and more educated individuals, especially for those with an MBA. Some of the other parameters are insignificant: the coefficient on the probability of needing long-term care (a factor of background risk), for example, is negative but insignificant.

[23] Comparing our estimates to the literature is not straightforward as most papers do not have cardinal proxies for the expectations and risk tolerance variables, and those that do estimate functional forms that are different from ours. Wherever we can make the comparison we find magnitudes that are very similar to our estimates. The closest to our specification are the estimates of Amromin and Sharpe (2012). On a sample of stockholders with positive expected returns they regress the log of the stock share on the log of their proxies of μ and σ. Their point estimates are +0.04 and -0.11, respectively. These magnitudes are very close to ours. The results of the Tobit model of Vissing-Jorgensen (2003), estimated on a sample of investors, imply that one percentage point higher returns expectations are associated with about 0.5

Table 2.6 shows results of analogous estimations that do not take care of measurement error in the survey answers (Table 2-A10 in the Appendix contains all results). Instead of the cardinal proxies $\hat{\mu}_i, \hat{\sigma}_i, \hat{\gamma}_i$, these regressions include the raw survey answers to the stock market expectation question (m_i), a crude transformation of the probability answers to approximate perceived risk,[24] and the median value of the CRRA risk tolerance parameter that corresponds to the answers to the first set of the risk tolerance questions (κ set to zero). The coefficient estimates are qualitatively similar to the baseline results reported in Table 2.5 above, but the magnitudes are considerably attenuated. The absolute values of the point estimates are one third to one half of the baseline estimates. These results are consistent with substantial measurement error in the raw survey answers. They show the importance of taking into account measurement error in the construction of the proxies and in using them in econometric models.

Table 2-A11 shows estimates analogous to our benchmark model presented in Table 2.5 above for the employer-sponsored subsample. Self-selection to Vanguard is arguably substantially less severe in this subsample. However, the differences are small, suggesting that selection bias is unlikely to have a substantial effect on our main results.[25]

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percentage point higher equity share. Kezdi and Willis (2011) estimate a coefficient of 0.3 in a truncated regression model estimated on a representative sample with stock shares on the left hand-side. Our log-linearized estimates imply that, around its mean, a one point difference in μ is associated with a 0.45 percentage point difference in stock shares. In a Tobit model of stock shares that combines the extensive and intensive margins Kimball, Sahm and Shapiro (2008) find a small magnitude for the association with the cardinal proxy of risk tolerance.

[24] $\tilde{\sigma}_i = 0.2 / \left(\Phi^{-1}(p_{0i}) - \Phi^{-1}(p_{20i}) \right)$. The denominator replaced with 0.2 if zero to obtain $\tilde{\sigma}_i = 1$, which is larger than the maximum of all other values. This imputation affects less than 10% of the observations. Alternative imputations that replace the denominator with other values yield very similar estimates.

[25] Tables 2-A12 through 2-A15 in the Appendix show that results from analogous regressions are very similar in various subsamples, such as the sample of individuals that joined Vanguard with their private accounts, the sample of individuals with high share of household wealth held at Vanguard, and the sample of individuals with directly held stocks.

2.4.3. Interpreting the magnitudes

How might one evaluate the estimates relative to an economic model? The simplest model of Merton (1969) with CRRA utility would imply that the coefficient on log μ should be 1, the coefficient on log σ should be -2, and the coefficient on log γ should be 1 again. The same implications hold if we modify the utility function in the Merton model to incorporate the subsistence level of consumption as in equation (2.1) above.

The *relative* magnitudes of the estimated coefficients report in Table 2.5 are remarkably close to these theoretical implications of the Merton benchmark. In the regressions on the survey measure of stock share, the coefficient on the (approximately log-linearized) expected value and risk tolerance proxies are close to each other, and the coefficient on the standard deviation proxy is close to be negative two times their magnitudes. At the same time, the magnitudes are indeed smaller than in the benchmark model: each estimate is about one twentieth of what a simple theory implies.

In principle, the attenuation bias may arise from classical errors in variables on the right hand-side or appropriate non-classical errors in the left hand-side variable. Recall that our measures of beliefs and preferences already take care of substantial survey noise that arise from noisy responses conditional on the latent variables. While it is of course possible for those latent variables to exhibit additional noise, due to, for example, mood effects, that noise would have to be extremely large for the observed attenuation. We believe that the magnitude of the attenuation and its similar strength across the coefficients call for an explanation beyond these measurement issues.

We can represent the substantially attenuated response of stock holding to beliefs and preferences by expressing observed stock shares as a linear combination of the individual optimum s_i^* and the average stock share $\bar{s}$ plus additional heterogeneity

$$s_i = \lambda s_i^*\left(\mu_i, \sigma_i, \gamma_i\right) + \left(1-\lambda\right)\bar{s} + v_i \tag{2.11}$$

where λ is the weight on the individual optimum given beliefs and preferences, (1- λ) is the weight on the average stock share, and v_i is heterogeneity in stock shares due to other factors. This model can be viewed as a simple statistical representation of the attenuation. It can be also interpreted as a behavioral model, in which investors consider the possibility that everyone else may choose the right stock share even if their own beliefs and preferences imply a different choice, and their decision combines the two. [26] Such behavior could account for the finding we discussed earlier that those who report negative expected returns in the survey continue to hold stock and those who are very optimistic do not have extreme exposure to the stock market.

Expressing equation (2.11) in deviations from averages, denoting the coefficients of the log-linearized optimal stock share by β^0 and decomposing heterogeneity due to other factors into observed and unobserved parts yields

$$\frac{s_i - \bar{s}}{\bar{s}} \approx \beta_0 + \lambda\beta_1^0 \frac{\mu_i - \bar{\mu}}{\bar{\mu}} + \lambda\beta_2^0 \frac{\sigma_i - \bar{\sigma}}{\bar{\sigma}} + \lambda\beta_3^0 \frac{\gamma_i - \bar{\gamma}}{\bar{\gamma}} + \beta_4' x_i + u_i. \tag{2.12}$$

This is a constrained version of equation (2.10), with the Merton solution implying $\beta_1^0 = 1$, $\beta_2^0 = -2$, $\beta_3^0 = 1$. We estimate the constrained versions of each unconstrained regression presented in Table 2.5 above. Table 2.7 shows the results. The estimated λ is around 0.05 when

[26] A possible reason for this behavior is mean reversion of beliefs combined with a strong inertia in portfolio choice. Some individuals who expect extreme returns currently think returns will revert back to more normal in the future, but do not make the high-frequency adjustments to their portfolios to align with current extreme expectations.

the left hand side variable is the survey measure of stock share, and it is around 0.03 when the left hand side variable is the administrative measure of stock share. The proportionality restriction holds reasonably well in the data as one would expect from inspection of the results in Table 2.5. The Wald test does not reject the null of proportionality for the survey data, but does marginally for administrative data (more so without covariates). These results suggest strong attenuation in the association of stock shares with beliefs and preferences, but that the degree of attenuation is well represented by a single factor, as expressed by equation (2.11).

The forgoing model of attenuation assumes that individuals down-weight both their preferences and beliefs in favor of the market average. A perhaps less radical behavioral model is that individuals keep to their preferences, but moderate their reactions to returns beliefs. In Appendix Table 2-A16 we present such estimates by excluding the preference measure from the s_i^*. The estimated λ increases slightly to 5 or 6 percent and the proportionality restrictions are far from the rejection region.

<u>2.4.4. Alternative Benchmark Model</u>

The Merton model is a simple and useful benchmark. However, it has assumptions that are very far from the way people invest in our sample as it requires continuous rebalancing, no background risk, and it allows for unlimited leverage and short sales. We therefore investigate whether adding these realistic features would move the predictions of the benchmark model more in line with what we observe in the data.

The model we use is a life cycle portfolio choice model in discrete time, with consumption and investment decisions at the yearly frequency and portfolio shares constrained to be between zero and one. The model incorporates background risk in income and longevity. Similarly to the Merton model, it has a risky asset (stocks) and a risk-free asset (bonds), and it is a model of demand, taking returns on those assets as given. It has no closed-form solution and is solved recursively. Our model can be viewed as a generalization of the model of Cocco, Gomes and Maenhout (2005). Appendix 2-C contains its details and main results.

The lifecycle model of portfolio choice implies magnitudes that are similar to the Merton model in the range of interior solutions, and it implies corner solutions of zero and 100 percent stock shares otherwise. Our estimates of these associations are substantially weaker. Stock share is close to fifty percent among those who expect non-positive stock returns in our sample, and it is substantially less than 100 percent on average among people with very high expectations even with low perceived risk and low risk tolerance. In the theoretical model, the share of stocks increases from zero to 100 percent if expected returns raise from the risk-free rate to seven percentage points above the risk-free rate even for investors that are in the top third of our estimated distribution of risk aversion and perceived risk. Our estimates imply that a seven percentage point difference in expected returns corresponds to less than a four percentage point difference in stock shares. Again, our estimate is about one twentieth of the magnitude implied by theory. Differences between the model and our estimates with respect to the role of perceived risk and risk tolerance are similarly large.

We investigate the attenuation of our estimates compared to the life cycle portfolio choice model by estimating equation (2.11) with the solution implied by this model for s_i^*, estimated for each individual using a linearized version of the model solution. The result is $\lambda = 0.043$ when the left hand side variable is the survey measure of stock share and we do not include other covariates. This result is very similar to our estimate based on the Merton solution, as presented in column (1) in Table 2.7.

Risk preferences, expected stock returns, and the risk of stock returns are fundamental elements of any portfolio choice model. People should not hold stocks if they think their returns will be lower than returns on risk-free assets, and they should avoid or embrace risk in their investment decisions in a way that is in line with their choices in other gambles with money. These features are implied both by the very stylized Merton model and our more realistic life cycle model, yet our estimates do not deliver them. The two portfolio choice models imply similar magnitudes in the range of an interior solution without short sales and leverage, and our estimates fall short of those magnitudes.

2.5 Conclusion

There is substantial heterogeneity in portfolio decisions across households. This paper uses a distinctive measurement and analytic strategy that combines high-quality measurement of portfolio shares, preferences about risk, and beliefs about returns in an attempt to explain this heterogeneity. The approach uses purposely-constructed measures to elicit measures of preferences and beliefs that have quantitative interpretations. This paper does find that risk preference and moments of the subjective returns distribution—both mean and variance—do have a role in understanding why portfolio choices differ. That the survey measures of preference and belief do align with portfolio choices provides external validation of our approach to measuring them.

The size of the estimated associations of the risk and belief parameters is, nonetheless, substantially smaller in magnitude than benchmark theories would suggest. We call this finding the "attenuation puzzle." Our methods produce risk and belief parameters that measure the precise, quantitative variables that should explain portfolio choice. Hence, the attenuation cannot be dismissed because the measures of preference and belief are only loosely related to what should drive portfolio choice. Moreover, the statistical procedure deals with measurement error in these parameters, which is the other most obvious source of such attenuation. The econometric procedure estimates the response error in the survey measures of preferences and beliefs and produces individual-specific preference and belief parameters that are immune from the standard effects of using noisy estimates as regressors.

We argue that the selected nature of the sample is unlikely to account for the small magnitudes. The results are nearly identical for the subset of the sample who came to Vanguard via their employer's choices, so individual selection to use Vanguard as a provider is not driving the findings.

Another explanation for the attenuated response could be background risk that would reduce stockholding given the perception of riskiness of stock returns per se. This source of attenuation, however, mostly affects the coefficient of our measure of perceived risk, and it should not lead to substantial bias in the estimates of the coefficients of risk tolerance or perceived expected returns.

The attenuated response of stock shares to beliefs and preferences is responsible for observing individuals who think that stocks are dominated in return often holding a high fraction of their portfolio in stock. Symmetrically, this attenuated response makes many individuals who think that stocks have very high returns hold too little stocks. What might account for such behavior? Our finding in Figure 2.2 that stock shares are very static suggests an answer: It is possible that people make their portfolio choice decision very infrequently, much less frequently than the annual rebalancing of the theory in Section 2.4. If household are cognizant of this inertia and if they feel that their preferences and beliefs might change, then it would make sense to have a damped response to them. We show that the estimated behavior is indeed consistent with individuals mixing their own preferences and beliefs with the market average behavior. While far from fully worked out as an explanation, our finding that there is a coherent but attenuated response to the vector of risk tolerance, mean return, and variance of return does perhaps point toward such explanations. Similarly, the deviations of the survey and administrative measures of portfolio shares suggest that many respondents do not follow their portfolios closely. If they are aware of this, that might well be a good reason for them to choose a portfolio closer to what the representative individual would choose than the one they would choose based on their preferences or beliefs at a particular moment.

The results are consistent with decision makers mixing their own risk preference and beliefs about stock market returns with the preferences and beliefs of the representative consumer. On the one hand, people may follow advice or buy what is offered despite their preferences and beliefs. On the other hand, changes in beliefs may not translate to changes in portfolio composition because of inertia, due to inattention or fixed costs. While our data do not allow us to sort out these explanations, our paper makes substantial progress by quantifying the role of individual risk preferences and beliefs about stock market returns in the heterogeneity in portfolio choice across households, using high-quality and precise measurements of preferences and beliefs.

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Table 2-1. Summary Statistics: VRI, HRS, and SCF

	VRI		HRS	SCF
	Entire sample	Analysis sample	VRI-eligible subsample	
Household-level variables				
Number of households	8,950	4,414	3,684	1,275
Number of stockholding households	8,636	4,323	2,356	1,216
Average financial wealth ($’000)	1,207	1,148	578	970
Average total wealth ($’000)	1,589	1,551	804	1,764
Average stock share among stockholders	0.56	0.56	0.55	0.46
Respondent-level variables				
Married	0.67	0.68	0.70	0.71
Male	0.64	0.65	0.56	0.79
Age	67.8	67.8	64.9	64.1
Less than college degree	0.30	0.26	0.51	0.45
College degree but not more	0.32	0.33	0.23	0.27
Post-college degree	0.38	0.41	0.26	0.28
Retired	0.56	0.60	0.53	0.34

Notes. For the HRS and SCF, the VRI-eligible subsamples are those who are not younger than 55, have access to the Internet at home, and have at least $10,000 in non-transactional accounts. Respondent-level variables for the HRS refer to the financial respondents; for the SCF they refer to the household heads. Variables in the VRI measured in 2013; HRS and SCF are from 2012 and 2013, respectively. Respondent-level variables are {0,1} binary variables except for age.

Table 2-2. Risk Tolerance: Distribution of Responses to SSQ

Response	Downside risk		Percent of answers	
category	accepted	rejected	riskless consumption $100K	riskless consumption $50K
1	none	1/10	23	28
2	1/10	1/5	26	34
3	1/5	1/3	26	26
4	1/3	1/2	13	9
5	1/2	3/4	10	3
6	3/4	none	2	1
Total			100	100

Choice between two plans. Plan A guarantees $W consumption next year. Plan B: doubles $W with 50% chance and cuts it by a fraction x with 50% chance. $W=100K or 50K, shown in the two columns; the x values are shown in second and third columns. 4414 observations.

Table 2.3. Stock Market Returns: Survey Responses versus Historical Statistics

	Survey answers				Historical statistics			
	Mean	25^{th} pctile	Median	75^{th} pctile	1959-2014	1995-2014	1995-2009	2010-2014
m	0.06	0.04	0.06	0.10	0.04	0.07	0.05	0.13
*p*0	0.51	0.25	0.55	0.75	0.58	0.65	0.53	1.00
*p*20	0.15	0.05	0.15	0.25	0.18	0.25	0.27	0.20

Notes. *m* is expected one-year ahead returns of the stock market index DJIA; *p0* is the probability that the DJIA would be higher a year from the date of the interview; *p20* is the probability that it would be higher by at least 20%. Historical statistics computed from yearly relative returns of the Dow Jones Industrial Average (year on year changes divided by base year value, first days of July in each year), deflated using the PCE chain price index (available beginning in 1959). Historical average values shown for *m*; the fraction of years when positive or greater than 0.2 are shown for *p0* and *p20*. 4414 observations.

Table 2.4. Distribution of Preferences and Beliefs

		Mean	Standard deviation	25^{th} pctile	Median	75^{th} pctile
Preferences						
Risk tolerance parameter	γ_i	0.41	0.33	0.20	0.32	0.50
Subsistence consumption	$-\kappa$	17,000				
Beliefs						
Mean of return	μ_i	0.06	0.06	0.02	0.06	0.10
Standard deviation of return	σ_i	0.12	0.03	0.10	0.12	0.14

Notes. Statistics are calculated from the estimated parameters in Table 2-A5; see the notes to Table 2-A5 for more detail.

Table 2.5. Stock Shares versus Cardinal Proxies for Preferences and Beliefs

	Survey Stock Share		Administrative Stock Share	
	(1)	(2)	(3)	(4)
$\hat{\mu}_i$	0.058***	0.055***	0.052***	0.047***
	(0.010)	(0.009)	(0.008)	(0.008)
$\hat{\sigma}_i$	-0.093*	-0.083	-0.068	-0.083*
	(0.046)	(0.051)	(0.040)	(0.038)
$\hat{\gamma}_i$	0.034***	0.033**	0.012	0.013
	(0.009)	(0.010)	(0.010)	(0.010)
constant	-0.001	1.136	-0.001	0.803
	(0.008)	(0.649)	(0.007)	(0.519)
covariates	N	Y	N	Y
R^2	0.019	0.045	0.013	0.038
N	4414	4414	4414	4414

Notes. Stock share in total financial wealth (survey measure) and in Vanguard accounts (administrative measure) are regressed on proxies for the expected stock returns ($\hat{\mu}_i$), perceived standard deviation of stock returns ($\hat{\sigma}_i$), and the parameter of risk tolerance ($\hat{\gamma}_i$). All variables are expressed as relative differences normalized to their mean values (as specified in equation **Error! Reference source not found.**). Control variables: married, male, age, whether respondent comes from the employer-sponsored subsample, education (below college; college; MBA; PhD, other higher degree); log financial wealth, log wage, dummy for owning a house, log annuity income (Social Security and DB pensions) for retired, log expected annuity income for non-retired; dummy for retired, log home stock; subjective probability of needing long-term care, and longevity expectations.
Bootstrap standard errors in parentheses. *, **, and *** implies significance at 5%, 1% and 0.1% level, respectively.

Table 2.6. Stock Shares Versus Error-Ridden Cardinal Measures of Preferences and Beliefs. Estimation without taking care of measurement error in the cardinal proxies.

	Survey Stock Share		Administrative Stock Share	
	(1)	(2)	(3)	(4)
m_i	0.017***	0.020***	0.020***	0.021***
	(0.004)	(0.004)	(0.004)	(0.004)
$\tilde{\sigma}_i$	-0.029***	-0.019**	-0.025***	-0.020**
	(0.006)	(0.007)	(0.006)	(0.006)
$\tilde{\gamma}_i$	0.021***	0.020***	0.013**	0.013**
	(0.005)	(0.005)	(0.004)	(0.004)
constant	-0.001	1.120*	-0.000	0.781
	(0.007)	(0.565)	(0.006)	(0.507)
covariates	N	Y	N	Y
R^2	0.013	0.039	0.012	0.038
N	4414	4414	4414	4414

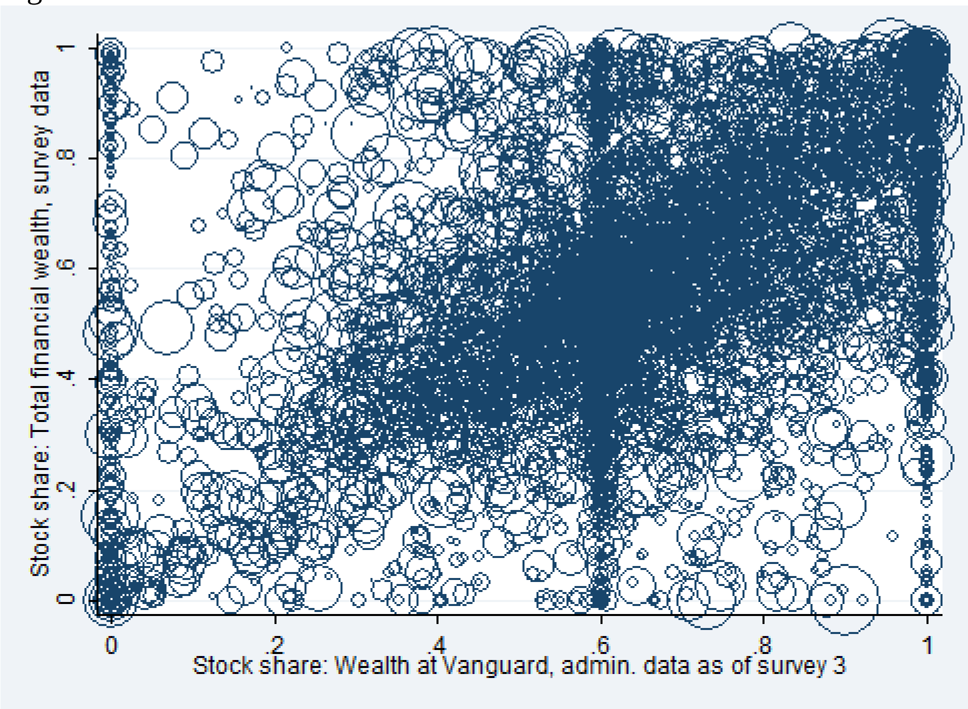
Notes. Left-hand-side variables and covariates as in Table 2.5. Main right-hand-side variables are the raw survey answers to the stock market expectation question (m_i), a crude transformation of the probability answers to approximate perceived risk ($\tilde{\sigma}_i = 0.2/\left(\Phi^{-1}(p_{0i}) - \Phi^{-1}(p_{20i})\right)$), and the median value of the CRRA risk tolerance parameter that corresponds to the answers to the first set of the risk tolerance questions (κ set to zero).
Bootstrap standard errors in parentheses. *, **, and *** implies significance at 5%, 1% and 0.1% level, respectively.

Table 2.7. Observed stock shares and theoretically optimal stock shares

	Survey Stock Share		Administrative Stock Share	
	(1)	(2)	(3)	(4)
λ	0.046***	0.045***	0.032***	0.032***
	(0.006)	(0.006)	(0.006)	(0.007)
covariates	N	Y	N	Y
R^2	0.017	0.044	0.010	0.036
N	4414	4414	4414	4414
p-value of Wald test on restriction	0.240	0.258	0.010	0.033

Notes. Regression results from equation (12) imposing $\beta_1^0 = 1$, $\beta_2^0 = -2$, and $\beta_3^0 = 1$. Bootstrap standard errors in parentheses. *, **, and *** implies significance at 5%, 1% and 0.1% level, respectively.

Figure 2.1. Stock Shares



Note: The figure plots the administrative measure of stock share at Vanguard at the time of Survey 3 on the horizontal axis versus the survey measure of stock share overall at the time of Survey 1 on the vertical axis. These are the main dependent variables in the analysis. The size of the marks on the figure is proportional to the Vanguard financial wealth of the respondents.

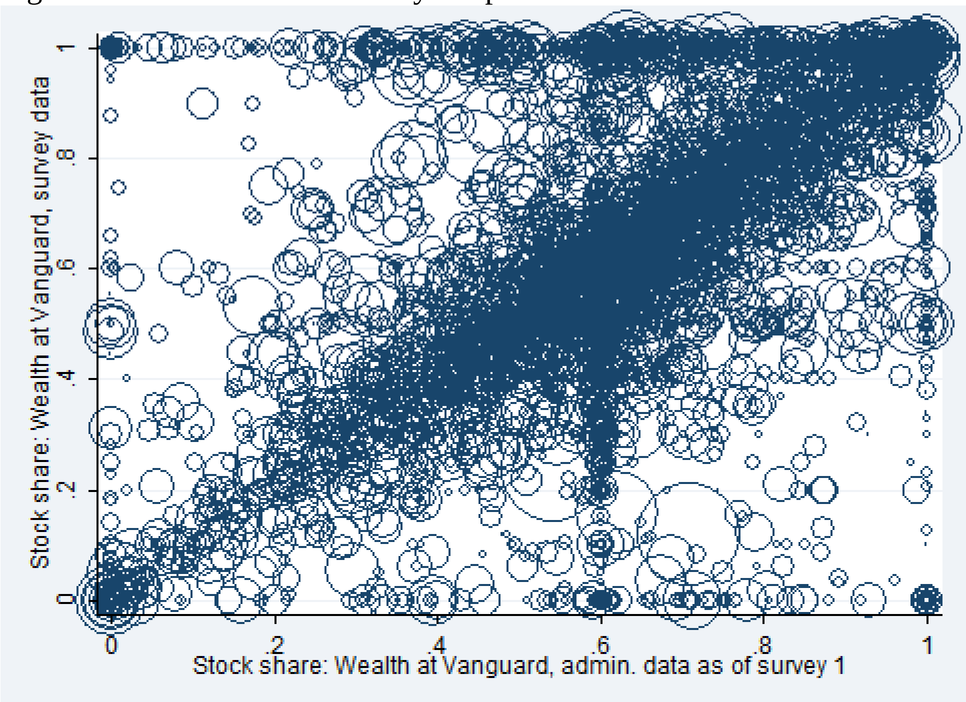
Figure 2.2. Stock Shares: Differences in Time

Note: The figure plots the administrative measure of stock share at Vanguard at the time of Survey 3 on the horizontal axis versus the administrative measure of stock share at Vanguard at the time of Survey 1 on the vertical axis. The size of the marks on the figure is proportional to the Vanguard financial wealth of the respondents.

Figure 2.3. Stock Shares: Total versus Vanguard

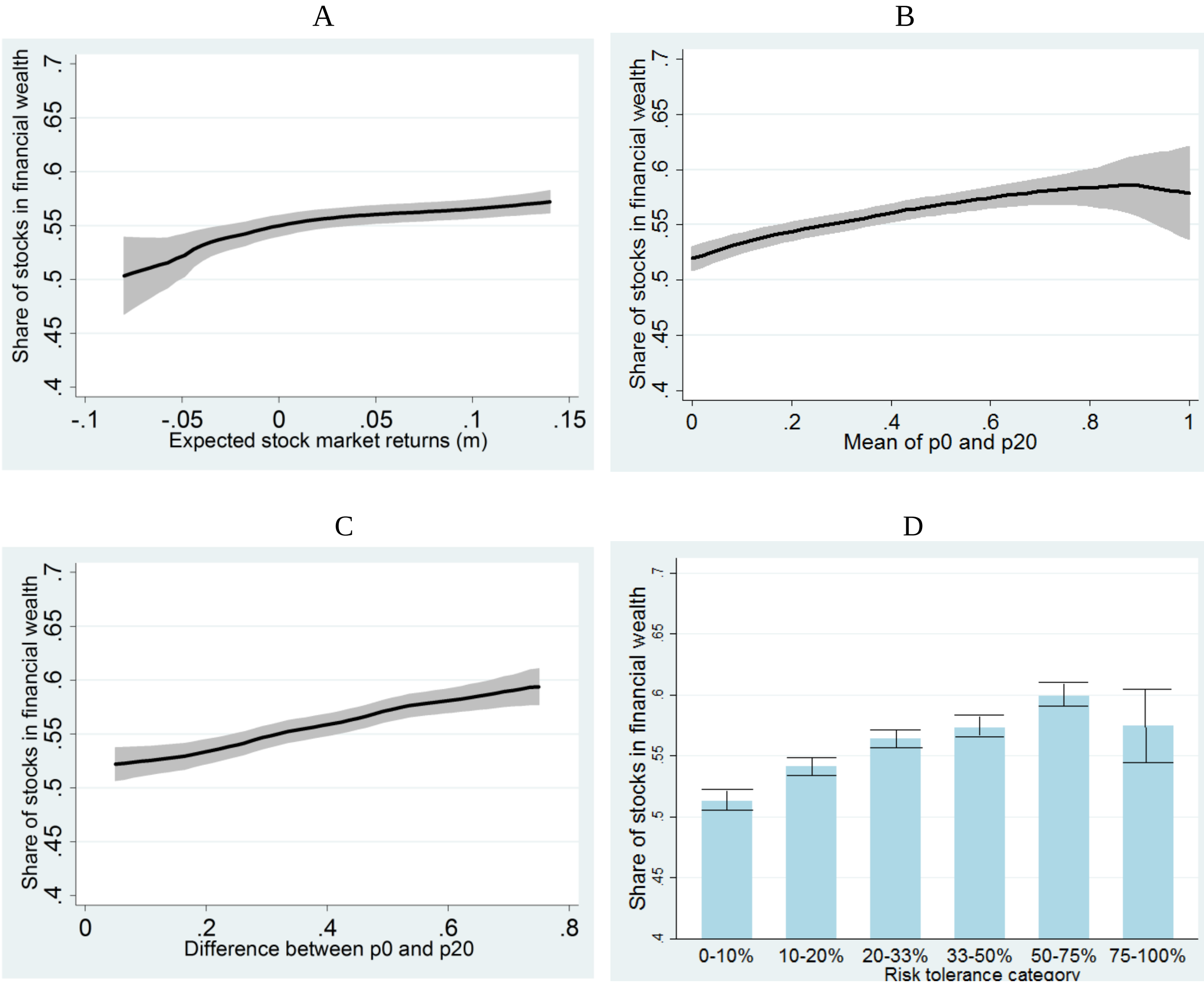
Note: The figure plots the survey measure of stock share at Vanguard on the horizontal axis versus the survey measure of stock share overall on the vertical axis. The size of the marks on the figure is proportional to the Vanguard financial wealth of the respondents.

Figure 2.4. Stock Shares: Survey Response Versus Administrative



Note: The figure plots the survey measure of stock share at Vanguard on the horizontal axis versus the survey measure of stock share overall on the vertical axis. The size of the marks on the figure is proportional to the Vanguard financial wealth of the respondents.

Figure 2.5. Stock Share versus Raw Survey Responses



Appendix 2-A. Additional Tables and Figures

Table 2-A1. Distribution of wealth in the VRI data (N=4414)

	Mean	Std	p10	p25	Median	p75	p90
Financial wealth	1,147,525	1,516,575	164,835	363,000	759,750	1,403,843	2,467,899
Home stock	360,782	578,045	31,500	125,000	235,000	420,000	1,060,000

Table 2-A2. Summary statistics of the control variables (N=4414)

	Mean	Standard deviation
Single male	0.14	
Female in couple	0.17	
Single female	0.18	
Age	67.8	7.4
Age squared	4649	1023
In the employer-sponsored sample	0.21	
College degree	0.33	
MBA	0.07	
PhD	0.06	
Other higher degree	0.28	
Log(wealth)	13.4	1.09
Log(home equity)	11.5	3.37
Zero home equity	0.07	
Retired	0.60	
Log(Wage)	4.3	5.5
Log(Annuity Income)	6.5	5.3
Expected Log(Annuity Income)	4.3	5.3
Subjective probability of needing long-term care	0.43	0.30
Subjective probability of survival to target age	0.75	0.23

Notes.

Log variables are set to zero if the levels of the variables are zero. Zero home equity equals 1 (0) if home equity is zero (positive). Annuity income is the sum of Social Security income, defined benefit pension income and immediate annuity income, for retired households. It is set to zero for non-retired households. Expected annuity income is the sum of expected values of Social Security income, defined benefit pension income and immediate annuity income, for non-retired households. It is set to zero for retired households. Subjective probability of needing long-term care is the subjective probability chance that the respondent would need long-term care service at least for one year during her remaining life. The target age in subjective probability of survival question is set to 75 if the respondent is younger than 70, to 85 if the respondent is younger than 80, and to 95 if the respondent is younger than 90.

Table 2-A3. The Risk Tolerance Strategic Survey Questions in VRI survey 2

Set up	Suppose you are 80 years old. Suppose, further, that for the next year: • You live alone, rent your home, and pay all your own bills. • You are in good health and will remain in good health. • You will have no medical bills or other unexpected expenses. • You do not work.
Hypothetical financial products	• Plan A guarantees that you will have \$W for spending next year. • Plan B will possibly provide you with more money, but is less certain. There is a 50% chance that Plan B would double your money, leaving you with \$2W, and a 50% chance that it would cut it by x%, leaving you with \$ $(1-0.01\times x)W$.
Rules	• You have no other assets or income, and so the only money you have available for all your spending next year is from either Plan A or Plan B. • Any money that is not spent at the end of next year cannot be saved for the future. • You cannot give any money away or leave it as a bequest. • If you need anything next year, you have to pay for it. No one else can buy anything for you. • At the end of next year you will be offered the same choice with another \$W for following year.
Parameters asked	W =100,000 and 50,000.
Question	Would you choose Plan A or Plan B?

Table 2-A4: The stock market expectation questions in VRI survey wave 3.

Variable name	Survey question
Question Order *p-m*	
p0	What do you think is the percent chance that the stock market will be higher in twelve months than it is today? Think of a stock market index such as the Dow Jones Industrial Average and do not adjust for inflation.
p20	And what do you think is the percent chance that it will be at least 20% higher in twelve months than it is today? [If answer is greater than the p0 answer: "Please enter a response that is less than or equal to you previous response or change your previous response."]
m	Instead of probabilities, we are now interested in your expectation. By what percentage do you expect the stock market to increase or decrease in the next twelve months? Please enter a positive number for increase and negative number for decrease.
Question order *m-p*	
m	By what percentage do you expect the stock market to increase or decrease in the next twelve months? Think of a stock market index such as the Dow Jones Industrial Average and do not adjust for inflation. Please enter a positive number for increase and negative number for decrease.
p0	And what do you think is the percent chance that the stock market will be higher in twelve months than it is today?
p20	What do you think is the percent chance that it will be at least 20% higher in twelve months than it is today? [If answer is greater than the p0 answer: "Please enter a response that is less than or equal to you previous response or change your previous response."]

Note: The question orders are randomized in the survey instrument. The distributions of responses are slightly different depending on which sequence is used.

Table 2-A5. Detailed results of the structural estimation model without covariates. (N=4,414)

	Preference	Beliefs		Bias in *p0*
	γ	μ	σ	ψ
constant	-1.148***	0.055***	0.118***	-0.539***
	(0.027)	(0.002)	(0.002)	(0.017)
Heterogeneity				
σ_u	0.704***	0.063***	0.032***	n.a.
	(0.011)	(0.001)	(0.001)	n.a.
Correlation across latent variables				
γ		0.011**	-0.004	
		(0.003)	(0.002)	
$\rho_{\mu\sigma}$		0.062**		
		(0.021)		
Measurement error				
$\sigma_{e\gamma1}$		0.812***		
		(0.015)		
$\sigma_{e\gamma2}$		0.544***		
		(0.016)		
σ_{em}		0.079***		
		(0.001)		
σ_{ep}		0.487***		
		(0.008)		
Log-likelihood		-48006		

Notes.

The third line reports how the latent risk tolerance parameter affects means of the belief parameter distributions. Statistics reported in Table 2.4 are calculated based on these parameters, where the means of belief parameter distributions are adjusted using the mean of the risk tolerance parameter multiplied with the numbers reported in the third row.

Standard errors in parentheses.

*, **, and *** implies significance at 5%, 1% and 0.1% level, respectively.

Table 2-A6. Detailed results of the structural estimation model with covariates. (N=4,414)

	Preference	Beliefs		Bias in *p0*
	γ	μ	σ	ψ
Constant	-1.415***	0.071*	0.181***	-0.373
	(0.412)	(0.031)	(0.024)	(0.833)
Single male	0.038	0.004	0.002	-0.019
	(0.042)	(0.004)	(0.003)	(0.041)
Female in couple	-0.207***	0.004	0.001	-0.171***
	(0.040)	(0.004)	(0.003)	(0.039)
Single female	-0.191***	0.011**	0.000	-0.294***
	(0.041)	(0.004)	(0.003)	(0.039)
Age	-0.020	0.000	-0.002***	-0.029
	(0.015)	(0.000)	(0.000)	(0.023)
Age sq.	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Employer-sponsored	-0.003	0.015***	-0.005*	-0.167***
	(0.039)	(0.003)	(0.002)	(0.037)
College degree	0.039	-0.009**	0.007***	0.294***
	(0.035)	(0.003)	(0.002)	(0.035)
MBA	0.116	-0.004	0.004	0.222***
	(0.060)	(0.006)	(0.004)	(0.064)
PhD	0.042	-0.019**	0.023***	0.465***
	(0.061)	(0.007)	(0.006)	(0.068)
Other higher degree	0.079*	-0.010**	0.014***	0.354***
	(0.038)	(0.004)	(0.002)	(0.038)
log(wealth)	0.037**	-0.007***	0.005***	0.131***
	(0.014)	(0.001)	(0.001)	(0.014)
log(home equity)	0.029	-0.002	0.000	-0.008
	(0.015)	(0.001)	(0.001)	(0.015)
No home equity	0.338	-0.018	-0.001	-0.155
	(0.191)	(0.014)	(0.010)	(0.179)
Retired	0.386	-0.039	-0.011	-0.016
	(0.410)	(0.030)	(0.024)	(0.375)
Log(Wage)	-0.004	0.001	0.000	-0.007
	(0.011)	(0.001)	(0.001)	(0.011)
Log(Annuity Income)	-0.030	0.008***	-0.003**	-0.048*
	(0.029)	(0.001)	(0.001)	(0.022)
Expected Log(Annuity Income)	0.015	0.004	-0.003	-0.046
	(0.030)	(0.003)	(0.002)	(0.029)
LTC probability	0.009	-0.016***	0.002	0.184***
	(0.045)	(0.004)	(0.003)	(0.044)

Longevity probability	0.191** (0.063)	0.028*** (0.006)	-0.004 (0.004)	0.034 (0.062)
Heterogeneity				
σ_u	0.688*** (0.011)	0.063*** (0.001)	0.030*** (0.001)	n.a. n.a.
Correlation across latent variables				
γ		0.011** (0.004)	-0.003 (0.002)	
$\rho_{\mu\sigma}$		0.009 (0.024)		
Measurement error				
$\sigma_{e\gamma 1}$		0.810*** (0.015)		
$\sigma_{e\gamma 2}$		0.557*** (0.016)		
σ_{em}		0.078*** (0.001)		
σ_{ep}		0.455*** (0.008)		
Log-likelihood		-47656		

Note: Standard errors in parentheses.
*, **, and *** implies significance at 5%, 1% and 0.1% level, respectively.
Reference categories are male in couple, individual client sample, not having a college degree. See notes to Table 2-A2 for detailed description of the right hand side variables.

Table 2-A7. Stock share regressions with raw survey answers on the right hand side (with m as a proxy for beliefs of mean returns μ)

	Dependent variable: survey measure of stock share		Dependent variable: administrative measure of stock share	
m	0.126**	0.153***	0.180***	0.192***
	(0.037)	(0.037)	(0.038)	(0.038)
$p0$-$p20$	0.107***	0.085***	0.098***	0.091***
	(0.016)	(0.016)	(0.017)	(0.017)
SSQ1 cat=2	0.026*	0.016	0.016	0.008
	(0.011)	(0.011)	(0.011)	(0.011)
SSQ1 cat=3	0.047***	0.035**	0.038**	0.028*
	(0.011)	(0.011)	(0.011)	(0.011)
SSQ1 cat=4	0.054***	0.044***	0.057***	0.049***
	(0.013)	(0.013)	(0.013)	(0.013)
SSQ1 cat=5	0.083***	0.073***	0.080***	0.075***
	(0.014)	(0.014)	(0.015)	(0.015)
SSQ1 cat=6	0.053	0.045	-0.023	-0.026
	(0.031)	(0.031)	(0.032)	(0.031)
Single male		0.045		0.013
		(0.031)		(0.012)
Female in couple		0.016		0.021
		(0.012)		(0.011)
Single female		-0.007		0.019
		(0.011)		(0.012)
Age		-0.007		-0.014
		(0.012)		(0.009)
Age sq.		0.000		0.000
		(0.001)		(0.000)
Employer-sponsored		-0.053***		-0.042**
		(0.011)		(0.011)
College degree		0.018		0.023*
		(0.010)		(0.010)
MBA		0.033		0.022
		(0.017)		(0.018)
PhD		0.009		0.068***
		(0.017)		(0.018)
Other higher degree		0.015		0.029**
		(0.011)		(0.011)
log(wealth)		0.017***		-0.001
		(0.004)		(0.004)
log(home equity)		0.004		0.008
		(0.004)		(0.004)

No home equity		0.031		0.080
		(0.054)		(0.055)
Retired		-0.254*		-0.318**
		(0.116)		(0.119)
Log(Wage)		0.005		-0.001
		(0.003)		(0.003)
Log(Annuity Income)		0.002		0.023**
		(0.008)		(0.008)
Expected Log(Annuity Income)		-0.023**		-0.002
		(0.008)		(0.008)
LTC probability		-0.027*		-0.035**
		(0.013)		(0.013)
Longevity probability		0.042*		0.034
		(0.018)		(0.019)
Constant		0.371***		1.028***
		(0.111)		(0.319)
R2	0.023	0.040	0.023	0.043
Observations	4414	4414	4414	4414

Note: Standard errors in parentheses.
*, **, and *** implies significance at 5%, 1% and 0.1% level, respectively.
Reference categories are male in couple, individual client sample, not having a college degree. See notes to Table 2-A2 for detailed description of the right hand side variables.

Table 2-A8. Stock share regressions with raw survey answers on the right hand side (with $(p_0 + p_{20})/2$ as a proxy for beliefs of mean returns μ)

	Dependent variable: survey measure of stock share		Dependent variable: administrative measure of stock share	
(p0+p20)/2	0.115***	0.118***	0.097***	0.089***
	(0.024)	(0.024)	(0.025)	(0.025)
p0-p20	0.076***	0.056**	0.075***	0.074***
	(0.018)	(0.018)	(0.018)	(0.018)
SSQ1 cat=2	0.023*	0.013	0.012	0.005
	(0.011)	(0.011)	(0.011)	(0.011)
SSQ1 cat=3	0.043***	0.031**	0.033**	0.024*
	(0.011)	(0.011)	(0.011)	(0.011)
SSQ1 cat=4	0.049***	0.040**	0.052***	0.045**
	(0.013)	(0.013)	(0.013)	(0.013)
SSQ1 cat=5	0.079***	0.069***	0.076***	0.071***
	(0.014)	(0.014)	(0.015)	(0.015)
SSQ1 cat=6	0.051	0.043	-0.024	-0.027
	(0.031)	(0.031)	(0.032)	(0.032)
Single male	0.051	0.043		0.014
	(0.031)	(0.031)		(0.012)
Female in couple		0.017		0.023*
		(0.012)		(0.011)
Single female		-0.006		0.023
		(0.011)		(0.012)
Age		-0.004		-0.014
		(0.012)		(0.009)
Age sq.		0.001		0.000
		(0.001)		(0.000)
Employer-sponsored		-0.052***		-0.041***
		(0.011)		(0.011)
College degree		0.014		0.020
		(0.010)		(0.010)
MBA		0.029		0.019
		(0.017)		(0.018)
PhD		0.004		0.064***
		(0.017)		(0.018)
Other higher degree		0.011		0.025*
		(0.011)		(0.011)
log(wealth)		0.017***		-0.001
		(0.004)		(0.004)
log(home equity)		0.004		0.008
		(0.004)		(0.004)

No home equity		0.033		0.080
		(0.054)		(0.055)
Retired		-0.256*		-0.321**
		(0.116)		(0.120)
Log(Wage)		0.005		-0.001
		(0.003)		(0.004)
Log(Annuity Income)		0.003		0.024**
		(0.008)		(0.008)
Expected Log(Annuity Income)		-0.022**		-0.001
		(0.008)		(0.008)
LTC probability		-0.028*		-0.037**
		(0.013)		(0.013)
Longevity probability		0.039*		0.034
		(0.018)		(0.019)
Constant		0.340**		1.010***
		(0.111)		(0.319)
R2	0.025	0.041	0.022	0.040
Observations	4414	4414	4414	4414

Note: Standard errors in parentheses.
*, **, and *** implies significance at 5%, 1% and 0.1% level, respectively.
Reference categories are male in couple, individual client sample, not having a college degree. See notes to Table 2-A2 for detailed description of the right hand side variables.

Table 2-A9. Stock share and preference and belief proxies. Detailed results corresponding to Table 2.5.

	Dependent variable: survey measure of stock share		Dependent variable: administrative measure of stock share	
$\hat{\mu}_i$	0.058***	0.055***	0.052***	0.048***
	(0.010)	(0.009)	(0.008)	(0.008)
$\hat{\sigma}_i$	-0.093*	-0.083	-0.068	-0.083*
	(0.046)	(0.051)	(0.040)	(0.038)
$\hat{\gamma}_i$	0.034***	0.033***	0.012	0.013
	(0.009)	(0.010)	(0.010)	(0.010)
Single male		0.027		0.022
		(0.022)		(0.019)
Female in couple		-0.025		0.023
		(0.021)		(0.018)
Single female		-0.031		0.013
		(0.020)		(0.019)
Age		-0.042*		-0.027
		(0.017)		(0.015)
Age sq.		0.000**		0.000
		(0.000)		(0.000)
Employer-sponsored		-0.115***		-0.081***
		(0.020)		(0.018)
College degree		0.048*		0.051**
		(0.021)		(0.017)
MBA		0.072**		0.048
		(0.027)		(0.032)
PhD		0.057		0.143***
		(0.032)		(0.025)
Other higher degree		0.053*		0.069***
		(0.022)		(0.019)
log(wealth)		0.044***		0.011
		(0.009)		(0.007)
log(home equity)		0.008		0.013*
		(0.009)		(0.006)
No home equity		0.052		0.120
		(0.118)		(0.079)
Retired		-0.448		-0.496**
		(0.244)		(0.196)
Log(Wage)		0.007		-0.002
		(0.005)		(0.005)
Log(Annuity Income)		-0.002		0.032*
		(0.016)		(0.015)

Expected Log(Annuity Income)		-0.045*		-0.006
		(0.019)		(0.012)
LTC probability		-0.032		-0.041
		(0.028)		(0.021)
Longevity probability		0.084*		0.050
		(0.033)		(0.032)
Constant	-0.001	1.136	-0.001	0.803
	(0.007)	(0.649)	(0.007)	(0.519)
R2	0.019	0.045	0.013	0.038
Observations	4414	4414	4414	4414

Standard errors in parentheses.
*, **, and *** implies significance at 5%, 1% and 0.1% level, respectively.
Reference categories are male in couple, individual client sample, not having a college degree. See notes to Table 2-A2 for detailed description of the right hand side variables.

Table 2-A10. Stock Shares Versus Error-Ridden Cardinal Measures of Preferences and Beliefs. Estimation without taking care of measurement error in the cardinal proxies.

	LHS variable: survey measure of stock share in total financial wealth		LHS variable: administrative measure of stock share in Vanguard	
	(1)	(2)	(3)	(4)
m_i	0.017***	0.020***	0.020***	0.021***
	(0.004)	(0.004)	(0.004)	(0.004)
$\tilde{\sigma}_i$	-0.029***	-0.019**	-0.025***	-0.020**
	(0.006)	(0.007)	(0.006)	(0.006)
$\tilde{\gamma}_i$	0.021***	0.020***	0.013**	0.013**
	(0.005)	(0.005)	(0.004)	(0.004)
Single male		0.027		0.021
		(0.022)		(0.019)
Female in couple		-0.024		0.025
		(0.020)		(0.018)
Single female		-0.026		0.019
		(0.021)		(0.019)
Age		-0.040*		-0.025
		(0.016)		(0.014)
Age sq.		0.000*		0.000
		(0.000)		(0.000)
Employer-sponsored		-0.099***		-0.067***
		(0.019)		(0.017)
College degree		0.037*		0.040*
		(0.019)		(0.017)
MBA		0.066*		0.041
		(0.031)		(0.028)
PhD		0.025		0.113***
		(0.032)		(0.028)
Other higher degree		0.036		0.052**
		(0.020)		(0.018)
log(wealth)		0.034***		0.002
		(0.008)		(0.007)
log(home equity)		0.008		0.013
		(0.008)		(0.007)
No home equity		0.054		0.118
		(0.098)		(0.088)
Retired		-0.454*		-0.497**
		(0.212)		(0.190)
Log(Wage)		0.007		-0.002
		(0.005)		(-0.005)
Log(Annuity Income)		0.004		0.037**
		(0.015)		(0.013)

Expected Log(Annuity Income)		-0.041**		-0.002
		(0.015)		(0.013)
LTC probability		-0.043		-0.050
		(0.023)		(0.021)
Longevity probability		0.106**		0.065*
		(0.033)		(0.030)
constant	-0.001	1.120*	-0.000	0.781
	(0.007)	(0.565)	(0.006)	(0.507)
R^2	0.013	0.039	0.012	0.038
N	4414	4414	4414	4414

Notes. In these regressions the cardinal proxies $\hat{\mu}_i, \hat{\sigma}_i, \hat{\gamma}_i$ are replaced with $m_i, \tilde{\sigma}_i, \tilde{\gamma}_i$, respectively, where m_i is the raw answer to the expected stock returns question, $\tilde{\sigma}_i = 0.2 / \left(\Phi^{-1}(p_{0i}) - \Phi^{-1}(p_{20i}) \right)$ (the denominator replaced with 0.2 if zero), and $\tilde{\gamma}_i$ is the median valie of the CRRA risk tolerance parameter that corresponds to the answers to the first set of the risk tolerance questions (κ set to zero).
Standard errors in parentheses.
*, **, and *** implies significance at 5%, 1% and 0.1% level, respectively.
Reference categories are male in couple, individual client sample, not having a college degree. See notes to Table 2-A2 for detailed description of the right hand side variables.

Table 2-A11. Stock Shares Versus Cardinal Proxies for Preferences and Beliefs. Employer-sponsored subsample

	LHS variable: survey measure of stock share in total financial wealth		LHS variable: administrative measure of stock share in Vanguard	
	(1)	(2)	(3)	(4)
$\hat{\mu}_i$	0.067***	0.062**	0.083***	0.080***
	(0.018)	(0.019)	(0.014)	(0.015)
$\hat{\sigma}_i$	-0.122	-0.037	-0.014	0.055
	(0.097)	(0.107)	(0.088)	(0.087)
$\hat{\gamma}_i$	0.070**	0.068*	0.016	-0.007
	(0.029)	(0.031)	(0.032)	(0.040)
constant	-0.074***	1.930	-0.030	3.388
	(0.017)	(1.896)	(0.015)	(1.836)
control variables	N	Y	N	Y
R^2	0.026	0.040	0.033	0.079
N	923	923	923	923

Notes.
Employer-sponsored sample are those who only have 401(k) type accounts at Vanguard.

Table 2-A12. Stock Shares Versus Cardinal Proxies for Preferences and Beliefs. Individual-client subsample

	LHS variable: survey measure of stock share in total financial wealth		LHS variable: administrative measure of stock share in Vanguard	
	(1)	(2)	(3)	(4)
$\hat{\mu}_i$	0.059***	0.055***	0.041***	0.036***
	(0.010)	(0.012)	(0.011)	(0.009)
$\hat{\sigma}_i$	-0.075	-0.089	-0.091	-0.112*
	(0.051)	(0.055)	(0.051)	(0.046)
$\hat{\gamma}_i$	0.027**	0.024*	0.012	0.013
	(0.010)	(0.010)	(0.010)	(0.011)
constant	0.024**	1.099*	0.011	0.765
	(0.009)	(0.525)	(0.007)	(0.570)
control variables	N	Y	N	Y
R^2	0.016	0.032	0.008	0.028
N	3491	3491	3491	3491

Notes.
Individual-client sample is the complement of Employer-sponsored sample.

Table 2-A13. Stock Shares Versus Cardinal Proxies for Preferences and Beliefs. Share of wealth at Vanguard at least 50 percent

	LHS variable: survey measure of stock share in total financial wealth		LHS variable: administrative measure of stock share in Vanguard	
	(1)	(2)	(3)	(4)
$\hat{\mu}_i$	0.057***	0.053***	0.045***	0.044***
	(0.015)	(0.013)	(0.011)	(0.011)
$\hat{\sigma}_i$	-0.139*	-0.131	-0.008	-0.018
	(0.067)	(0.076)	(0.055)	(0.053)
$\hat{\gamma}_i$	0.035**	0.038*	0.029*	0.029**
	(0.012)	(0.015)	(0.012)	(0.014)
constant	0.005	0.776	-0.032***	1.193
	(0.009)	(0.870)	(0.007)	(0.756)
control variables	N	Y	N	Y
R^2	0.020	0.034	0.018	0.042
N	1909	1909	1909	1909

Table 2-A14. Stock Shares Versus Cardinal Proxies for Preferences and Beliefs. Share of wealth at Vanguard at least 70 percent

	LHS variable: survey measure of stock share in total financial wealth		LHS variable: administrative measure of stock share in Vanguard	
	(1)	(2)	(3)	(4)
$\hat{\mu}_i$	0.058***	0.054**	0.060***	0.058***
	(0.016)	(0.017)	(0.013)	(0.013)
$\hat{\sigma}_i$	-0.127	-0.107	-0.018	-0.008
	(0.084)	(0.075)	(0.061)	(0.067)
$\hat{\gamma}_i$	0.041**	0.045**	0.036**	0.039**
	(0.013)	(0.015)	(0.012)	(0.014)
constant	0.004	0.470	-0.046***	0.698
	(0.015)	(1.225)	(0.012)	(1.032)
control variables	N	Y	N	Y
R^2	0.019	0.036	0.003	0.061
N	1241	1241	1241	1241

Table 2-A15. Stock Shares Versus Cardinal Proxies for Preferences and Beliefs. Households with directly held stocks

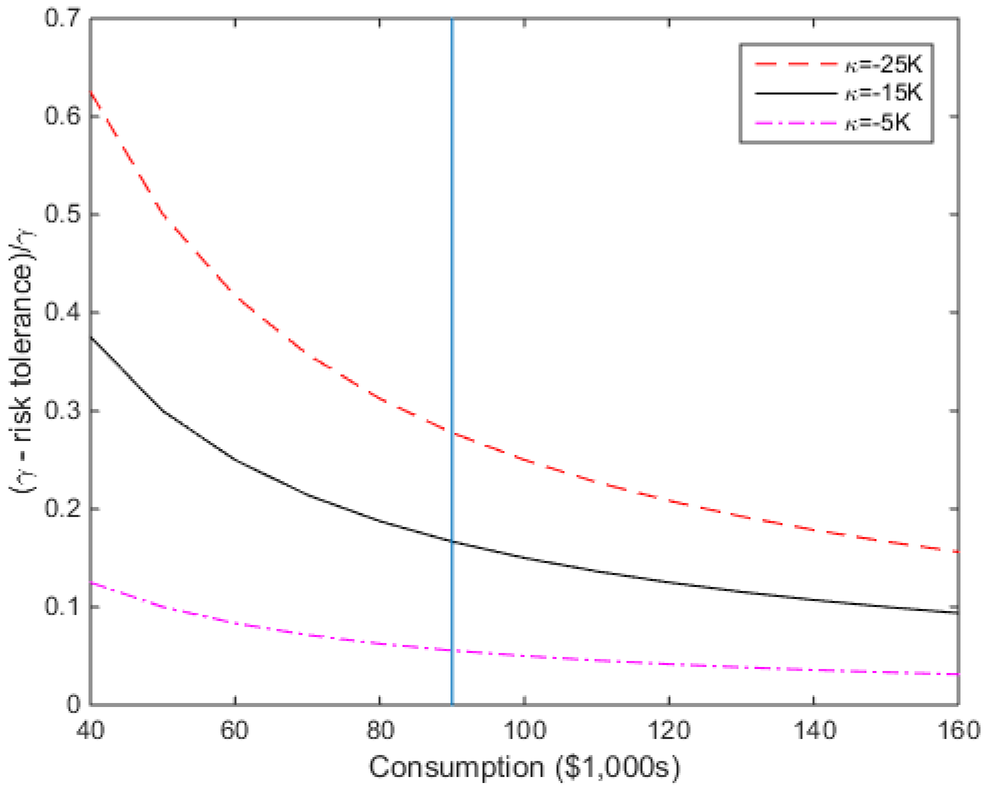
	LHS variable: survey measure of stock share in total financial wealth		LHS variable: administrative measure of stock share in Vanguard	
	(1)	(2)	(3)	(4)
$\hat{\mu}_i$	0.051*	0.067**	0.045*	0.039*
	(0.024)	(0.023)	(0.020)	(0.019)
$\hat{\sigma}_i$	-0.147	-0.136	-0.169	-0.095
	(0.156)	(0.126)	(0.149)	(0.107)
$\hat{\gamma}_i$	0.023	0.022	-0.001	0.011
	(0.017)	(0.024)	(0.030)	(0.036)
constant	0.070***	1.321	0.045*	3.797**
	(0.018)	(1.771)	(0.018)	(1.600)
control variables	N	Y	N	Y
R^2	0.013	0.026	0.011	0.042
N	639	639	639	639

Table 2-A16. Observed stock shares and theoretically optimal stock shares. Attenuation to belief heterogeneity.

	Survey Stock Share		Administrative Stock Share	
	(1)	(2)	(3)	(4)
λ	0.063***	0.059***	0.052***	0.049***
	(0.010)	(0.010)	(0.008)	(0.008)
control variables	N	Y	N	Y
R^2	0.015	0.042	0.012	0.038
N	4414	4414	4414	4414
p-value of Wald test on restriction	0.605	0.520	0.386	0.644

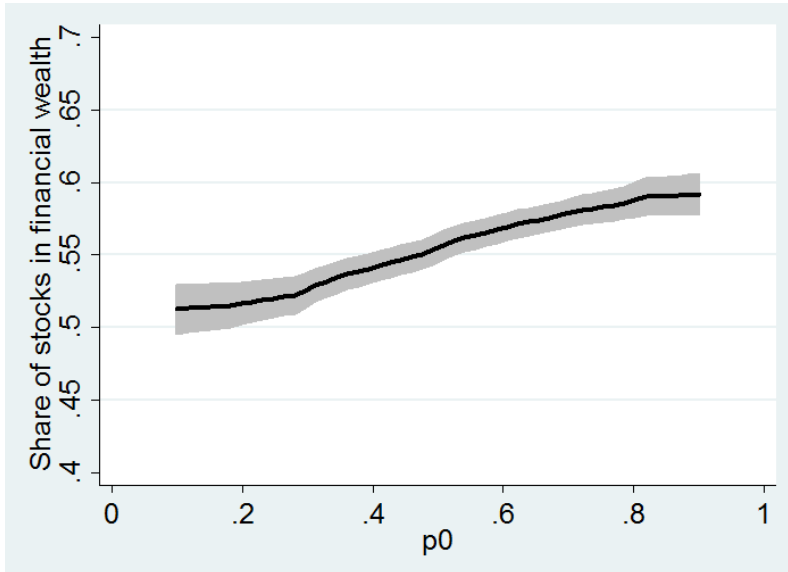
Notes. Regression results from equation (12), imposing $\beta_1^0 = 1$, $\beta_2^0 = -2$, and omitting risk tolerance term ($\lambda\beta_3^0 \frac{\gamma_i - \bar{\gamma}}{\bar{\gamma}}$). The correlation between the distribution of the risk tolerance parameter and that of belief parameters is estimated to be negligible (see Table 2-A5 and A6), so omitting risk tolerance term does not affect inferences on the effect of belief heterogeneity. λ in this exercise can be interpreted as the attenuation factor to belief heterogeneity only.
Bootstrap standard errors in parentheses. *, **, and *** implies significance at 5%, 1% and 0.1% level, respectively.

Figure 2-A1. Difference between relative risk tolerance and γ (as a fraction of γ) over different levels of consumption and κ .

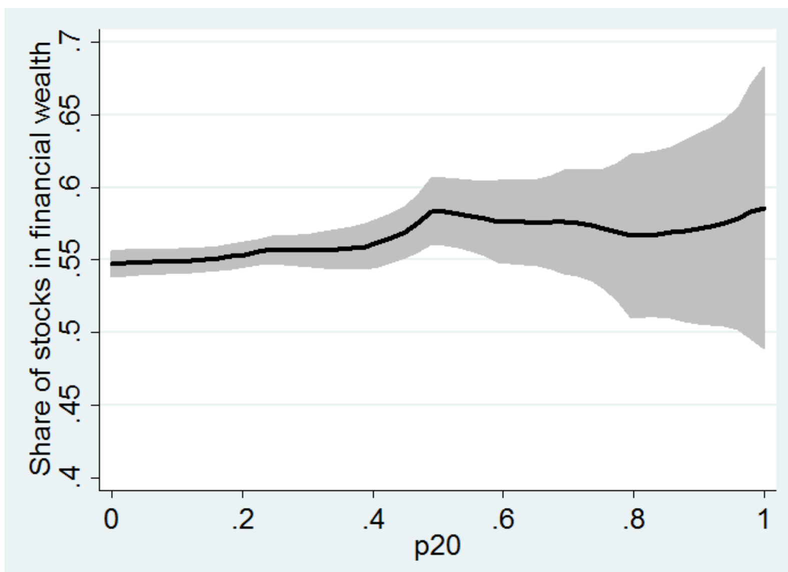


Notes.
The vertical line shows the mean level of household income in the VRI (before retirement), to approximate the average level of household consumption.

Figure 2-A2. Bi-variate non-parametric regression of stock share in total financial wealth on each probability questions on stock market expectation



p0



p20

Appendix 2-B. Details on Structural Estimation Procedure

The distributions of the true latent variables are assumed as (2.8), (2.9) and (2.10) in the main text:

$$\begin{aligned} \mu_i &= \bar{\mu} + u_{\mu i} \\ \sigma_i &= \bar{\sigma} + u_{\sigma i} \end{aligned}, \begin{pmatrix} u_{\mu i} \\ u_{\sigma i} \end{pmatrix} \sim N\left(\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} \sigma_{u\mu}^2 & \rho_{\mu\sigma}\sigma_{u\mu}\sigma_{u\sigma} \\ . & \sigma_{u\sigma}^2 \end{pmatrix} \right) \tag{2-B.1}$$

$$\log(\gamma_i) = \bar{\gamma} + u_{\gamma i},\ u_{\gamma i} \sim N(0, \sigma_{u\gamma}^2) \tag{2.B.2}$$

We allow the beliefs about returns to depend on risk preference, so the covariates of $\bar{\mu}$ and $\bar{\sigma}$ include the latent γ_i.

These latent variables are related to observed survey responses in the following way.

$$\begin{aligned} &\log(\tilde{\gamma}_{ij}) = \log(\gamma_i) + \varepsilon_{\gamma ij} \qquad \text{for } j = 1, 2 \\ &\varepsilon_{\gamma ij} \sim N(0, \sigma_{\varepsilon\gamma j}^2) \end{aligned} \tag{2.B.3}$$

$$\frac{(W+\kappa)^{1-1/\tilde{\gamma}_i}}{1-1/\tilde{\gamma}_i} \ \text{ vs. } 0.5\frac{(2W+\kappa)^{1-1/\tilde{\gamma}_i}}{1-1/\tilde{\gamma}_i} + 0.5\frac{((1-x)W+\kappa)^{1-1/\tilde{\gamma}_i}}{1-1/\tilde{\gamma}_i} \tag{2.B.4}$$

$$\tilde{m}_i = \mu_i + \varepsilon_{mi},\ \varepsilon_{mi} \sim N(0, \sigma_{\varepsilon m}^2) \tag{2.B.5}$$

$$\tilde{p}_{0i} = \Phi(\frac{\mu_i}{\sigma_i} + \varepsilon_{0i}),\ \varepsilon_{0i} \sim N(\psi, \sigma_{\varepsilon p}^2) \tag{2.B.6}$$

$$\tilde{p}_{20i} = \Phi(\frac{\mu_i - 0.2}{\sigma_i} + \varepsilon_{20i}),\ \varepsilon_{20i} \sim N(0, \sigma_{\varepsilon p}^2) \tag{2.B.7}$$

The variables $\tilde{m}_i$, $\tilde{p}_{0i}$, and $\tilde{p}_{20i}$ are before rounding. Actual survey response m_i is a rounded version of $\tilde{m}_i$ as m_i is restricted to take an integer value. Survey responses p_{0i} and p_{20i} are to take a value from the set $\{0,5,10,15,25,35,\ldots,75,85,90,95,100\}$, we assume that $\tilde{p}_{0i}$ and $\tilde{p}_{20i}$ are rounded to the closest values allowed for each response. Also note that the survey does not allow for p_{20i} to be larger than p_{0i}. Hence when we observe $p_{20i} = p_{0i}$, we consider the possibility that the survey response error actually generated $\tilde{p}_{20i} > \tilde{p}_{0i}$ but after imposing the constraint we observe the equality in the actual responses. Together with interval responses, these formulae tell the range of survey response error terms that generate the responses of individual i that we observe, given μ_i, σ_i, and γ_i. The parameter values governing the distribution of the survey response errors allow us to calculate the conditional probability of the joint responses.

The parameters to be estimated are $\bar{\gamma}, \bar{\mu}, \bar{\sigma}, \psi, \rho_{\mu\sigma}, \sigma^2_{u\mu}, \sigma^2_{u\sigma}, \sigma^2_{u\gamma}, \sigma^2_{\varepsilon m}, \sigma^2_{\varepsilon p}, \sigma^2_{\varepsilon\gamma 1}, \sigma^2_{\varepsilon\gamma 2}$. We allow for $\bar{\gamma}$, $\bar{\mu}$, $\bar{\sigma}$, and ψ to vary with covariates.

Algorithm of likelihood function calculation

We use the Gaussian quadrature approximation of the normal distribution to numerically integrate the density functions over multiple dimensions. Let θ be the vector of parameters. Given a fixed θ_0 the likelihood function is calculated through the following algorithm:

(1) Based on the parameter values that govern the true belief and preference parameter distributions in θ_0, and using Gaussian Quadrature approximation, generate K nodes $\{\mu_k, \sigma_k, \gamma_k\}_{k=1}^K$ of belief and preference parameters, with corresponding probabilities $\{\pi_k\}_{k=1}^K$ such that $\sum_{k=1}^K \pi_k = 1$.

(2) For each $\{\mu_k, \sigma_k, \gamma_k\}$ and each individual, calculate $[\varepsilon_{mi}^{low}, \varepsilon_{mi}^{high}]$, $[\varepsilon_{0i}^{low}, \varepsilon_{0i}^{high}]$, $[\varepsilon_{20i}^{low}, \varepsilon_{20i}^{high}]$, $[\varepsilon_{\gamma 1i}^{low}, \varepsilon_{\gamma 1i}^{high}]$, $[\varepsilon_{\gamma 2i}^{low}, \varepsilon_{\gamma 2i}^{high}]$ such that survey response error terms realized in these ranges generate the observed responses after rounding and corresponding constraints.

(3) For each $\{\mu_k, \sigma_k, \gamma_k\}$ and each individual, calculate the joint likelihood of the realization of the error terms in the range found in (2), using Gaussian CDF under the parameter values governing the error term distributions in θ_0. Let π_{ki}^{ε} denote this joint likelihood.

(4) The likelihood for each individual is calculated as integration over *k* nodes as following:

$$L_i = \sum_{k=1}^{K} \pi_{ki}^{\varepsilon} \pi_k \tag{2.B.8}$$

Then the joint likelihood is calculated as products of L_i over individuals.

Calculation of the proxy variables

Under the estimated parameters, the proxy variables are calculated as expected values conditional on the observed responses. The individual-specific proxy variables are obtained using the econometric model outlined above. The likelihood function of the model specifies the probability distribution of the observed responses conditional on the latent beliefs and preferences. The distribution of the latent variables conditional on the observed responses can be obtained from the likelihood function using Bayes' theorem. Integrating out this function yields the individual-specific proxy variables ($\hat{\mu}_i$, $\hat{\sigma}_i$ and $\hat{\gamma}_i$) as the conditional expectations of the latent variables given the observed survey responses. We use the same numerical approximation for this calculation. Using the Bayes' Rule, $\hat{\theta}_i$ is calculated as:

$$\hat{\theta}_i \equiv E[\theta_i \mid m_i, p_{0i}, p_{20i}, SSQ_{1i} SSQ_{2i}] = \frac{1}{L_i} \sum_{k=1}^{K} \theta_k \pi_{ki}^{\varepsilon} \pi_k \ . \tag{2.B.9}$$

Appendix 2-C. Details on Structural Life-Cycle Model of Portfolio Choice

Health Transition and Preferences The model starts from age 55, which is the lowest value in the VRI, and the household can live up to age 110 at most.[27] The probability of survival up to next period $(1-\pi_D)$ is a function of age. The household evaluate flow utility from the consumption using (2.1). It discounts next period utility by time discount factor β. When it dies, it leaves the bequest, and bequest utility is modeled as:

$$U_{Beq,i}(B)=\theta_{Beq}\frac{(B+\kappa_{Beq})^{1-1/\gamma_i}}{1-1/\gamma_i} \tag{2-C.1}$$

where θ_{Beq} determines the strength of the bequest motive and κ_{Beq} determines whether it is necessity or luxury, compared to its own consumption.

Labor Income Process The household retires at age 65. Until then, the labor income is exogenously determined as:

$$\log(Y_{it})=\log(\bar{y}_i)+\nu_{it},\ \ \nu_{it}\sim N(0,\sigma_\nu^2)\text{ for }t<65. \tag{2-C.2}$$

Given that households have only 10 years until retirement in this model, we abstract from permanent income shocks. After retirement, the household receives annuity income which captures Social Security income and defined benefit pension income and hence is not exposed to any uncertainty. This annuity income is modeled as a fraction (λ) of the mean income before retirement:

$$\log(Y_{it})=\log(\lambda)+\log(\bar{y}_i)\text{ for }t\geq 65. \tag{2-C.3}$$

[27] To avoid the complications arising from the joint survival process, we assume that the household dies when the head dies. Essentially, the model is looking at the single households' portfolio choice. Stock share regression using singles only give the essentially the same results as our baseline results using the full sample.

Financial Assets Households can invest in two different assets, a riskless asset and a risky asset where the latter represents stocks. The gross real return on a risk free asset is set as a constant $\bar{R}_f$. The subjective belief on distribution of the real gross return on a risky asset, R_t, is modeled as:

$$R_{t+1,i} = \mu_i + \eta_{t+1}, \ \ \eta_{t+1} \sim N(0, \sigma_i^2) \quad \text{(2-C.4)}$$

where η_{t+1} is an i.i.d. stock return shock. Note that this subjective belief process is heterogeneous across households. We assume that the aggregate stock return shock is uncorrelated with the idiosyncratic labor income shock, following Cocco, Gomes and Maenhout (2005).

Optimization problem of the households Let W_{it} be beginning-of-period cash in hand of a household and α_{it} be share of savings of this period invested to stocks. We assume that short sales and leveraged stock holdings are not allowed.[28] Then the household solves the following optimization problem (we drop the subscripts *i* and *t*):

$$\begin{aligned} V(W,t) = \max_{C,W',\alpha} \ & \{U(C) + \beta E[(1-\pi_D(t))V(W',t+1) + \pi_D(t)U_{Beq}(W')]\} \\ s.t. \ \ & \mathrm{W}' = [(W-C)((1-\alpha)\bar{R}_f + \alpha R_s)] + y' \\ & \mathrm{C} \le W \\ & \alpha \in [0,1] \end{aligned} \quad \text{(2-C.5)}$$

Computation We solve for the optimal policy function numerically using backward induction. The last period (at age 110) maximization is a static one so the value function is trivially obtained. This value function is used as a continuation value for the maximization program of

[28] Optimal stock share could go over 100% if we allowed leveraging, since labor earnings and retirement income are close substitutes to the risk-free asset, due to zero correlation with stock return for the former and the absence of risk for the latter. In addition, when we approximate the labor income process as a discrete process, even the worst possible realization of income guarantees positive resources net of the subsistence level of consumption (as in Cocco, Gomes and Maenhout (2005)) since mean level of labor income is much higher than the subsistence level of consumption.

the penultimate period. We repeat this until we solve for the maximization problem at the first period. For the choice over continuous spaces, i.e. over C and α, the optimization is done using grid search. With the curvature parameters the problem is no more homogenous to the scale, so it cannot be normalized as typically done in the literature (see Cocco, Gomes and Maenhout (2005) and Pang and Warshawsky (2010) for example). This does not increase computational burden too much since we abstract from permanent income shocks.

Calibration We solve this model for various sets of subjective belief and risk tolerance parameter values that are in the range supported by the evidence from the VRI, to understand the effects of heterogeneous belief and preference on the optimal stock share. The curvature parameter for the ordinary utility function (κ) is fixed at the value estimated from the VRI (-17K). Time discount factor (β) is set to be 0.96, a value that is typically used in the literature for annual models.

The probability of survival π_D is estimated from the HRS (1994 – 2010). For the parameters for the bequest utility function we use the median values ($\theta_{Beq} = 32,\ \kappa_{Beq} = 64K$) from Ameriks et al. (2015) who estimate heterogeneity in preferences regarding long-term care expenditure and bequests. The parameters imply that a bequest is a luxury good compared to the ordinary consumption, but once the bequest motive kicks in for wealthy households the marginal utility from leaving bequest is large. Risk free return ($\bar{R}_f$) is set to be 1.02. In the baseline model we use $90,000 for the mean income before retirement ($\bar{y}$) and assume 0.5 for the replacement rate after retirement (λ). These values are close to means from the VRI data. The variance of transitory income shocks (σ_{ν}^{2}) is set to be 0.07, which is close to the value used in Cocco et al. (2005).[29]

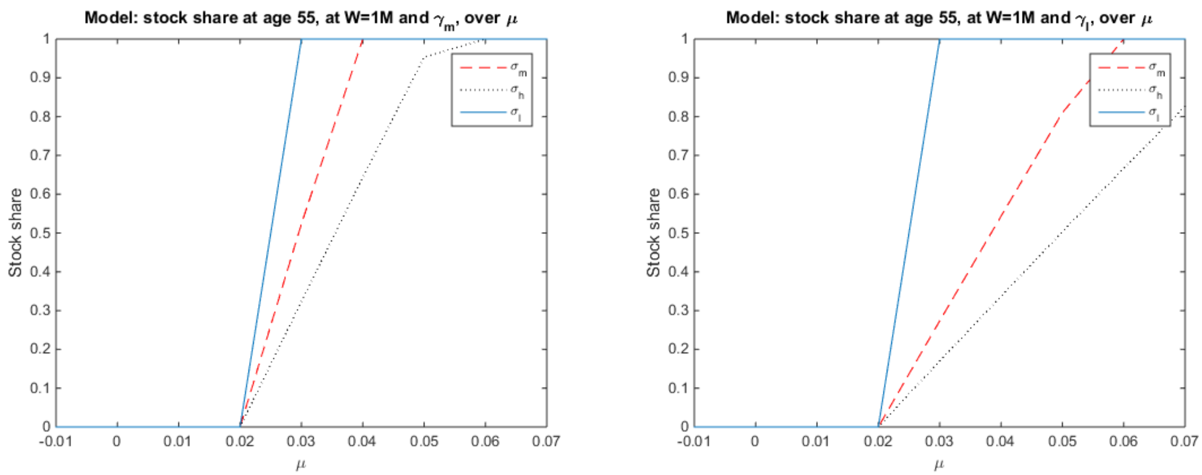
Table 2-C1 summarizes the calibration of the parameters, and figure 2-C1 summarizes the results.

[29] They estimated it to be 0.058 for college graduates. We set it slightly larger here given that our model does not have permanent income shocks.

Table 2-C1. Calibration of Parameters for the Life-Cycle Model

Parameters	Value	Target/Source
κ	-17K	VRI estimation
β	0.96	Standard
π_D		HRS estimation
$\bar{R}_f$	1.02	Cocco, Gomes and Maenhout (2005)
θ_{Beq}	32	Ameriks et al. (2015)
κ_{Beq}	64K	Ameriks et al. (2015)
$\bar{y}$	$80,000	VRI data
λ	0.5	VRI data
σ_v^2	0.07	Cocco, Gomes and Maenhout (2005)

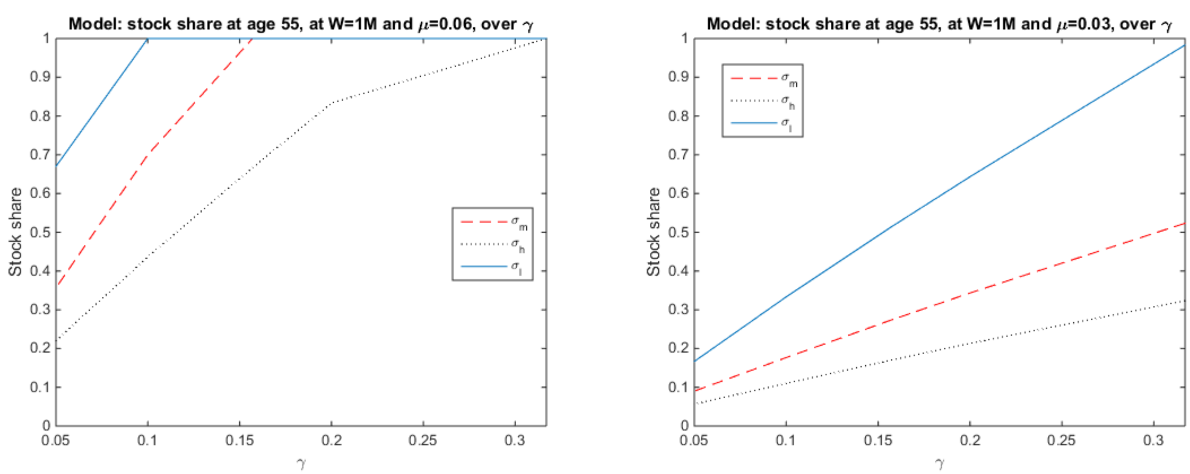
Figure 2-C1. Stock share and the expected value of stock returns (μ) at different levels of the standard deviation of stock returns (σ) and risk tolerance (γ). Results from the life cycle portfolio choice model.



Portfolio choice model,
medium level of risk tolerance (γ = 0.32)

Portfolio choice model,
low level of risk tolerance (γ = 0.16)

Figure 2-C2. Stock share and the risk tolerance (γ) at different levels of the standard deviation of stock returns (σ) and expected value of stock returns (μ). Results from the life cycle portfolio choice model.



Portfolio choice model,
medium level of expected return (μ = 0.06)

Portfolio choice model,
low level of expected return (μ = 0.03)

Chapter 3. The Wealth of Wealthholders

3.1 Introduction

As defined benefit pension plans become rare and as the generosity of a pay-as-you-go Social Security system becomes increasingly limited by aging of the population, households are increasingly responsible for financing their own retirement. Hence, understanding how individuals' financial assets affect their retirement decisions and well-being in retirement is of utmost importance for understanding behavior and the welfare of the retired population, as well as policy changes that may affect them. Though the transition from a defined benefit to a defined contribution retirement system has been underway for decades, about half of households approaching or in retirement have relatively low financial assets. Datasets designed to represent the population, therefore, have surprisingly little information on older Americans with wealth sufficient to finance a non-trivial fraction of their retirement consumption. Our research fills this gap by producing an innovative new dataset containing a large number of households with significant financial assets to potentially use in retirement. To highlight the value of these new data, the paper shows that the relationship between wealth and retirement plans differs dramatically over the range of wealth that is sufficient to sustain consumption in retirement compared to that in the population reflected in standard datasets such as the Health and Retirement Study and the Survey of Consumer Finance.

This paper presents results from a collaboration between the Vanguard Group, Inc. and academic researchers to provide measurements and analysis surrounding the behavior, preferences, expectations, and information of older Americans managing spending in retirement. Specifically, the paper presents findings from the Vanguard Research Initiative (VRI), which provides high-quality, linked administrative and survey data on a large sample of households that face or will soon face the problem of managing assets in retirement. The VRI attempts to improve on measurements from surveys that are justifiably called the gold standard for wealth measurement—namely, the Health and Retirement Study (HRS) and the Survey of Consumer Finances (SCF)—along multiple dimensions:

- First, we target the population of interest—i.e., older Americans with nontrivial financial assets. Even though the overall sample sizes are similar, the HRS and SCF actually have relatively small samples of the population of interest. The HRS—since it is representative of the entire age-eligible population—has many respondents with trivial wealth. The SCF—since it is representative of the overall population—has many respondents who are younger.

- Second, using a combination of administrative and survey data, we can address the question of whether—apart from having non-negligible wealth—the Vanguard population is different from the overall population. We draw respondents from two lines of business—those with individual and those with employer-sponsored accounts. We find that, especially for the employer-sponsored sample, the Vanguard population is broadly representative of the U.S. older population with non-negligible financial wealth and Internet eligibility. The VRI is broadly representative of households in the upper half of the wealth distribution.

- Third, we take a comprehensive account-based approach to measuring assets. Under this approach, respondents are asked to report their financial assets account-by-account. The aim of this approach—which is used selectively in the HRS and SCF—is to get information from respondents in the form that they have it or think of it rather than by requesting responses using accounting or economic categories that may not be meaningful to them.

- Fourth, we employ a set of survey techniques designed to elicit more accurate survey measures of financial assets. Respondents give meaningful nicknames to their accounts. The survey provides a summary of accounts and balances at various stages, so respondents can check whether they missed or double-counted accounts or misreported balances. Respondents can then make corrections without having to reenter correct items.

- Fifth, we use the administrative data to validate the survey responses. We are able to show that our novel survey approach provides unbiased measures of the level of assets as opposed to the understatement typically observed in survey responses. Additionally, we can show that our correction mechanism does reduce the variance of response errors.

Given the cost and difficulty of collecting asset data from respondents, our use of account data and survey data in tandem provides a roadmap for augmenting or replacing survey-based measures of assets in large-scale surveys. Therefore, in addition to its specific findings, this paper documents and analyzes an approach that could be applied very broadly for improving measurement of wealth.[1]

This paper shows the importance of having ample observations in the relevant range of wealth by analyzing non-linear relationship between wealth and retirement horizon. There is a puzzling finding in the literature on wealth and retirement: even following very large stock market declines—such as in 2000 to 2002 and 2007 to 2009—changes in wealth have either a small or no effect on retirement or on retirement plans of older Americans. Comparing changes in retirement rates between defined-contribution (DC) and defined-benefit (DB) pension holders for the period 1992–1998 using the HRS, Sevak (2002) finds that DC pension holders tended to reduce retirement age more during the stock market boom in the 1990s. Coronado and Perozek (2003) and Kthitatrakun (2004), by comparing expected and actual retirement age, show that a wealth gain caused by a stock market boom reduces retirement age compared to households' previous expectations. In contrast, Goda, Shoven and Slavov (2012), Hurd, Reti and Rohwedder (2012) and Kezdi and Sevak (2004), using risky asset holdings in the HRS data as a measure of exposure to the stock market, estimate the wealth effect on the retirement decision and find no evidence of such an effect. Coile and Levine (2004) focus on aggregate labor supply measures from the HRS and Current Population Survey and also find no evidence. Using pre- and post-crash interviews from the CogEcon survey conducted in 2007 and 2009, McFall (2011) finds a

[1] This research is therefore related to an emerging program to augment or replace survey data with administrative records, including private account data. See Gelman et al. (2014) for high-frequency spending and income data; Kapteyn and Ypma (2007) for earnings data; Agarwal, Liu, and Souleles (2007) for credit card data to measure the response of spending to income; Aguiar and Hurst (2007) for linking administrative data on price paid to survey data on demographics and time use. For the difficulties of measuring wealth and earnings in surveys, see Juster and Smith (1997). For systematic bias in economic measurement in surveys, see Gorodnichenko and Peter (2007) and Hurst, Li, and Pugsley (2014). See Krimmel, Moore, Sabelhaus, and Smith (2013) for problems with the timeliness of asset data, which are addressed by the VRI approach.

relationship between wealth change and retirement age in the expected direction, though the estimated size of the effect is modest.[2]

The VRI is designed to have greater power to detect these effects by collecting a large amount of high-quality asset data for households where such changes in wealth might be more relevant. Therefore, it addresses the problem, identified by Poterba (2014), Poterba, Venti, and Wise (2011) and Gustman, Steinmeier and Tabatabai (2010), that in the survey datasets commonly used in this literature, most households do not have significant retirement wealth or stock market exposure. In this paper, we estimate the relationship between wealth and retirement plans in the VRI, HRS, and SCF. We demonstrate that this relationship is highly non-linear and that we can estimate the effect of wealth at the relevant range of wealth levels to be significant only when we have dense observations in that range. We then show, for households with enough wealth to typically have significant stock market exposure, that the expected retirement horizon varies significantly with wealth.

Admittedly, such estimates from the VRI are “out of sample” for the population of older Americans in the US—about half of whom have little wealth and little exposure to the stock market. Making such out-of-sample inferences is precisely the aim of the VRI. As noted at the outset of the paper, policy changes and changes in employer offering of pensions are pushing older Americans to save and invest for their retirement through 401(k) and similar accounts. To understand the ultimate effects of this transformation of the retirement landscape, data such as those from the VRI are essential. There is the concern, however, that the VRI respondents are different—not just because they have significant retirement savings, but because they are

[2] Some studies use other sources of variations in wealth changes. Imbens, Rubin and Sacerdote (2001) use lottery windfall gains, while Holtz-Eakin, Joulfaian and Rosen (1993) use inheritance information in IRS data and Joulfaian and Wilhelm (1994) use inheritance data in the PSID. Estimated effects are mostly modest, with the exception of Holtz-Eakin, Joulfaian and Rosen (1993), who find a sizeable effect.

different from the population in terms of their demographics, socioeconomic status, or other characteristics. Are Vanguard clients so special that they are not a valid population for drawing inferences more generally? We address this question head-on in the paper. We show that Vanguard clients are different from the HRS and SCF respondents mainly because they have more financial wealth. For HRS and SCF respondents of similar wealth, education and other attributes are not that different. This is particularly true in the subsets of HRS and SCF respondents with 401(k) plans, compared to the Vanguard employer-sponsored sample. Our approach to sampling Vanguard respondents—drawing separately from individual clients and those in employer-sponsored plans—substantially obviates concerns about selection. The VRI employer-sponsored sample has a retirement/wealth relationship that looks quite similar to the overall VRI sample. We conclude that the findings from the VRI are driven by having dense observations of households with significant levels of wealth and stock market exposure, not by differences in households that select Vanguard as a financial institution.

3.2 Innovations in Wealth Measurement: Vanguard Research Initiative (VRI) Approach

What makes the VRI innovative? First, it surveys financial wealth by accounts, not by asset classes. Its aim is to ask respondents to report numbers that closely correspond to how they receive statements and to how they might classify assets. The approach avoids asking respondents to map their balances into accounting or economic constructs, and does not require them to do addition or distribution of amounts. Second, after each step where the survey instrument elicits the composition or amount of assets, it shows a summary of responses in tabular form and allows respondents to modify their answers. Third, the survey is integrated with administrative data. Administrative data create the sample frame, allow validation of survey responses, and create a high-frequency panel of asset data. In this section of the paper, we describe the design of the VRI sample and how the wealth measurements are implemented in the VRI survey.

Table 3.1 shows in tabular form the main survey design elements and how they compare with those of the HRS and SCF. Section 3.4 provides a detailed comparison of these surveys.[3]

3.2.1. The VRI Sample Design

The administrative data and, more generally, the collaboration with Vanguard are critical in achieving the VRI objective of creating a large sample of older wealthholders. By construction, Vanguard clients have some wealth. Additionally, information in the Vanguard administrative data on customer type, account balances, age, geography, and use of the Internet are all essential for creating the sample. This information allows us to reach a large population of relevant households.

The population for the VRI is Vanguard Group account holders aged 55 and older who are Web-survey eligible (must be registered for use of the Vanguard website, have a valid email address, and have logged on in the past six months). We stratified the sample based on the following characteristics from the administrative data: individual versus employer-sponsored accounts; age; and administratively-single status. We sampled evenly from five-year age intervals from 55 to 74 and from 75 and above. For those under 65, we divided the sample evenly between the two client types. After age 65, those in the employer-sponsored line tend to exit this group as they roll over their employer-sponsored accounts into IRAs accounts (either at Vanguard or elsewhere). For this age group, we sample the types in the proportion they appear in the population.

[3] Ameriks et al. (2014) describes the VRI in greater detail. Readers interested in the specifics of sampling, testing, and design, as well as in more-detailed tabulations, are referred to that paper.

A variety of research questions are more difficult to answer in the context of multi-person households. There are relatively few single households in the Vanguard population. Thus, we felt it useful to oversample singles to secure an adequate sample size of singles. The administrative data contain an imperfect indicator of single status. In particular, Vanguard constructs a household indicator by using common address and joint registration. Being in a single-member household using this indicator is strongly, but not perfectly, correlated with the survey measure of single status. Using information on the relationship between the survey and administrative measures of single status in a pilot survey, we increased the sampling rate of administratively-single accounts in the production survey. See Ameriks et al. (2014).

These sampling criteria are all imposed *ex ante* based on the administrative data. To draw the sample that we invited to complete the survey, we randomly selected from the specified populations of account holders. We monitored our success at hitting the desired sample proportions, but made no adjustments after drawing the sample. We did not impose quotas of any kind on responses.

3.2.2. Survey Measurement of Wealth in the VRI

A key innovation of the VRI approach is to elicit assets on a comprehensive, account-by-account basis. This section describes this approach. The next section will show that it yields highly accurate measurements of assets.[4] Appendix 3-A shows screen shots of the wealth section for a hypothetical respondent. The steps in the wealth section are as follows.

[4] The VRI approach is unique in taking a comprehensive, account-based approach to wealth measurement. The HRS and SCF take approaches that mix the account- and asset-class approaches. For non-retirement assets, the HRS asks respondents to aggregate the balances across accounts into the following asset classes: stocks and stock mutual funds; bonds and bond mutual funds; checking, savings, and money market accounts; and CDs, government bonds, and Treasury bills. The SCF takes a mixed approach. For checking, savings/money market, and mutual funds, it asks for the number of accounts and the balance for each account. For CDs, savings bonds, individual stocks, and brokerages, it asks for asset-

Step 1: Account Type. The respondents are shown a list of 15 account types divided into groups. The rows in Table 3.2 after Total Financial Assets show the types. The major groups are "Tax deferred-retirement accounts" (IRA, employer sponsored plans, pension with account balance, and other retirement assets); "Savings/Investment accounts that are not in a tax-deferred retirement plan or account" (checking, savings, money market mutual funds, CDs, brokerage, and directly held securities); "Insurance-related accounts" (annuities with cash value and life insurance with cash balance); "Educational accounts"; and "Other." The survey displays a table with these account types and a checkbox for having each type.

Step 2. Number of accounts. The survey shows a list of account types that the respondent has checked in step 1. The respondent is asked to indicate the number of each type of account using a drop-down menu.

Step 3. Nicknames of accounts; verification. The survey then shows a list of accounts. The respondent is asked to give a nickname for each account. After the respondent enters all the nicknames, the survey displays a summary table (see Appendix 3-A, Figure 3-A4). Respondents are then asked whether all the information is correct. If not, they are asked whether they want to correct the list of accounts (either add or delete an account type or change the number of accounts for any type). Depending on their answers, they are brought back to either step 1 or step 2.

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class totals as in the HRS. For IRAs, it asks for an inventory of types of IRA (regular, Roth, rollover) and then asks for total by type.

For pensions, the HRS and SCF take a pension-by-pension approach. The SCF household head reports up to three separate pension accounts for each household member; the HRS respondent and spouse report up to three separate pension accounts. The HRS 2012 has taken a step toward creating a longitudinal record of pensions. The HRS asks about IRAs (up to three accounts per respondent and spouse) as part of the pension module. The bifurcated structure of the HRS wealth measures (household basis for non-retirement assets and individual basis for pensions and retirement accounts) results from a strategic design decision made at the outset of the HRS to collect pension data as part of the labor section rather than the wealth section.

Step 4. Balances. The survey then loops over accounts. Respondents are asked to input the balance of each account by its nickname.

Step 5. Summary table of balances; verification. The survey displays a summary table of accounts as well as a total (see Figure 3-A6). For each account, there are checkboxes for "referred to records." There is also a checkbox at the bottom of the table that asks whether everything is correct. If the respondent checks "No, I need to go back and make an update," the screen updates with two checkboxes asking whether the respondent needs to add/delete accounts or correct the dollar amount. (Both can be checked. See Figure 3-A7.) If the respondent indicates a need to correct amounts, the account summary table updates with a new column of checkboxes asking which need to be corrected. (See Figure 3-A8.) The survey asks only for the required corrections. Specifically, if the respondent clicks on the "add/delete account" box, they are taken back to step 1 with all previous responses pre-filled. On the other hand, if the respondent needs to correct only the amounts, the survey returns to step 4. Once the respondent returns to step 5, the respondent is again asked if the answers are correct and again allowed to make corrections. There is no limit on the number of times respondents can go through the correction sequence.

After the respondent indicates that the summary table of balances needs no correction, the survey presents follow-up questions about the composition of the accounts. First, for accounts other than saving/checking/MMMF, the respondents are shown the table with balances and asked to enter the share of stock held in each account. The table updates and translates the share into dollars of stock for each account.

Finally, the respondent again sees the table with balances. The table presents a checkbox for indicating whether or not each account is held at Vanguard. This table excludes account categories not offered at Vanguard (e.g., life insurance). This step enables comparison of responses with the administrative data.

At the end of the wealth section, the survey displays a summary table of financial wealth combined with two pie charts showing the stock share in the overall portfolio and the share of wealth at Vanguard (see Figure 3-A13 for an example). The survey prompts respondents to print out this page, if desired. This summary was provided in the hope that this potentially useful measurement for survey respondents would increase the likelihood of their continued participation in the survey.

3.2.3. Summary of VRI Wealth Measurements

Table 3.2 summarizes the distribution of financial assets from the survey. The mean of total financial assets (sum of accounts surveyed as described above) is over a million dollars. The median is about $660,000. Other than checking accounts, IRAs are the most common asset class and account for about one third of total assets. Employer-sponsored plans are by construction held by almost all employer-sponsored plan respondents, but are also common among individual Vanguard account holders. Similarly, mutual funds and brokerage accounts are significant non-retirement assets in the population of Vanguard account holders.

Ameriks et al. (2014) describes how we collected data on non-account-based assets (housing, businesses, etc.). That paper also describes in greater detail the findings from the account-by-account approach. Notably, respondents were perhaps surprisingly willing to provide details on many accounts. The median respondent provided information on seven accounts. One quarter provided information on 12 or more accounts. The respondents were also willing to refer to records, with the strong majority referring to records for all accounts. Hence, it appears that our approach gives us a comprehensive and accurate measure of assets. We provide evidence for that contention in the next section.

3.3 Comparing Administrative and Survey Measures of Assets

A key feature of the VRI is its combination of administrative account data and survey measurements of assets. As discussed above, the administrative data are a powerful tool for obtaining a sample frame for a wealth survey. Additionally, administrative data can supplement survey data by providing alternative measures of wealth, potentially at very high frequency. The administrative data also can be used to verify the survey measures. This section of the paper investigates the joint measurement properties of the survey and account data both to evaluate the quality of the VRI and to guide future use of administrative account data in surveys.

3.3.1. Quantifying Response Errors

The VRI contains administrative data on the account holders' total wealth and information about its composition. The administrative data, though exact, are not perfect. The linking of accounts to clients might not be perfect, especially for married clients. Additionally, the administrative data are end-of-month, so intra-month transactions and changes in value can cause discrepancies between survey and administrative data. Nevertheless, the administrative wealth data give an unusually good reference point for evaluating the quality of the survey data and vice versa.

The administrative data are, of course, limited to accounts at Vanguard. The survey was designed to capture all assets. To facilitate comparison of survey and administrative data, at the end of the account section of the survey the respondent is shown a table listing each account and the survey report of its balance. Using the same format as shown in Figure 3-A6 (used records), the respondent is asked to check a box indicating whether or not the account is at Vanguard. In this section, the survey measure of Vanguard wealth relies on these survey responses. Figure 3.1 shows the distribution of the survey reports of Vanguard assets relative to the administrative data. For each decile of administrative assets, the figure shows a box and whiskers diagram of the distribution of the survey report of Vanguard assets. The responses are tightly bunched along the 45-degree line, though there are also substantial outliers. There is a slight over-reporting of assets in the survey relative to the administrative data. The fraction over-reported declines as assets increase.

To shed some light on the difference between the administrative and survey measures, Table 3.3 splits the sample by line of business and single status. The first line of each panel shows the survey data, the second line the administrative, the third line the survey minus the administrative data, and the last line the percent difference.[5] For the employer-sponsored sample, the median difference is $890, or 0.6%; for the individual client sample, the median difference is $2,623, or 1.4%. Yet, for both samples, the interquartile ranges of the differences are substantial.

A long-standing concern in wealth measurement is that assets are under-reported—because individuals forget about accounts and because they are reluctant to share account amounts (see Juster, Smith and Stafford (1999)). The VRI, with its account-by-account approach, builds on the insights of Juster and the designers of the HRS and SCF by presenting the respondents with a detailed list of asset types, so that they do not neglect to report certain items.

[5] The administrative data are the weighted average of the end of month before the survey and after the survey with the weight equal to the fraction of the month elapsed on the survey date. Percentage difference is calculated in the following way. Let SW and AW denote the survey wealth and the administrative wealth. Following Davis and Haltiwanger's (1992) formulation from the gross flow literature, we define the percentage difference as $2 \times (SW - AW)/(SW + AW)$. The main advantage of this formula is that it can be applied even when either SW or AW is 0.

Remarkably, the VRI data show no evidence of such under-reporting on average, so this approach appears to be effective.

A potential reason for survey over-reports is that some accounts might not be linked to the survey respondent in the administrative data. Since the administrative records are at the account-holder level, they will not include a spouse's account if it is registered solely under the spouse's name. To address this issue, we conduct the same comparison only for singles, that is, respondents who report in the survey that they are not married or partnered. The results are reported in Table 3.3, Panels C and D. For singles, the tendency to over-report is essentially gone. For the singles in the individual account holder sample, median deviation is almost zero (-0.03%) and the interquartile range of the deviation is -2.9% to 2.2%. The difference is most acute for the individual client sample because employer-sponsored respondents are less likely to have a family-level relationship with Vanguard. In particular, note that the large upper tail of difference in the individual sample is dramatically reduced for singles relative to the overall sample in Panel B.[6]

3.3.2 Corrections and Wealth Measurement

In this section, we examine how the VRI's correction mechanism works to enhance the accuracy of the account data. The survey instrument not only captures the final responses, but also saves the initial answers. Therefore, for respondents who modified their answers after seeing the summary tables, we can check whether or not their answers got closer to the administrative data. Figure 3.2 summarizes the paths respondents took through the wealth section given that they have multiple opportunities to correct their account inventories and balances:

[6] We are also able to examine whether checking records matters for accuracy of survey responses. Interestingly, checking records shrinks the deviation of administrative and survey reports, but being logged on to the Vanguard website during the survey does not play a significant role in this result. See Ameriks et al. (2014).

Path 1. No corrections. About two thirds of the sample (62.49%) completed the wealth section without making any corrections.

Path 2. Inventory corrected before balance entered; balance not corrected. About 15% of respondents corrected their inventory (the first checkpoint in step 3 described in Section 3.2.2), but did not correct balances.

Path 3. Only balance corrected. About 11% of respondents corrected their balances (the second checkpoint in step 5) without either previously correcting their inventory or going back to correct after entering balances.

Path 4. Inventory corrected, then balance corrected. About 5% of respondents corrected their inventory, entered their balances and then corrected their balances, but did not go back to revise inventory subsequent to entering balances.

Path 5. Non-sequential corrections. About 6% of respondents made complex corrections. Specifically, these respondents typically went back to the start of the wealth section to correct the inventory of their accounts after having entered balances. Hence, about one third used the correction mechanism in some way.

In Table 3.4, we again show the percentage difference between the survey and the administrative Vanguard wealth, but for the initial and the final survey answers separately. Respondents are grouped according to the correcting paths they took. Again, the comparisons are done only for singles.

When respondents did not make any corrections, their initial responses were already very close to the administrative information. The interquartile range is -3.3% to 2.6% for those who made no corrections; for those who corrected account inventory only, it is very similar, -3.5% to 2.5%. For respondents who corrected their balances, their initial responses seem to be noisier. Though the median percentage difference is close to that of those who do not correct balances, the pre-correction interquartile range for those who correct balances is much larger. After the corrections, however, the width of the interquartile range shrinks dramatically toward that with no corrections. Indeed, the corrected range is a bit smaller than for those who made no corrections at all. Therefore, the correction mechanism did prove to be effective.

3.4 Representing Wealthholders versus Representing Households: VRI, HRS, and SCF

This paper studies households with non-negligible financial wealth approaching or in retirement. The previous sections document that the VRI provides accurate and comprehensive data on this group. This section addresses two interrelated questions. First, why is the VRI needed? The answer is that leading surveys aimed at measuring wealth contain remarkably few respondents in the relevant age range with significant levels of wealth. Second, is the VRI—having achieved the aim of representing such wealthholders in significant numbers—unrepresentative of the population apart from having targeted individuals with non-negligible wealth? We answer these questions through a detailed comparison of the VRI with the HRS and SCF.

3.4.1. Comparing VRI, HRS, and SCF Design

Table 3.1 summarizes and compares the overall features of the VRI, HRS, and SCF. The VRI is composed of Vanguard clients at least 55 years old with non-negligible assets. The HRS is a representative sample of those at least 50 years old and their spouses. The SCF aims to be representative of wealth across all age groups. Because high-wealth individuals are hard to survey, its frame includes a list sample of high-income households. The VRI oversamples singles and, as discussed above, screens for Web-survey eligibility and stratifies the samples by Vanguard line of business. The HRS and SCF do not impose these screens, but we use relevant variables on the HRS and SCF to construct subsets that match VRI sampling criteria.

The last panel of Table 3.1 shows summary statistics for the three surveys for observations that meet the VRI age-eligibility (age 55 years or older). For HRS, we use the age of the financial respondent. The VRI is comparable in size to the HRS in this age range—about 9,000 households in the VRI and about 11,500 in the HRS. The SCF has less than a third the number of respondents in this age range compared to the VRI.

The VRI sample is much more affluent than the HRS or SCF samples. Of course, by design the VRI targets wealth holders while the HRS and SCF are representative, that is, they include the older Americans with very low assets, who are about half the population. The next set of results explores these differences and shows the extent to which they derive from VRI sampling restrictions.

3.4.2. Comparing VRI, HRS, and SCF Respondents

Table 3.5 shows the distribution by wealth and age of raw household counts in the VRI age-eligible range of 55 years and older for the VRI, HRS, and SCF.[7] It reminds us how little financial wealth the lower half of older households has. The total number of observations in the VRI and HRS are comparable, but their distributions of wealth are very different. Ninety percent of the VRI respondents have financial wealth of more than $100,000, and one third of them have more than a million dollars. In contrast, the HRS distribution has a very fat left tail. One third of the HRS sample has a negligible amount of financial wealth (less than $10,000) and only about a third has more than $100,000.

The SCF, which is age-representative overall, has less than a third of the number of observations in the age-eligible range compared to the VRI and HRS. With the list sample of high-income households, the SCF has disproportionately high-wealth respondents. Even so, given that the SCF is not aiming at the population near or after retirement, for most of the wealth-age bins with non-negligible wealth, the number of households in the SCF is much smaller than in the VRI.

The age distributions are also quite different across surveys. The VRI, by construction, has a similar number of observations for age bins 55-64 and 65-74, and about half the size for

[7] The wealth measure used in the comparisons is total net financial wealth. Values of houses and mortgages are excluded. See Appendix 3-B for the definition of the total financial wealth for each survey and how we impose similar sampling screens in the VRI, HRS, and SCF.

age 75+. The HRS has relatively more observations in the oldest age bin, while the SCF has about half in the youngest.

These tabulations illustrate vividly how the VRI is targeted for studying the financial decisions of those approaching or in retirement with non-trivial financial wealth. Given the stark differences in the VRI wealth distribution relative to the population, we need to understand the main determinants of these differences. In particular, *does the relative affluence of the VRI sample derive mainly from our sampling screens or, even taking into account these screens, is a sample based on Vanguard clients very different from the U.S. population*? In the following, we try to disentangle these effects by examining the effect of *VRI eligible* screens in the HRS and SCF. The screen requires Internet eligibility and that households have at least $10,000 in a non-transactional financial account.

These screens are restrictive in the HRS and SCF samples in this age group. Table 3.6 shows how the screens affect the number of eligible households by age. For the HRS and SCF, the first columns of counts impose just age-eligibility. The second columns impose "VRI eligibility" (Internet eligibility and the $10,000 minimum balance in non-transactional financial accounts). The third column imposes "401(k) subset" (at least $10,000 in a DC pension account). Note that these screens are imposed *ipso facto* in the VRI for both employer-sponsored and individual client groups.[8] For the HRS and SCF, the screen yields relatively small subsets of age-eligible respondents. For the HRS, only about a third satisfy VRI eligibility. In the SCF, a relatively larger fraction of households satisfy these conditions owing to oversampling of high-income households. The size of the 401(k) subset group is much smaller in both the HRS and the SCF. In VRI, the age distribution is flat by design. (Everywhere, there are few of the oldest

[8] The two screens in VRI are constructed to be mutually exclusive to avoid inviting respondents twice. Therefore, the second and third columns of VRI counts sum to the first column.

groups represented in the employer-sponsored samples because most retirees roll over their 401(k) to an IRA and therefore are represented in the individual client sample.) In the HRS and SCF, the screen has more of a bite for older groups. See Appendix 3-C for implications for wealth by age.

In Table 3.7, we show that the effects of the VRI screens are similar in the HRS and SCF in terms of weighted sample.[9] Imposing Internet eligibility alone reduces the weighted sample by about half in both HRS and SCF. The asset cut-off has a similar effect. Because these two conditions are highly correlated, there is an only incremental additional effect when taken together. Within the VRI-eligible samples in both the HRS and the SCF, only half of the weighted sample has at least $10,000 in DC pension accounts.

A key question is, after imposing comparable sampling screens, how similar are the characteristics of VRI compared to those of the subsamples of the HRS and SCF? The answer is that they are not so different under VRI-equivalent sampling screens. Table 3.8 shows the wealth distributions from the VRI, HRS and SCF. From this point forward, HRS and SCF tabulations use sampling weights. With only age eligibility, median values from the HRS and SCF are an order of magnitude smaller than the corresponding numbers from the VRI. When we impose the VRI eligibility screen, the gaps are dramatically reduced, though there are still important differences. The remaining gap is smaller if the HRS and SCF subsamples are compared with the employer-sponsored sample in the VRI. The 90th percentile from the VRI-eligible subsample of the SCF is actually larger than the one from the VRI employer-sponsored group. Recall that for

[9] Up to now, we have focused on raw counts of observations in order to give a concrete sense of the size of the samples across the surveys. Since the SCF oversamples high-income individuals, these households are assigned smaller sampling weights. Similarly, the HRS oversamples blacks and Hispanics (in order to make statistically significant inferences by groups) and residents of Florida (because of the cost saving in reaching older respondents there). In the following analysis, all the comparisons are made after weighting observations from the HRS and SCF with the corresponding sampling weights.

the employer-sponsored group the potential self-selection issue is mitigated, since the availability of Vanguard funds in their retirement plan results from their employers' decision making. To more closely mimic the asset cut-off imposed on the employer-sponsored group in the VRI, we also made tabulations on the HRS and SCF subgroup composed of households with at least $10,000 in their 401(k) or similar pension accounts. The results are reported in the third row of the HRS and SCF panels. On average, the 401(k) subset of the HRS is wealthier than the overall HRS VRI-eligible sample, while the 401(k) subset in the SCF is less wealthy. The means of the 401(k) subsets in the SCF and HRS are closer to those of the VRI employer-sponsored sample, though the VRI is less right-skewed. Nonetheless, it is reassuring that there is broad similarity between the 401(k) subsets of the SCF and HRS and the VRI employer sample.

Appendix 3-C provides a more detailed comparison across the surveys. It compares across dimensions including income and demographics. Compared to the total population of the HRS and SCF in the same age range, the VRI sample has much more wealth, a much higher education level, better health, and a greater likelihood of being coupled. Most of these differences, however, can be explained by the effect of the sampling screens we imposed in the VRI panel. What is special about the VRI sample is that it is selected for non-trivial asset holding and use of the Internet. Once these criteria are imposed, the VRI looks quite similar to the upper half of the wealth distribution in the HRS and SCF. There is a bit of residual higher education, better health, and high wealth-to-income ratio in the VRI compared to the relevant HRS and SCF populations. Yet the principal differences between the VRI and the general populations do not appear to be attributable to selection to Vanguard participation *per se*. For the employer-sponsored sample, the differences in the characteristics essentially disappear once VRI-eligible criteria are imposed on the HRS and SCF.

3.4.3. Stock Share

The extent of stock ownership looms large in discussions of how individuals will manage under defined-contribution retirement plans. The VRI wealth survey asks for stock share on an account-by-account basis. Table 3.9 compares the stock share of the VRI with those of the HRS and SCF. Panel A reports stock shares while Panel B reports stock amount. Again, we see the importance of having a relevant sample. Compared to the VRI, if we impose only age eligibility, the HRS and SCF have much lower stock shares across almost all of the distribution. Compared to the median share of 55% in VRI, the median share is 0% in the HRS and close to 0% in the SCF. Conditioning, however, on the VRI sample screens, the median shares in HRS and SCF are still lower, but much closer to those of VRI. The left tail in the HRS still shows less stock ownership, but SCF and VRI are similar across the distribution.[10] The picture is similar with regard to the amounts of stock in panel B of Table 3.9. Hence, as with the level of wealth, the Vanguard respondents are less unrepresentative once the screen is imposed. But again, note that the VRI has a much larger sample of stock holders, so any analysis of portfolios should be much more precise.

3.5 Wealth and Retirement: Lessons from Data on Wealthholders

We have established that the VRI approach leads to substantially larger samples of older households with relevant levels of wealth for many important decisions surrounding retirement and well-being in older age. Having dense observations across the relevant ranges is particularly important if the relationships between wealth and other behaviors are non-linear. Poterba, Venti and Wise (2011) show that for the majority of households surveyed in the HRS, the lack of

[10] Note that the HRS 2012 stock shares in 401(k) or similar accounts are not yet cleaned and imputed, so they are excluded (numerator and denominator) from these HRS stock shares.

demand for additional annuity income simply comes from having very low annuitizable wealth. Similarly, there is a substantial literature on how wealth and shocks to wealth affect retirement (e.g., Sevak (2002), Bosworth and Burtless (2010), Goda, Shoven and Slavo (2012), McFall (2011), and Coronado and Dynan (2012), among others). Again, for the majority of households that approach retirement with little financial wealth, how levels or changes in wealth affect decision-making is a very different question than for those who have significant savings for retirement.

In this section, we demonstrate that for the relationship between expected retirement date and wealth, having data that are dense in the VRI wealth ranges yields substantially clearer inferences than is possible with existing datasets. In particular, we investigate the relationship between current accumulated financial wealth and how long individuals plan to keep working.

The VRI is designed as a panel, though this paper analyzes the first survey. To study the wealth/retirement relationship, we use the relationship between retirement expectations and wealth in the cross-section.[11] Thus, we build on the tradition of using expectations rather than realizations as the outcome variable. See McGarry (2004), Chan and Stevens (2004), and Szinovacz, Davey, and Martin (2014). The use of subjective probability variables relies on substantial experience showing the validity of these measures in the HRS and other surveys. See Dominitz and Manski (1997) and Hurd and McGarry (2002).

[11] The VRI holds the promise to examine reaction to events as the panel builds over time. We do, however, have a panel aspect even with the cross-section of wealth from the survey from the administrative data. We have done some exploratory work using the administrative data panel to examine the effect of the financial crisis on VRI respondents. Note that the VRI was collected in 2013. By then, the stock market had recovered from the 2008/9 decline. By consulting the administrative data, we find that most VRI respondents invested passively over the financial crisis. That is, their stock share moved by roughly the amount consistent with little rebalancing. As a consequence of this prudent investment strategy and the recovery of the market, there is, in fact, little lasting effect of the crisis on VRI respondents’ wealth overall.

3.5.1. Specification

In this section we present an exploratory analysis that is designed to reveal how data such as the VRI can shed light on variables that determine retirement decision-making. The estimates should not be taken as a structural relationship because of the obvious joint determination of retirement and saving.

To measure current financial wealth in a way that is meaningful for thinking about expected retirement, we construct normalized financial wealth W_i^R as

$$W_i^R = (0.06 \times W_i \times (1.03)^{(65-age_i)}) / Y_i$$

where W_i is annuitizable financial wealth, Y_i is current income, and age_i is the current age of the main earner of the household.[12] Normalized wealth is a rough-and-ready measure of how much *current* wealth could replace current income assuming no additional saving. See Brown (2001) for a similar measure, but converting flows to a stock. The calculation assumes a 0.06 annuitization rate and a 3 percent real rate of return. The use of a fixed rate of return and a uniform annuity rate is a simple way to put current wealth of future retirees into common units. We compound returns until age 65 rather than the expected retirement date to avoid putting expected years of work on both sides of the equation. We estimate the relationship

$$H_i = \beta_1(W_i^R)W_i^R + \beta_2 Y_i^R + Z_i\gamma + \varepsilon_i \tag{3.1}$$

where H_i is the difference between the expected age of retirement and current age, W_i^R is normalized financial wealth, Y_i^R is expected DB pension plus Social Security divided by current

[12] Annuitizable financial wealth is the sum of retirement and non-retirement financial assets. To put these on the same tax basis, we use another rough-and-ready approximation. Specifically, we presume a 25 percent average tax rate on withdrawals from qualified plans. Note that we do not have good data separating Roth and non-Roth treatment, so all qualified plans are combined in this calculation. The main findings are robust with respect to the assumed tax rate.

income, and Z_i is a vector of covariates (age, dummies for education and health, and marital status).[13] The coefficient $\beta_1(W_i^R)$ is a potentially non-linear function of normalized wealth.

3.5.2. Variables and Sample for Wealth-Retirement Analysis

We focus on estimates of this relationship in the VRI and HRS. We also show the same analysis using the SCF data, but due to the small number of observations in the relevant age group and lack of some variables used—health of respondents and expected Social Security income—the results are not entirely consistent with the specification used for the VRI and HRS and the estimated relationship is much less precise. In the VRI, expected retirement is measured using the response to a question, "At what age do you expect to completely retire?"[14] Both VRI and HRS have questions about current and expected pension and Social Security income. For singles, Y_i^R is simply the sum of expected pensions and Social Security divided by current income. For couples, it is this sum across the couple.[15]

For simplicity, we limit the sample to households with just one main earner who has not yet retired and is aged 65 or younger. For singles, anyone not retired and is aged 65 or younger is in the sample. For single worker couples, the household is included if the worker is aged 65 or younger. These include single-worker households or dual-worker households in which one is now retired. For both these households and singles, the retirement decision is for a single worker. The assets and income used in the analysis reflect any retirement income or assets of the already-retired spouse. For dual-worker households, the joint retirement is more complex. We only

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[13] We assume that DB pension is taxed at the same 25 percent average rate as distributions from qualified plans. To account for the partial non-taxability of Social Security benefits, we apply a 15 percent average tax rate to them. The main findings are again robust with respect to different tax rates assumed.
[14] In HRS, the expected retirement age is the result of a complex sequence starting with whether an individual plans to retire and at what age or date.
[15] If one member of the couple is retired, we use the current retirement income for that person plus the expectations for the non-retired person.

include households that appear to have only one primary earner, and we base the retirement decision on that household member.[16] There are 2,026 households in the VRI sample and 1,053 in the HRS sample. See Appendix 3-D for details.

3.5.3.1 Estimates: Entire Sample

Figure 3.3 compares the distribution of normalized wealth across the VRI and HRS. The curves shown are kernel densities where the solid lines are for the VRI while the dashed lines are for the HRS. Panel A shows the entire sample analyzed in this section, while Panel B examines the employer-sponsored subsets. Panel A shows the stark difference in the wealth distribution between the two surveys documented in Section 3.4. Recall that normalized wealth is roughly the extent to which current wealth could replace current income at retirement if all assets were devoted to retirement income. In the VRI, observations are dense and fairly uniformly spread in the range from 0 to 0.5, and observations with normalized wealth between 0.5 and 1 are not rare. A non-negligible fraction of households have normalized financial wealth larger than 1. In contrast, in the HRS the vast majority of the households have a replacement rate lower than 0.5. A trivial fraction of observations has a replacement rate close to or higher than 1. This observation confirms the point made by Poterba, Venti, and Wise (2011): relatively few households in the broad population have significant levels of potentially annuitizable wealth.

Now consider the relationship between this measure of current assets and plans for continued work. To capture the non-linear relationship between retirement horizon and wealth

[16] To determine the primary earner, we use expected Social Security income and defined benefit pensions as a proxy for who has larger lifetime earnings. If one of the members has expected Social Security and DB pension at least four times larger than the other earner, he or she is classified as the main earner and the household is included in the sample. Otherwise, the household is dropped from this analysis.

holdings without imposing a restrictive functional form, we estimate LOESS regressions.[17] Figure 3.4 shows the results for the VRI and HRS. Again, Panel A shows the entire sample analyzed in this section. Panel B examines the employer-sponsored subsets.[18] In Figure 3.4, “x” denotes HRS (orange/dashed) and “o” denotes VRI (blue/solid). The LOESS curve is shown as a line with the shaded area indicating the 95% confidence interval. The y-axis of Figure 3.4 is measured in expected remaining years of work (mean zero because it is a residual). In the VRI for the entire sample in Figure 3.4A, we see the clear negative relationship between normalized wealth and retirement horizon up to the full replacement rate around 1. Moving from zero annuitizable wealth to annuitizable wealth that could replace current income corresponds to a reduction in expected years of work by about 1.7 years. After that level, the estimated relationship flattens out. (For very high levels of annuitizable wealth, the bulk of wealth likely will not be used for routine consumption in retirement.) Over the entire range, the estimates are quite precise. In the HRS, the estimated relationship is very different. It shows a negative relationship up to the replacement rate 0.3, a slightly positive correlation in the range of 0.3 to 0.4, and then becomes flat after that. The change in years worked is about the same as in the VRI, but it occurs at much lower levels of annuitizable wealth. Given the low density of data in this range, the flattening of the LOESS line for higher levels of wealth occurs by construction. The HRS data simply cannot capture how the relationship changes over this range because there are so few observations.

Having ample data over the relevant ranges of wealth clearly affects the precision of the estimates. The VRI confidence interval is narrower due to the larger number of observations. The

[17] LOESS is a bivariate procedure. To deal with the covariates, we first project the retirement horizon on the variables in equation (3.1) excluding normalized wealth. The LOESS estimate is the regression of this residual on normalized wealth. For the HRS sample, both stages used sampling weights.

[18] The ranges of the horizontal and vertical axes are truncated to exclude outliers. Appendix 3-D, Figure 3-D1, shows the data in Figure 3.4A for the entire sample including outliers.

HRS confidence interval gets wider after the replacement rate of 0.25, as the number of observations gets smaller very quickly for individuals with annuitizable wealth sufficient to replace even a quarter of their income prior to retirement.

3.5.3.2. Estimates: Employer-Sponsored Sample

One concern about the VRI design is that the behavior of Vanguard clients might be very different from that of the general population. We can address this issue by considering whether or not the behavior of the VRI employer-sponsored sample differs from that of the individual client sample. Because the employer-sponsored clients come to Vanguard owing mainly to their employers' choices, they are much less self-selected than the individual account holders. This prior is borne out by the Section 3.4 results, which show that the characteristics of the VRI employer-sponsored sample are quite similar to subsets of the HRS and SCF with DC pension accounts. Figure 3.3B confirms that after imposing similar screens, the distribution of normalized wealth looks much more similar across the VRI and HRS.

In Figure 3.4B, we show the relationship between wealth and retirement plans for the employer-sponsored samples of the VRI and HRS. The general inference drawn by comparing the VRI and HRS for the entire sample also holds for this subset, though the HRS curve is somewhat closer to the VRI curve. The HRS relationship in Panel B has a steep decline for lower levels of wealth, but then goes essentially flat as in Panel A. Likewise, the change in retirement plans shown in Panel B for the VRI is larger than in the HRS over the relevant range, e.g., 0.25 to 0.75, and the HRS LOESS line is below the VRI confidence interval in this range. Hence, although the HRS estimates are quite imprecise for the 401(k) subset in Panel B owing to the paucity of data, the basic message of the entire VRI sample holds in the employer-sponsored samples. Therefore, the key results derived from the VRI appear to be driven by having dense data over relevant wealth ranges and not by self-selection by individuals into a relationship with Vanguard.

In Appendix 3-D, we estimate the version where we include Y_i^R in normalized wealth instead of treating it as a control. Since HRS households have significant pension and Social Security wealth, the support of retirement resources is different—but less so—from the VRI than for financial resources alone. Nonetheless, a similar picture emerges in the analysis that includes Y_i^R because of the difference in financial wealth.

3.5.3.3. Estimates: SCF

Figure 3.5 reports the result from the SCF for the entire sample (Panel A) and the 401(k) subset (Panel B). Due to a small number of households in the relevant age interval, we have only 233 observations satisfying all the criteria to be included in the analysis (we use only one replicate from each household). The SCF does not have expected Social Security benefit information, so the estimates are not entirely parallel with those for the VRI and HRS, which is why we do not plot the VRI in Figure 3.5. The small sample size makes the estimates extremely imprecise. The LOESS curve moves substantially, but not statistically significantly. The SCF was not specifically designed to study retirement saving, so it is not a criticism of that dataset that it has little power to address the relationship between wealth and expected retirement. Nonetheless, our finding points to the importance of collecting data that are relevant for the question.

3.5.4. Would a Stock Market Crash Significantly Impact Retirement Plans?

In the future, as workers increasingly rely on DC pension plans, they will need to have sufficient DC wealth in order to sustain retirement consumption. If history is precedent, many will invest significantly in equities during their working years. As such, ever more households will find their retirement finances to be vulnerable to equity-market crashes. How these crashes affect retirement horizons is therefore of great interest. In this section we show that the VRI panel is far better suited than is the HRS to understanding these effects.

An important approach to estimating the relationship between wealth and the retirement horizon is to examine how individuals react to stock market crashes. In their HRS-based work on this topic, Goda, Shoven and Slavov (2012) estimate the difference in the retirement horizon associated with the reduction in wealth associated with a 40% drop in the stock market to be essentially zero, even when they condition on stock ownership. In Figure 3.6, we use the LOESS estimates presented in Figure 3.4 to make a parallel calculation. Specifically, we take a representative stockholder to have mean normalized wealth of 0.51 and mean stock share of 55%. These are the means from the VRI sample used in the LOESS estimation. When we apply the 40% drop in the stock market to this representative stockholder, the effect on wealth is $0.4 \times 0.51 \times 0.55 = 0.112$. This 11 percent drop in the replacement rate of income is non-negligible. Using data from the HRS, the LOESS estimates suggest a flat relationship between wealth and the retirement horizon at the wealth level of the representative stockholder. Hence, our calculation confirms the finding of Goda, Shoven, and Slavov that there is no clear effect of stock market crashes on the retirement horizon in HRS data. The estimated relationship in HRS data is much steeper at the wealth level of the typical HRS individual, but the effect is still limited due to lower mean wealth and stock share.

In the VRI, the relationship is quite different because it shows a strong correlation between wealth and the retirement horizon at the wealth level of the representative stockholder. Since a significant wealth change is combined with the steep slope of the wealth-retirement horizon relationship estimated in the relevant wealth range, the implied change in the retirement horizon corresponds to an additional 4 months of work. Also, the narrow confidence intervals in this wealth range that we observed from the VRI curves in Figure 3.4 imply that the estimated effect would be statistically significant. (Panel B of Figure 3.6 considers alternative scenarios under the VRI estimate. With a higher stock share (70%) the increase in retirement horizon is about 6 months. At a higher replacement rate (1.0), however, the effect is smaller due to the flatter LOESS curve.) Hence, the representative stockholder is so poorly represented in the HRS that estimates of effects of stock market crashes on expected retirement will be very misleading using HRS data.

As the analysis in this section makes clear, with the HRS and SCF it is hard to capture the relationship between wealth and retirement behavior of those with high levels of annuitizable wealth. The bottom line is that VRI respondents have far more potential in exploring the effect of wealth on the retirement behavior of the population under an institutional and policy regime in which DC plans are the dominant source of retirement income. Developing and estimating a full structural model that can capture the impact of exogenous stock market shocks on labor market behavior is one of the many tasks ahead of us in further developing the VRI.

3.6 Conclusions

This paper has introduced a new approach and new dataset—the Vanguard Research Initiative—for measuring the wealth of wealthholders. Based on a partnership between academic researchers and the Vanguard Group, we have developed a new survey-administrative dataset. It provides a large, high-quality sample of households that have substantial wealth for financing retirement corresponding to the upper half of the wealth distribution of older Americans. Wealth measurement is based on a comprehensive account-by-account approach that is designed to elicit accurate information in the form that respondents think about it and have at their disposal. The data infrastructure makes use of high-quality administrative data at all stages of the analysis—establishing the sample frame, sending invitations, evaluating selective responses, evaluating quality of survey responses, and—ultimately—providing a distinct dataset. By collecting survey and administrative data in tandem, this project aims to demonstrate how large-scale surveys can make increasing and effective use of administrative data for wealth measurement. Given the challenges and costs of collecting surveys, these advances should inform measurement practice going forward. Based on the approach presented in this paper, it may be possible to replace expensive, infrequent, and error-ridden survey measures of wealth with administrative account data.

The research also informs practice for collecting wealth data within surveys. In particular, the account-based approach to survey measurement of wealth yields measurements that are unbiased relative to administrative measurements. In contrast, many surveys appear to undercount assets. Additionally, the paper demonstrates that the correction mechanism significantly reduces the variance of errors relative to the administrative account data.

Administrative data are by definition free from reporting error, so tend to have much less measurement error. Administrative data alone, however, might not provide enough information for research. In many cases, they do not include a rich set of important demographic variables. Sometimes they capture only a part of the household balance sheet (examples include the administrative Vanguard wealth data used in VRI and TIAA-CREF data used in Ameriks and Zeldes (2004)). Measurement error can also occur while processing data. Browning, Crossley and Winter (2014) provide a valuable summary of these issues. Hence, to get a better picture of households' economic conditions, it is often necessary to link survey data to administrative data so that we can address the shortcomings of both types of data. As a linked dataset with, on the one hand, detailed survey measures of household finance and other economically important characteristics and, on the other hand, monthly-frequency observations on balances and compositions of their Vanguard assets, the VRI enables us not only to validate survey responses with the administrative data, but also to conduct research that requires high-frequency data on financial situations.

The design of this VRI infrastructure is targeted at measuring the wealth of households with sufficient financial assets so they face wealth allocation and accumulation decisions concerning whether to work longer, whether to annuitize, whether to buy long-term care insurance, how much to bequeath, and so on. In other papers that also leverage the VRI, we are investigating some of these questions in detail. In this paper, we make several substantive contributions beyond evaluating the quality of the VRI measurement. We show that the VRI is dense in data on older Americans in the upper half of the wealth distribution compared to other excellent surveys with wealth data, namely the HRS and SCF. We show that for one key variable—how much longer they expect to work—the VRI indeed provides a very different picture from the HRS and SCF precisely because it has sufficient observations with households with substantial financial wealth as they approach retirement.

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Table 3.1. Design of VRI, HRS, and SCF

	VRI	HRS	SCF
Sampling			
Population	Vanguard clients	U.S. Population	U.S. Population
Frequency	Multiple surveys per year; monthly admin. data	Biennial	Triennial
Panel/cross-section	Panel	Panel	Cross-section[1]
Main target	Age 55+ with non-negligible financial assets	Age 50+ and spouses	Representative of wealth
Oversampling	Singles	Blacks and Hispanics; Residents of Florida	High-income list sample
Additional screens	Internet eligible; Employer-sponsored and individual client samples		
Wealth measurement			
Account-based approach	Comprehensive	401(k)/IRA[2]	Transactional and pension accounts
Administrative data	Yes	No	No
Summary (age≥55)			
Households	8,950	11,595	2,624
Median Financial Wealth	$663,100	$60,000	$33,200
Median Income	$121,481	$30,400	$42,610

Note: Table refers to most recent wave of each survey (VRI 2013, HRS 2012, and SCF 2013). Observations are restricted to respondents aged 55 and older. The VRI and SCF survey only one member of couples. The age of the household is determined by the age of respondent. The HRS surveys HRS respondents and their spouses. The age of the household is determined by the age of the financial respondent as defined by the HRS.

[1] The SCF occasionally (1983-89, 2007-09) has a panel structure.

[2] HRS implemented account-based approach for retirement accounts in 2012.

Table 3.2. Survey Financial Assets: All respondents

		Conditional on having positive amount						
				Percentiles				
Account type	Mean	N	Mean	10	25	50	75	90
Total financial assets	1,189,358	8,948	1,189,358	122,000	296,673	656,962	1,266,651	2,254,000
IRA	359,181	7,303	440,184	29,000	83,931	234,033	556,527	1,021,000
Employer sponsored	215,620	4,630	416,803	26,000	83,000	222,000	475,000	842,402
Pension	25,365	1,016	223,437	10,518	34,000	100,000	251,000	590,714
Other retirement asset	13,237	602	196,801	10,000	26,136	80,466	213,000	450,000
Checking	16,888	8,637	17,500	1,000	2,200	5,500	15,000	40,000
Saving	23,020	6,162	33,436	500	2,100	10,000	32,000	84,382
Money market	28,308	4,076	62,158	1,200	5,367	22,177	69,303	151,023
Mutual fund	231,577	3,942	525,777	8,500	30,000	114,000	309,000	690,000
Certificate of deposit	16,576	1,634	90,794	4,000	11,000	34,450	100,000	230,803
Brokerage	181,872	4,184	389,042	6,400	27,100	110,000	347,000	854,000
Directly held securities	22,634	1,801	112,477	2,000	10,000	30,000	100,000	235,664
Annuity	20,811	1,163	160,150	13,000	35,000	94,500	200,000	365,000
Life insurance	21,053	2,696	69,891	5,000	10,000	26,000	70,000	150,000
Educational related	3,022	613	44,119	3,400	8,300	20,000	48,000	100,000
Other accounts	9,930	429	207,165	1,500	10,000	46,000	195,000	478,000

Note: Pension, annuity, and life insurance are current cash values.

Table 3.3. Total Vanguard Assets: Survey versus Administrative Data

A. Employer-Sponsored (N=2,243)

		Percentiles				
	Mean	10	25	50	75	90
Survey	331,753	27,000	75,000	195,485	432,000	755,000
Administrative	299,540	29,519	69,668	181,375	400,707	656,832
Difference	32,213	-27,394	-4,093	890	12,999	95,978
% Difference	3.92%	-17.44%	-2.48%	0.63%	9.10%	47.83%

B. Individual client (N=6,705)

		Percentiles				
	Mean	10	25	50	75	90
Survey	517,724	29,000	87,017	260,000	615,081	1,178,158
Administrative	380,277	25,345	67,382	193,682	472,732	900,747
Difference	137,447	-23,315	-1,637	2,623	91,950	380,262
% Difference	18.53%	-14.42%	-1.20%	1.44%	32.89%	100.32%

C. Employer-Sponsored, Singles (N=585)

		Percentiles				
	Mean	10	25	50	75	90
Survey	240,488	22,000	49,000	125,000	300,000	574,000
Administrative	231,306	22,757	46,236	127,630	282,362	529,760
Difference	9,183	-24,297	-3,867	365	7,483	35,390
% Difference	2.05%	-22.06%	-3.04%	0.33%	6.21%	29.68%

D. Individual client, Singles (N=2,349)

		Percentiles				
	Mean	10	25	50	75	90
Survey	317,004	21,000	57,000	165,400	420,000	790,000
Administrative	305,997	22,501	58,759	160,638	406,609	744,563
Difference	11,008	-32,803	-4,180	-19	3,902	39,677
% Difference	-0.64%	-22.23%	-2.91%	-0.03%	2.18%	24.34%

Table 3.4. Comparison of Total Vanguard Wealth: Different Correction Paths (Singles only)

			Percent Difference		
Correction paths	N	Measure	25 percentile	median	75 percentile
None	1927	Final	-3.3	-0.0	2.6
Accounts only	426	Initial	-3.5	0.1	2.5
		Final	-3.5	0.1	2.5
Balances only	308	Initial	-12.2	-0.0	13.6
		Final	-2.6	-0.0	2.7
Accounts and balances (restarted)	121	Initial	-5.3	-0.1	12.1
		Final	-1.1	0.2	2.1
Accounts and balances (other paths)	153	Initial	-18.1	-0.1	2.7
		Final	-1.4	0.1	2.7

Table 3.5. Comparing VRI to Age-Eligible HRS and SCF Households (unweighted counts): Age and Financial Wealth

		Financial Wealth							
Age		<$0	$0-10K	$10K-100K	$100K-500K	$500K-1M	$1M-2.5M	>$2.5M	All
55-64	VRI	48	36	292	1,147	871	762	181	3,337
	HRS	1,459	586	933	897	287	160	41	4,363
	SCF	228	170	196	254	102	119	212	1,281
65-74	VRI	16	19	258	1,117	985	1,066	377	3,838
	HRS	746	487	727	817	290	162	35	3,264
	SCF	93	114	118	155	68	91	178	817
> 74	VRI	2	4	95	549	461	472	192	1,775
	HRS	800	712	1,030	927	284	172	43	3,968
	SCF	60	93	115	107	31	30	90	526
Total	VRI	66	59	645	2,813	2,317	2,300	750	8,950
	HRS	3,005	1,785	2,690	2,641	861	494	119	11,595
	SCF	381	377	429	516	201	240	480	2,624

Note: Numbers are raw counts (unweighted) of households. Note that only age-eligible households are included in the table. For SCF, only one replicate is included. For HRS, only those households surveyed in both the 2010 and 2012 waves are included. Age of HRS households based on financial respondent. Financial wealth is the sum of financial assets (both retirement and non-retirement assets) minus non-mortgage debt.

Table 3.6. Comparing Age-eligible VRI, HRS, and SCF Households (unweighted counts): VRI Sampling Screens

	VRI			HRS			SCF		
Age	All	Employer-Sponsored	Individual client	Age Eligible	VRI Eligible	VRI Eligible 401(k) subset	Age Eligible	VRI Eligible	VRI Eligible 401(k) subset
All	8,950	2,244	6,706	11,595	3,684	1,553	2,624	1,275	665
55-59	1,549	810	739	2,364	976	628	668	397	280
60-64	1,788	823	965	1,999	756	411	613	350	205
65-69	1,931	419	1,512	1,282	535	214	462	257	112
70-74	1,907	157	1,750	1,982	638	178	355	161	51
75-100	1,775	35	1,740	3,968	779	122	526	110	17

Note: Table shows total age-eligible number of households in total and after imposing the VRI-equivalent screen. VRI-eligible screen imposes Internet eligibility plus having at least $10,000 in any non-transactional financial accounts. The 401(k) subset imposes $10,000 wealth cut-off on DC type pensions. See text for details. See also the note to Table 5.

Table 3.7. Effect of Imposing VRI Sampling Screens: Fraction of weighted observations

Screens	HRS	SCF
Age-eligible	100%	100%
Internet eligibility	56%	58%
$10,000 asset cut-off	58%	45%
Internet eligible and $10,000 cut-off	41%	35%
401(k) subset	19%	18%

Note: Table shows the fraction of the sample in HRS and SCF (measured by the fraction of weighted observations) remaining after imposing VRI sampling screens. See text and note to Table 6 for descriptions of screens.

Table 3.8. Effect of Imposing VRI Sampling Screens: Wealth distribution

		Mean	Percentiles 10	25	50	75	90
VRI	All	1,206,594	115,337	292,000	663,100	1,286,000	2,291,235
	Employer-sponsored	847,349	65,050	185,600	496,350	1,029,700	1,856,005
	Individual client	1,326,807	140,100	330,636	715,790	1,383,209	2,421,840
HRS	Age eligible	293,596	-900	500	60,000	300,000	745,000
	VRI eligible	578,069	34,000	98,036	272,000	660,000	1,247,800
	VRI eligible, 401(k) subset	623,954	46,300	130,000	342,700	733,000	1,364,000
SCF	Age eligible	404,668	-6,300	320	33,200	220,550	794,700
	VRI eligible	970,294	28,860	96,350	262,100	792,400	2,109,000
	VRI eligible, 401(k) subset	871,897	18,000	76,870	219,500	674,000	1,953,500

Note: HRS and SCF tabulations use sampling weights.

Table 3.9. Stock Ownership

A. Share: VRI, HRS, and SCF (Percent)

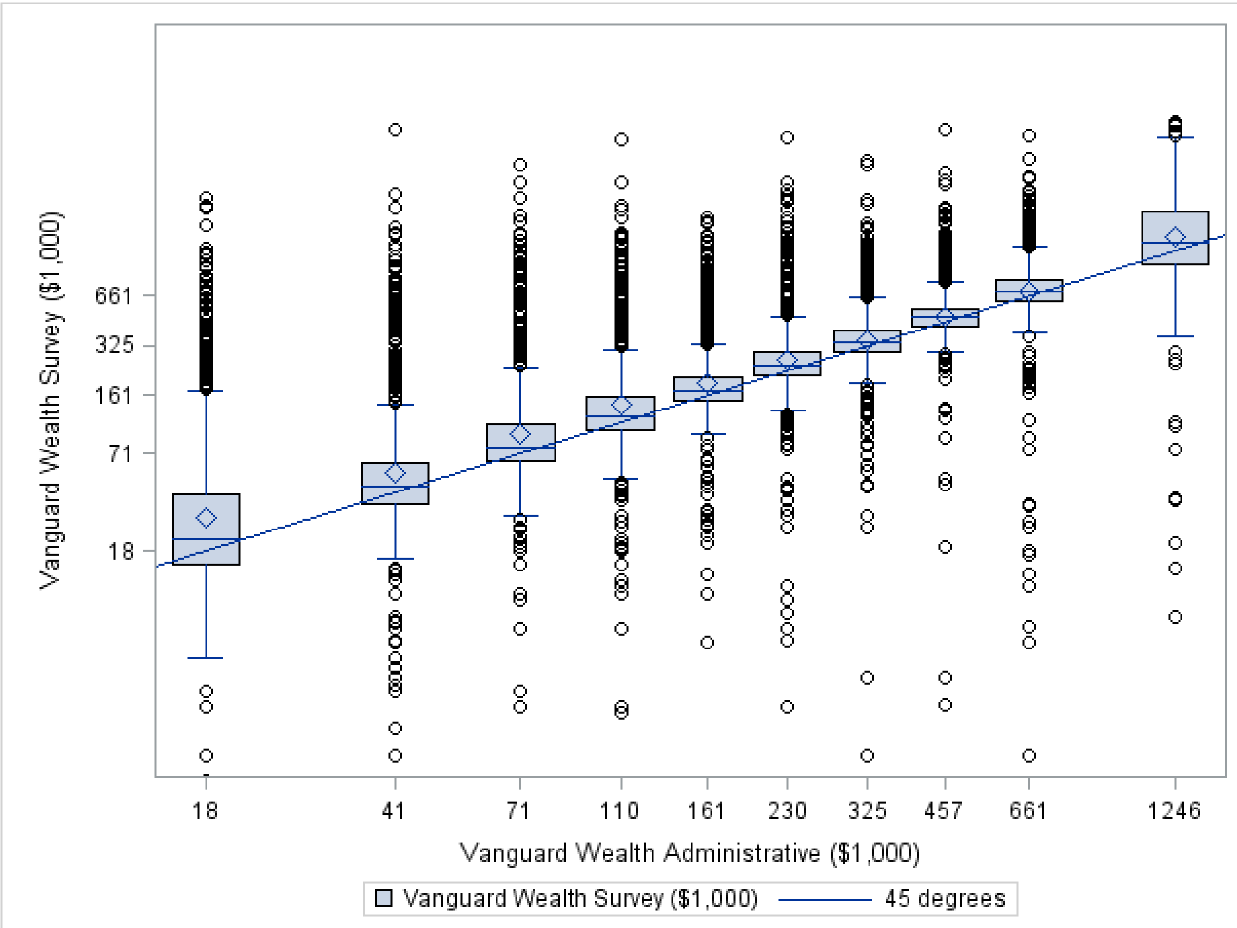
		Percentiles					
	Sample Screen	10	25	50	75	90	N
VRI	All	14.96	35.12	54.76	74.71	91.14	8905
	Employer-sponsored	8.42	28.88	50.00	72.04	90.00	2233
	Individual client	18.55	37.37	56.06	75.33	91.52	6672
HRS	Age eligible	0	0	0	40.32	81.48	11595
	VRI eligible	0	0	29.20	70.75	90.54	3684
	VRI eligible, 401(k) subset	0	0	20.93	67.86	89.05	1553
SCF	Age eligible	0	0	0.70	43.39	71.24	2624
	VRI eligible	2.77	19.94	42.34	61.85	84.74	1275
	VRI eligible, 401(k) subset	6.98	21.51	40.66	61.04	83.33	665

Note: See text and note to Table 4 for sample screens. Respondents with less than $1000 in financial assets are coded as having a zero stock share.

B. Amount: VRI, HRS, and SCF (Dollars)

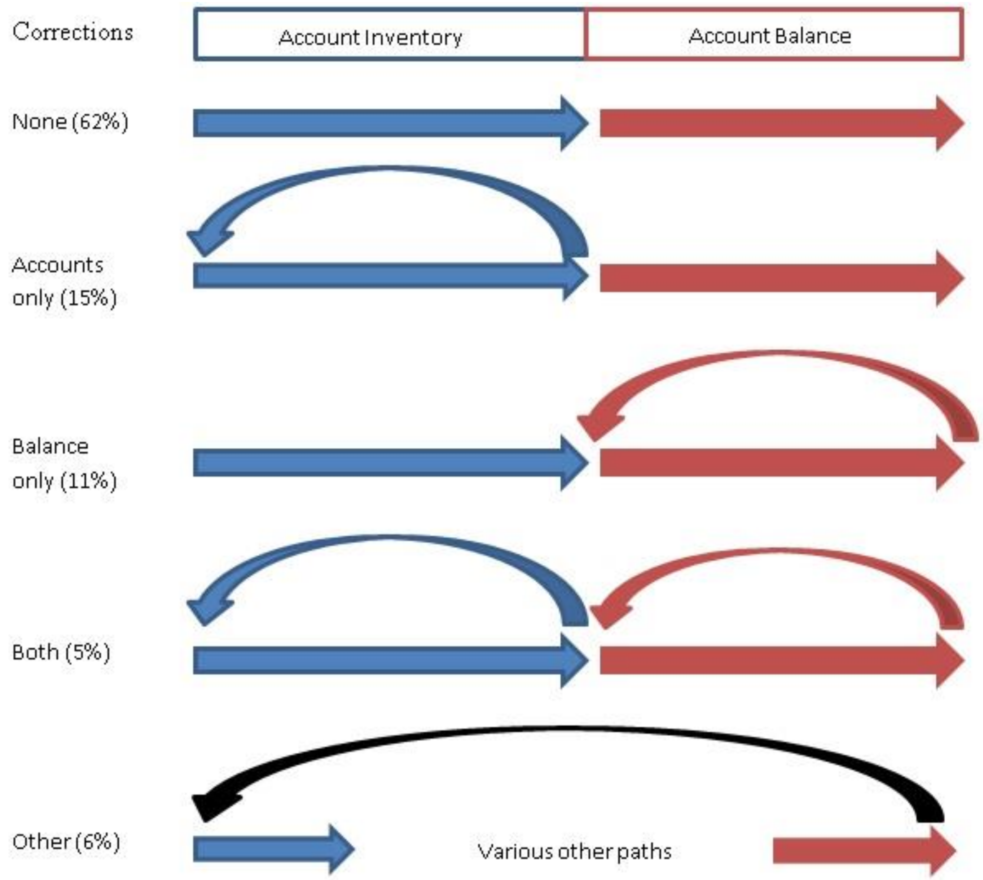
		Percentiles					
	Sample Screen	10	25	50	75	90	N
VRI	All	30,000	113,800	326,162	712,200	1,397,710	8905
	Employer-sponsored	13,500	65,428	221,443	551,365	1,047,212	2233
	Individual client	41,415	138,220	365,174	765,400	1,477,515	6672
HRS	Age eligible	0	0	0	45,000	270,000	11595
	VRI eligible	0	0	30,000	200,000	520,000	3684
	VRI eligible, 401(k) subset	0	0	15,000	150,000	453,700	1553
SCF	Age eligible	0	0	0	78,000	360,000	2624
	VRI eligible	3,000	22,750	105,000	357,000	1,227,600	1275
	VRI eligible, 401(k) subset	4,500	21,000	86,000	306,500	1,168,500	665

Figure 3.1. Administrative versus Survey Financial Assets at Vanguard



Note: The figure compares Vanguard administrative assets with survey report of Vanguard assets. See the text for how Vanguard assets are determined in survey. The chart shows box and whiskers figures for each decile of administrative assets (diamond is the mean; middle line is median; box is inter-quartile range [IQR]; outer lines upper and lower fences [1.5 times the IQR from the box]; and circles denote outliers). Amounts on the horizontal axis are medians of each decile ($1000). Log scale is used on both axes.

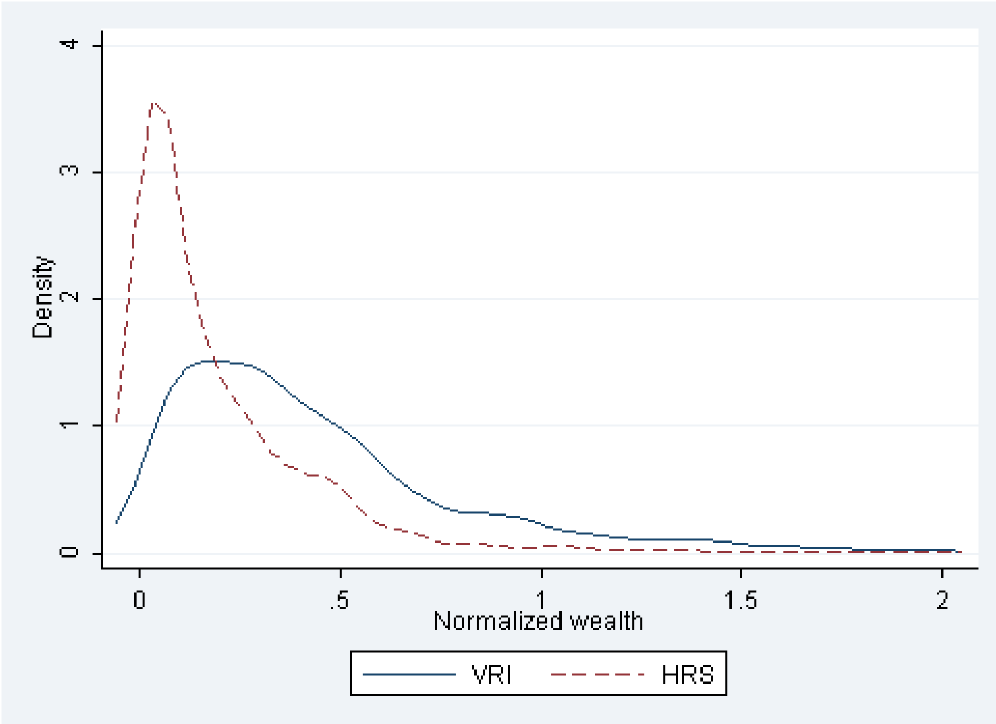
Figure 3.2. Correction Paths through Wealth Section.



Note: The figure shows the fraction of respondents taking various paths through the account-based wealth section. Other includes those who started over and then took various paths to complete.

Figure 3.3. Distribution of normalized financial wealth (kernel estimation)

A. VRI vs HRS



B. VRI employer-sponsored versus HRS 401(k) subset

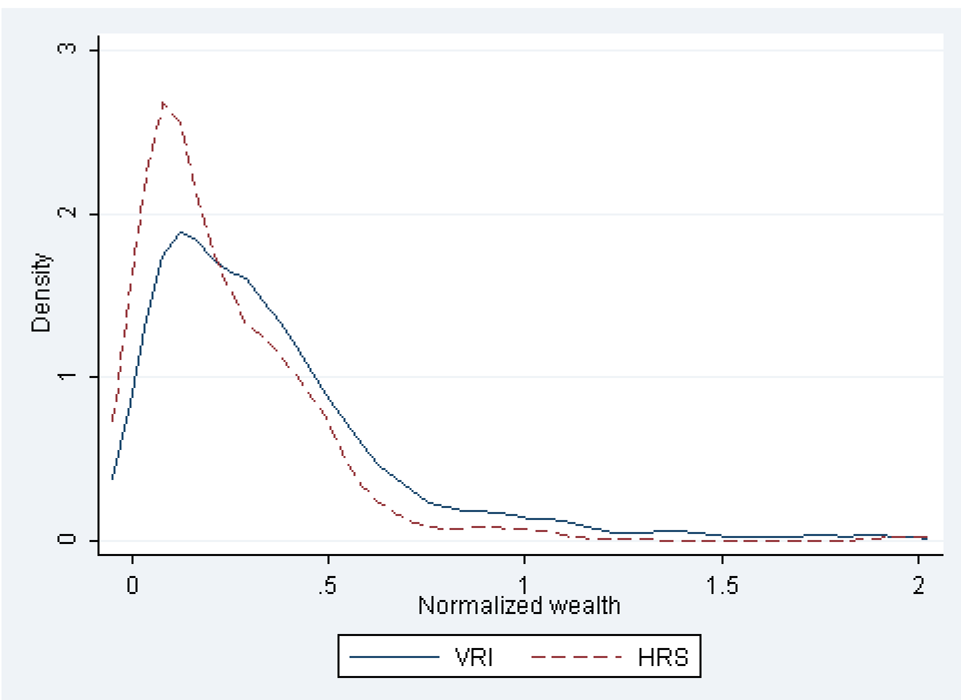
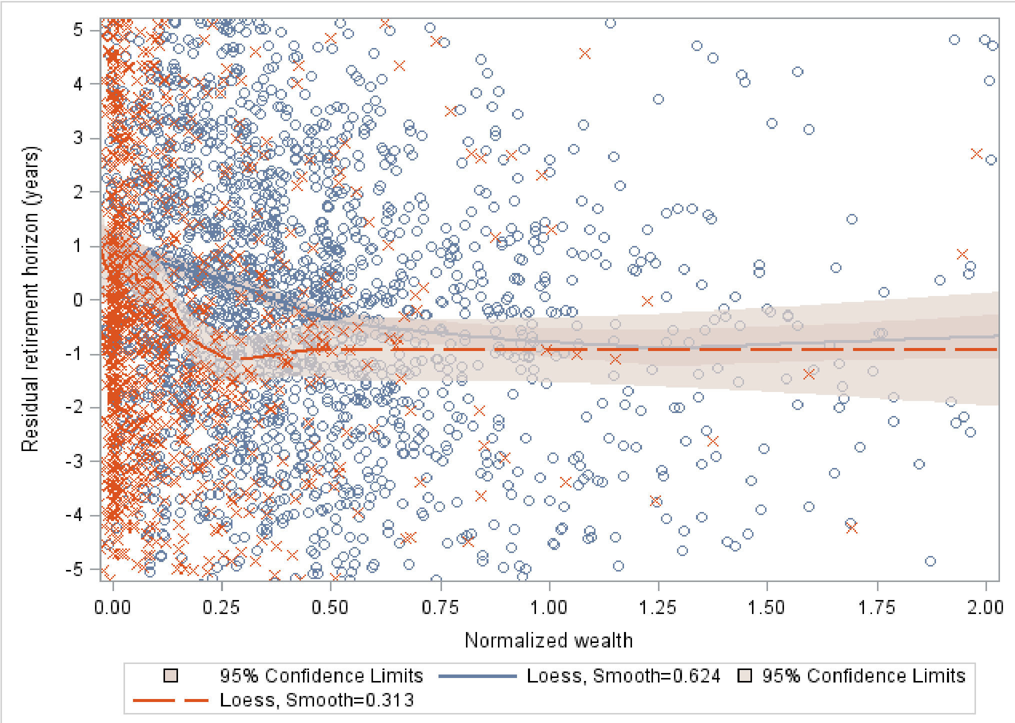
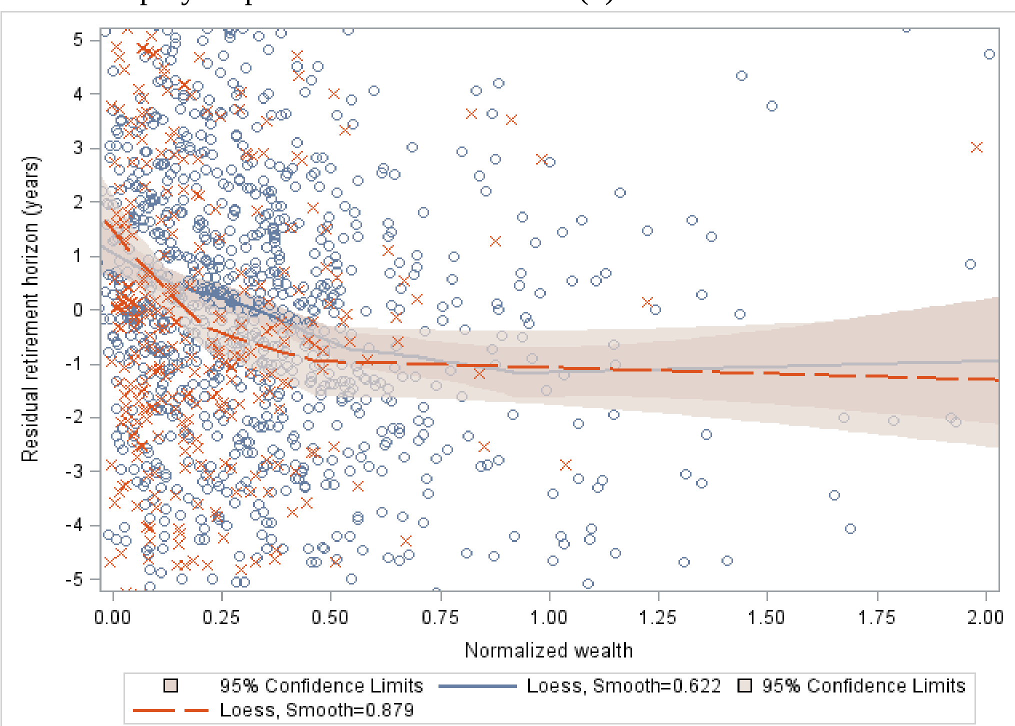


Figure 3.4. Retirement horizon versus normalized financial wealth: LOESS
A. VRI vs HRS



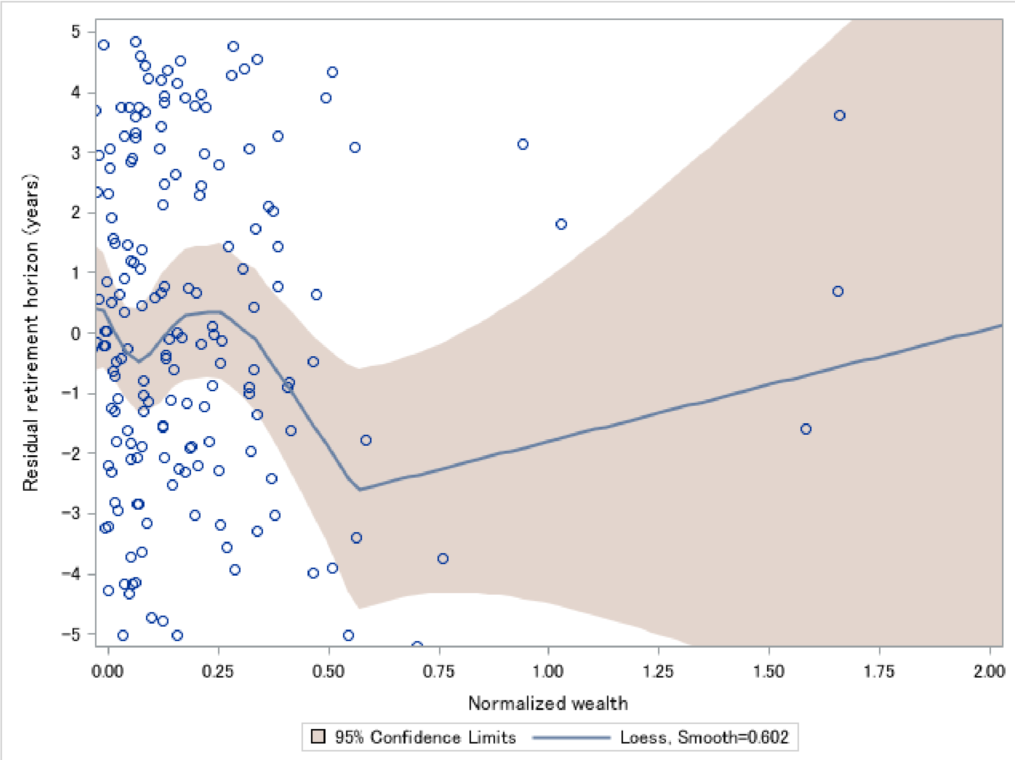
Note: x denotes HRS (orange/dashed line) and o denotes VRI (blue/solid line).

B. VRI employer-sponsored versus HRS 401(k) subset



Note: x denotes HRS (orange/dashed line) and o denotes VRI (blue/solid line).

Figure 3.5. Retirement horizon versus normalized financial wealth: LOESS
A. SCF



B. SCF 401(k) subset

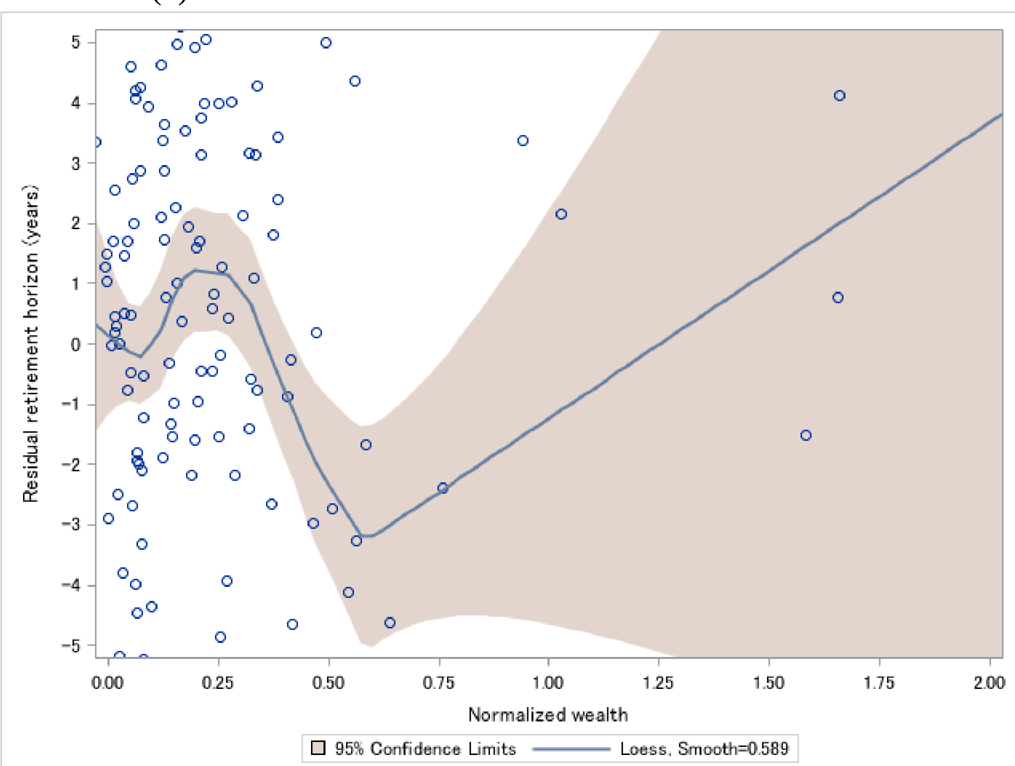
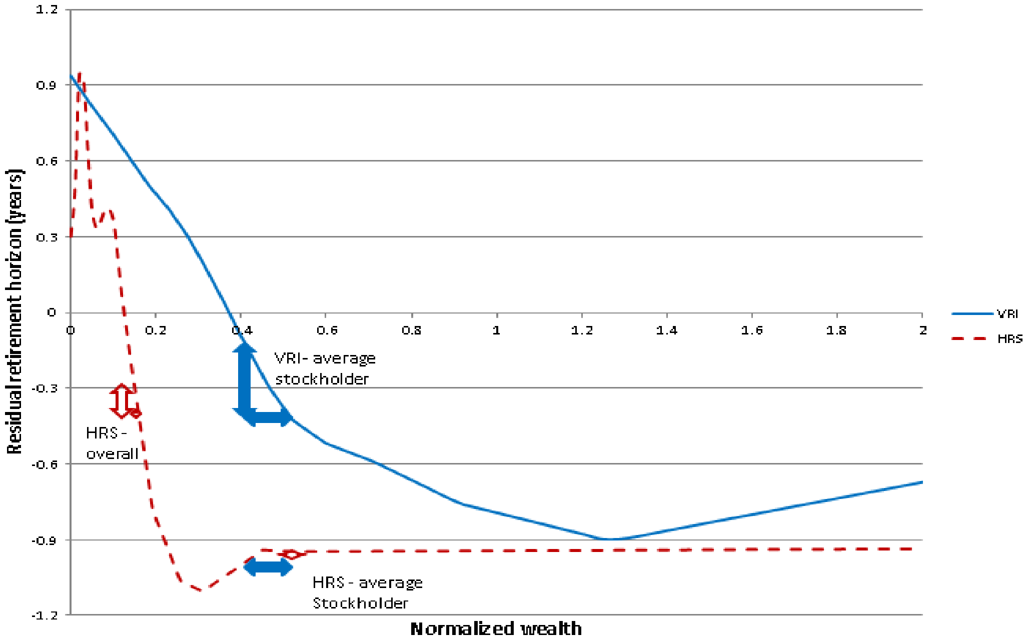
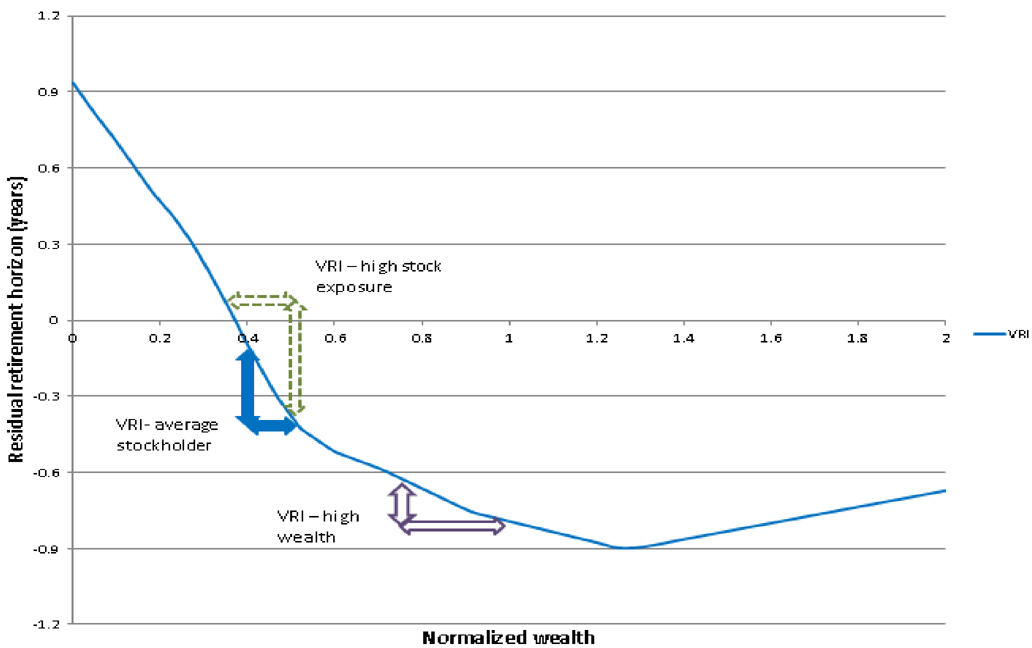


Figure 3.6. Implied Changes in Retirement Horizon: 40% Decline in Stock Market
A. Comparison of VRI and HRS Estimates



B. Alternative Scenarios using VRI Estimates



Note: Lines are LOESS estimates from Figure 4 (confidence intervals and observation not shown). The figure shows the predicted change in the retirement horizon (years to retirement) resulting from a 40% decline in the stock market. In panel A, the HRS-overall applies the mean HRS wealth and stock share to the HRS estimates. The HRS-average stockholder applies the mean VRI wealth and stock share to the HRS estimates while the VRI-average stockholder applies the same mean VRI wealth and stock share to the VRI estimates. In panel B, the VRI-average stockholder is same as in panel A. The other two treatments show high stock exposure and high-wealth households. See text for details.

Appendix 3-A. Account Sequence Example

Section 3.2.2 of the main text explained the structure of the wealth section of the survey in detail. In this appendix, we show actual screen shots from the wealth section for a hypothetical respondent who has two IRAs, one 401(k) pension, one checking account and one mutual fund account.

The respondent starts the wealth section by entering all the types of accounts she has (Figure 3-A1). She answers how many accounts she has for each type using a drop-down menu (Figure 3-A2) and then gives each of the accounts a nickname (Figure 3-A3). The survey shows the summary of responses so far (Figure 3-A4) and asks whether all the information given is correct. If the respondent clicks no, then she can either add/delete the account type or add/delete accounts within each type.

After this first check point, the survey then loops over the accounts and asks the balance of each (Figure 3-A5 is one example). After the loop, the survey displays a summary table of account balances as well as a total (Figure 3-A6). In this example, the respondent did not provide a response to the balance question for the second IRA account ("Roth IRA"), so she sees "No response provided" for Reported Value under that account. Let us say that the respondent clicks "No" to "Is this correct?" under the summary table. Then the respondent is asked whether she wants to add/delete accounts or correct balances (Figure 3-A7). In this example, the respondent chooses to correct balances, indicates that she wants to correct the balance for "Roth IRA" (Figure 3-A8), and then corrects the balance for that account (Figure 3-A9). During the corrections, the previously provided answers are shown above the question (in this case "Not answered"). The respondent comes back to the summary screen again, indicates whether she referred to records to provide information on each account, and then confirms that all the responses are correct (Figure 3-A10).

The survey then asks two follow-up questions for each account: stock share (Figure 3-A11) and whether that account is held at Vanguard (Figure 3-A12). Note that the survey does not ask these questions about the checking account that this respondent reported since it is a transactional account not offered at Vanguard. Based on these responses, the survey calculates the share of wealth held at Vanguard and the stock share of the total portfolio, and it shows these as charts along with the summary table of balances (Figure 3-A13). The respondent can print this summary page as a record.

Figure 3-A1. Types of Accounts

Which of the following types of investment, savings, and retirement accounts do you have? We are asking for a complete list of financial accounts that you own. Please answer for your own accounts only.

We have grouped the accounts listed below into categories to help make it easier for you to think about all of the various types that you may own. The purpose of this question is to obtain a comprehensive view of the various types of investment, savings and retirement accounts that households may own.

For each account that you own, please include it under only one type of account.

Tax-deferred retirement accounts

- [x] IRA (including ROTH, traditional, an IRA rolled-over from an employer-sponsored plan)
- [x] Employer-sponsored retirement plan account (401(k), 403(b), 457, etc.)
- [ ] Pension with an account balance which you can access as a lump sum
- [ ] Other type of tax-deferred retirement account (such as SEPs, Keoghs, etc.)

Savings/investment accounts that are not in a tax-deferred retirement plan or account

- [x] Checking account
- [ ] Savings account
- [ ] Money market account
- [x] Mutual fund account (other than money market mutual fund)
- [ ] Certificate of deposit (CD) portfolio (aggregate of all CD holdings)
- [ ] Brokerage account (including stocks, municipal, corporate, or other bonds, mutual funds, ETFs and other assets)
- [ ] Directly held securities or other financial assets (US Treasury Bonds or savings bonds at Treasury Direct, stocks, bonds or individual securities you own that are not at a brokerage, Dividend Reinvestment Programs.)

Insurance contracts/accounts with a cash value or balance

- [ ] Annuity accounts with a balance or cash value *(excluding immediate annuities reported in the previous section)*
- [ ] Life insurance with cash value *(excluding term life insurance)*

Educational Accounts

- [ ] Section 529 College Savings Plans or Coverdell Accounts

Other accounts

- [ ] Other accounts not specified above

Figure 3-A2. Number of Accounts

You mentioned that your household has the following types of investment, savings, and retirement accounts. How many of each type does your household have?

For example, your household may have three checking accounts. In this case, you would enter '3' below for 'checking account'.

Or, for example, your household may have two IRAs (one owned by you, one owned by your spouse/partner) and one CD. In this case, you would enter a '2' below for 'IRA' and a '1' below for 'Certificate of Deposit (CD)'.

- Note, when you are counting, there is not a need to break out the subcomponents of an account. You can just count the overall account.

Please indicate the number after each.

		Number of accounts
Tax-deferred retirement accounts	IRA (including ROTH, traditional, rolled-over from an employer-sponsored plan)	2
	Employer-sponsored retirement plan (401(k), 403(b), 457, etc.)	1
Savings/investment accounts that are not in a tax-deferred retirement plan or account	Checking account	1
	Mutual fund account (other than money market)	1

Figure 3-A3. Nickname Accounts

We will be asking you additional questions about each of the investment, savings, and retirement accounts you mentioned that your household has. To assist with this, it would be helpful if you give each account a "nickname." The nickname you assign could be any name, as long as it helps you keep track of which specific investment or savings account you are responding about in future questions.

Nicknames should be descriptive and are meant to help you remember the account types you have just selected - for example, if your household has two IRAs, one 401(k), and one checking account, you may elect to name your accounts as follows:

- *IRA 1:* My IRA
- *IRA 2:* Mary's IRA
- *Employer-sponsored retirement plan (401(k), 403(b), 457, etc.) 1:* Her 401(k)
- *Checking account 1:* Joint checking account at credit union

Please type in a nickname for each.

IRA 1:	Rollover IRA
IRA 2:	Roth IRA
Employer-sponsored retirement plan (401(k), 403(b), 457, etc.) 1:	Retirement
Checking account 1:	Chase
Mutual fund account (other than money market) 1:	Vanguard

Figure 3-A4. Account Verification

Please scroll down to see a summary of your household's investment, savings, and retirement accounts. Please review this summary for accuracy - does this correctly reflect all of your household's investment, savings, and retirement accounts? What's most important is that nothing significant is forgotten or double-counted in the list.

If this information is not correct, you will be able to go back to the beginning of this section to update your information.

It is very important for the rest of the survey that your responses here be as complete and accurate as possible and we appreciate you taking the time to thoroughly review and update if necessary.

Please select one.

- ○ Yes - this is accurate and I am ready to continue
- ○ No – I need to go back to make an update

Summary of My Household's Investment, Savings and Retirement Accounts
Tax-deferred retirement accounts
IRA
1: Rollover IRA
2: Roth IRA
Employer-sponsored retirement plan (401(k), 403(b), 457, etc.)
1: Retirement
Pension with an account balance which you can access as a lump sum
None
Other type of tax-deferred retirement account (such as SEPs, Keoghs, etc.)
None
Savings/investment accounts not in a tax-deferred retirement plan or account
Checking account
1: Chase
Savings account
None
Money market account
None
Mutual fund account
1: Vanguard
Certificate of deposit (CD)
None
Brokerage account
None
Directly held securities or other financial assets
None
Insurance- and Education-related accounts
Annuity Accounts with a Balance or Cash Value
None
Life insurance with cash value
None
Educational-Related accounts
None
Other accounts
None

Figure 3-A5. Account Balance

IRA 1:
Rollover IRA

Please enter your total balance in this account. You can reference any documents or records that may help you obtain this information. You may also give us your best estimate from memory. Please feel free to round, but try to be accurate at least to the nearest thousand dollars. For example, if the account balance was $24,823, you may enter '25000' below. We appreciate any effort you give to specify an amount as precisely as possible. The information you provide will be kept completely confidential.

$ 120,000

Figure 3-A6. Balance Verification

Please refer to the below table and verify the balances you reported for each of your accounts, and indicate whether you referred to records or statements in supplying these figures.

	REPORTED VALUE	REFERRED TO RECORDS?	
		YES	NO
IRA 1: Rollover IRA	$120,000	○	○
IRA 2: Roth IRA	No response provided		
Employer-sponsored retirement plan (401(k), 403(b), 457, etc.) 1: Retirement	$400,000	○	○
Checking account 1: Chase	$15,000	○	○
Mutual fund account (other than money market) 1: Vanguard	$275,000	○	○
TOTAL	$810,000		

Is this correct?

- ○ Yes – this is accurate and I am ready to continue
- ○ No – I need to go back to make an update

Figure 3-A7. Indicate What Type of Correction(s)

Please tell us which of these activities you need to do...

- ☐ I need to ADD and/or DELETE an account
- ☑ I need to fix the dollar amount of what I have already provided.

Figure 3-A8. Indicate What Needs to Be Corrected

Please tell us which Account(s) you need to correct.

	REPORTED VALUE	For Which Account(s) Do You Need To Correct the Reported Value?
IRA 1: Rollover IRA	$120,000	☐
IRA 2: Roth IRA	No response provided	☑
Employer-sponsored retirement plan (401(k), 403(b), 457, etc.) 1: Retirement	$400,000	☐
Checking account 1: Chase	$15,000	☐
Mutual fund account (other than money market) 1: Vanguard	$275,000	☐

Figure 3-A9. Correction of Previous Response(s)

Your Previous Response was... Not Answered

IRA 2:
Roth IRA

Please enter your total balance in this account. You can reference any documents or records that may help you obtain this information. You may also give us your best estimate from memory. Please feel free to round, but try to be accurate at least to the nearest thousand dollars. For example, if the account balance was $24,823, you may enter '25000' below. We appreciate any effort you give to specify an amount as precisely as possible. The information you provide will be kept completely confidential.

$ 150,000

Figure 3-A10. Revised Balance Summary

Please refer to the below table and verify the balances you reported for each of your accounts, and indicate whether you referred to records or statements in supplying these figures.

	REPORTED VALUE	REFERRED TO RECORDS?	
		YES	NO
IRA 1: Rollover IRA	$120,000	●	○
IRA 2: Roth IRA	$150,000	●	○
Employer-sponsored retirement plan (401(k), 403(b), 457, etc.) 1: Retirement	$400,000	●	○
Checking account 1: Chase	$15,000	○	●
Mutual fund account (other than money market) 1: Vanguard	$275,000	●	○
TOTAL	$960,000		

Is this correct?

● Yes – this is accurate and I am ready to continue
○ No – I need to go back to make an update

Figure 3-A11. Account-by-account Stock Share

Thinking about all of the investment, savings, and retirement accounts that your household currently has, what percentage, if any, of each account is held in stocks or stock market investments? In other words, what percentage of the underlying assets or funds in each account is held in stock investments?

Please note: Checking accounts, Savings accounts, Money Market accounts, CDs and Life insurance are not displayed in the table below since they have no stock/stock market investment value. The amounts on the far right of the table will compute after you click out of the box where you enter the approximate percentage.

	APPROXIMATE PERCENTAGE HELD IN STOCKS/STOCK MARKET	IMPLIED VALUE OF STOCK INVESTMENTS IN THIS ACCOUNT
IRA 1: Rollover IRA	50 %	$60,000
IRA 2: Roth IRA	100 %	$150,000
Employer-sponsored retirement plan (401(k), 403(b), 457, etc.) 1: Retirement	25 %	$100,000
Mutual fund account (other than money market) 1: Vanguard	100 %	$275,000

Figure 3-A12. Which Accounts at Vanguard

Which accounts are currently held at Vanguard?

Please select one for each row.

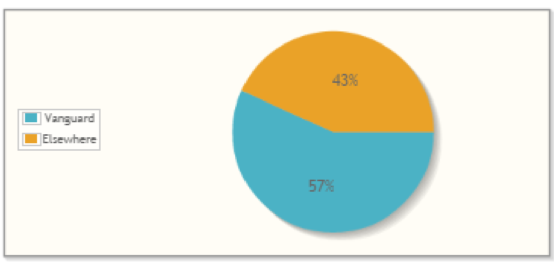
Accounts	Held at Vanguard	
	Yes	No
IRA 1: Rollover IRA	◉	○
IRA 2: Roth IRA	◉	○
Employer-sponsored retirement plan (401(k), 403(b), 457, etc.) 1: Retirement	○	◉
Mutual fund account (other than money market) 1: Vanguard	◉	○

Figure 3-A13. Summary Table and Charts

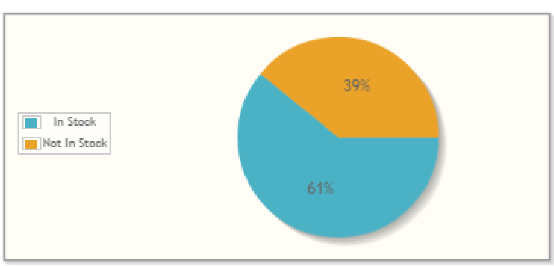
Thank you very much for providing this detailed information about your financial assets. Before continuing with the final sections of the survey, we would like to present you with a summary of your assets. You may wish to print this for your own use:

FINANCIAL ASSETS	
Retirement	**Total: $670,000**
IRA	$270,000
Employer-sponsored retirement plans (401(k), 403(b), 457, etc.)	$400,000
Pension with an account balance which you can access as a lump sum	--
Other (such as SEPs, Keoghs, etc.)	--
Non-retirement	**Total: $290,000**
Checking	$15,000
Savings account	--
Money market account	--
Mutual fund account	$275,000
CDs	--
Brokerage account	--
Other stocks and bonds	--
Annuity accounts	--
Life insurance with cash value	--
Section 529 College Savings Plans or Coverdell Accounts	--
Other accounts	--
Total	**$960,000**

Percent of Financial Assets at Vanguard vs. Elsewhere



Percent of Financial Assets in Stocks vs. Not in Stocks



Appendix 3-B. Definition of concepts

This appendix defines concepts used for the VRI and how we measure them in the HRS and SCF.

Total financial wealth. In the VRI, total financial wealth is the sum of all financial account balances (the items listed in Table 3.2) plus miscellaneous financial items (in non-account, cleanup questions) minus non-mortgage debt. For the SCF, financial wealth is total financial assets (FIN in the public version of data) minus non-mortgage debt (sum of CCBAL, INSTALL and ODEBT in the public version of data). For the HRS, financial wealth is the sum of total financial wealth (atof in RAND version), IRA wealth, and employer-sponsored plan and pension account balances. For the HRS 2012, we constructed these variables using RAND definitions. (We are grateful to Margaret Lay for sharing her construction of these variables.)

Web-survey eligibility. For the VRI, respondents are Web-survey eligible if the client is registered for Web access with Vanguard, if the registration has a valid email address, if the client logged in to the Vanguard Website at least once in the last six months, and if the client was not been recently included in another survey by Vanguard, and if the client had not requested exclusion from contacts for surveys. We need to simulate this set of screens in the HRS and SCF in order to select comparable respondents. We designate HRS respondents as Web-survey eligible if they use the Internet regularly. In the SCF, respondents are designated Web-survey eligible if they use the Internet to obtain information about borrowing/investing.

Asset cut-off. In the HRS, we impose a $10,000 cut-off on total financial assets net of checking, saving and money market balances. In the SCF, we impose a $10,000 cut-off on the sum of IRA, mutual funds and account type pensions.

Appendix 3-C. Detailed Comparisons: VRI, HRS and SCF

This appendix compares the VRI with the most recent waves of the HRS (2012) and SCF (2013) in more detail. It compares surveys along dimensions including wealth, income and demographics. For each dimension, we also provide comparisons conditional on age groups to control for the effect of different age compositions across surveys.

Recall that the age distribution differs across the samples. Table 3-C1 compares median value of wealth by age group to see whether the difference in the overall wealth distribution is caused by differences in age. Even after imposing the similar sampling screens, the VRI sample has a higher median wealth for almost all the age groups. Again, the gap is much smaller when the HRS and SCF samples are compared with the employer-sponsored sample of the VRI. For the HRS, the gap shrinks further if we condition on respondents with at least $10,000 in 401(k)s or similar pension accounts. (Statistics for the age group 65+ under employer-sponsored conditions or 401(k) subset conditions are not very informative due to the small number of observations.)

Income. Tables 3-C2 and 3-C3 compare household annual income across samples. Compared to the overall population of the HRS and SCF, the VRI sample is not only wealthier, but also has higher income. The difference in income is, however, much smaller than the difference in wealth. If we impose the VRI screens, except for the oldest age group, income levels from the SCF are actually higher than the VRI; those from the HRS are quite comparable to those from the VRI. As a result, the wealth-to-income ratio is much higher for the VRI sample, as shown in Tables 3-C4 and 3-C5. This suggests that the high level of wealth of in the VRI sample is not just due to the high level of lifetime income. They likely also save more, though other differences (e.g., inherited wealth) might be relevant.

Demographics. Table 3-C6 compares education, health and marital status across samples. Tables 3-C7, 3-C8 and 3-C9 compare the distributions of each of these variables by age bins. The VRI sample has a very high education level. Approximately 70% of the sample has a college degree with over half of those having an advanced degree. The education level is higher for the individual client sample. In contrast, only about 30% of that sample has a college degree in the HRS and the SCF. If we impose the VRI-equivalent screen, however, this gap almost disappears when compared to the employer-sponsored sample in the VRI. The college degree rates from the SCF and HRS are, under VRI-eligible conditions, similar to the VRI rate. For the HRS, the gap is further reduced for the 401(k) subset. Compared to the individual client sample, the HRS and SCF rates are still lower, though the gap is reduced considerably under the VRI-eligibility condition.

The VRI respondents are much healthier than the overall population with more than 70% reporting that their health is either excellent or very good. The corresponding percentage in the total HRS is about 40%. The SCF uses a different four-point scale, without the "very good" category. The fraction of respondents with excellent health is much higher in the VRI (31%) than in the SCF (18%). The gap is much smaller, though does not fully disappear, after imposing the VRI sampling screens on the HRS and the SCF.

The fraction of coupled households (defined as either married or partnered) in the VRI is 67%, which is roughly what was targeted by oversampling administrative singles. Even after this oversampling of singles, the fraction of coupled households is larger than that in the overall sample of the HRS and the SCF. Without imposing the VRI screens, the corresponding percentages are about 51% in the HRS and 53% in the SCF. After imposing the VRI sampling criteria, coupled rates from the HRS and the SCF overshoot the VRI levels for most of the age groups owing to the VRI's oversampling of singles.

Table 3-C10 compares retirement rates. Because the incidence of retirement changes so much with age, it makes sense to compare by age groups. Overall, once the VRI screens are imposed, the retirement rates are quite similar across the SCF and VRI. HRS respondents retire somewhat earlier relative to both the SCF and the VRI.

Table 3-C1. Effect of Imposing VRI Sampling Screens: Median wealth by age

	VRI			HRS			SCF		
Age	Total	Employer-sponsored	Individual client	Age Eligible	VRI Eligible	VRI eligible, 401(k) subset	Age Eligible	VRI Eligible	VRI eligible, 401(k) subset
All	663,100	496,350	715,790	60,000	272,000	342,700	33,200	262,100	219,500
55-59	518,289	428,280	607,900	55,000	226,400	283,000	21,940	208,700	197,070
60-64	601,556	521,245	669,000	58,600	276,000	364,000	36,580	236,100	225,100
65-69	715,627	574,250	750,750	83,000	350,000	435,000	57,000	299,400	463,500
70-74	746,000	671,000	755,550	64,000	310,000	434,000	52,000	410,700	348,000
75-100	726,604	605,300	729,950	50,000	284,000	334,500	27,000	275,500	143,000

Note: HRS and SCF tabulations use sampling weights.

Table 3-C2. Effect of Imposing VRI Sampling Screens: Income distribution

		Mean	Percentiles 10	25	50	75	90
VRI	All	121,481	27,004	50,000	82,017	125,000	191,616
	Employer-sponsored	122,800	42,370	65,000	100,000	146,000	218,201
	Individual client	121,040	24,000	45,000	76,655	119,133	180,000
HRS	Age eligible	65,856	8,476	15,384	30,400	70,300	145,604
	VRI eligible	110,274	17,532	31,600	63,000	123,240	230,000
	VRI eligible, 401(k) subset	134,119	25,927	48,001	87,030	153,010	262,000
SCF	Age eligible	90,848	13,189	22,320	42,601	85,221	160,296
	VRI eligible	177,786	36,219	54,785	91,308	160,296	295,229
	VRI eligible, 401(k) subset	197,214	43,625	66,959	101,453	173,484	320,592

Note: HRS and SCF tabulations use sampling weights.

Table 3-C3. Effect of Imposing VRI Sampling Screens: Median income by age

	VRI			HRS			SCF		
Age	Total	Employer-sponsored	Individual client	Age Eligible	VRI Eligible	VRI eligible, 401(k) subset	Age Eligible	VRI Eligible	VRI eligible, 401(k) subset
55-64	92,100	100,000	84,943	50,500	84,003	97,000	57,785	94,351	96,380
65-74	79,704	100,698	75,130	29,756	46,659	62,051	45,654	91,308	115,657
75-	71,755	73,343	71,703	18,660	30,432	38,437	28,407	66,553	92,322

Note: HRS and SCF tabulations use sampling weights.

Table 3-C4. Effect of Imposing VRI Sampling Screens: Wealth to income ratio

			Percentiles				
		Mean	10	25	50	75	90
VRI (SCF measure)	All	42.97	1.95	4.28	8.37	15.15	24.13
	Employer-sponsored	57.63	0.96	2.25	4.93	8.87	14.31
	Individual client	38.05	2.74	5.31	9.77	17.17	26.30
HRS	Age eligible	44.89	-0.04	0.04	1.46	5.95	16.39
	VRI eligible	95.97	0.59	1.50	3.80	10.39	24.49
	VRI eligible, 401(k) subset	25.30	0.64	1.54	3.35	8.04	17.38
SCF	Age eligible	3.13	-0.21	0.02	0.76	3.34	7.94
	VRI eligible	5.70	0.42	1.20	3.01	6.51	13.00
	VRI eligible, 401(k) subset	4.02	0.26	1.01	2.21	4.90	8.24

Note: HRS and SCF tabulations use sampling weights.

Table 3-C5. Effect of Imposing VRI Sampling Screens: Median wealth to income ratio by age

	VRI			HRS			SCF		
Age	Total	Employer-sponsored	Individual client	Age Eligible	VRI Eligible	VRI eligible, 401(k) subset	Age Eligible	VRI Eligible	VRI eligible, 401(k) subset
55-64	5.90	3.79	7.13	1.01	2.70	2.88	0.53	2.24	2.01
65-74	9.53	5.16	10.1	1.71	5.89	5.88	1.01	4.38	3.27
75-	11.36	9.36	11.11	2.55	9.08	9.85	0.92	4.87	1.41

Note: HRS and SCF tabulations use sampling weights.

Table 3-C6. Effect of Imposing VRI Sampling Screens: Education, Health, and Marital Status.

		VRI			HRS			SCF		
		Total	Employer-Sponsored	Individual client	Age Eligible	VRI Eligible	VRI eligible, 401(k) subset	Age Eligible	VRI Eligible	VRI eligible, 401(k) subset
Education	College grad.	32.18%	33.69%	31.67%	14.25%	22.62%	23.26%	16.26%	27.43%	25.87%
	Post grad.	38.45%	26.24%	42.53%	14.64%	26.36%	30.54%	14.32%	28.39%	28.55%
Health	Poor	0.84%	0.53%	0.94%	7.60%	2.25%	1.71%	10.32%	2.50%	2.42%
	Fair	4.77%	3.48%	5.20%	19.10%	11.10%	9.01%	26.19%	15.67%	17.02%
	Good	21.77%	22.33%	21.58%	31.81%	29.39%	30.29%	45.34%	55.46%	53.51%
	Very good	41.84%	42.25%	41.71%	31.43%	41.30%	42.27%			
	Excellent	30.78%	31.42%	30.57%	10.06%	15.95%	16.71%	18.14%	26.37%	27.05%
Marital Status	Coupled	67.21%	73.88%	64.97%	52.46%	69.89%	77.82%	53.18%	71.04%	74.97%
	Single	32.79%	26.12%	35.03%	47.54%	30.11%	22.72%	46.82%	28.96%	25.03%

Note: HRS and SCF education is based on years of schooling (college grad is exactly 16 years and post-grad is more than 16 years). VRI education is based on degree attainment. SCF health has a four-point scale, while VRI and HRS health have five-point scales. HRS and SCF tabulations use sampling weights.

Table 3-C7. Effect of Imposing VRI Sampling Screens: Fraction with College Degree by Age

	VRI			HRS			SCF		
Age	Total	Employer-sponsored	Individual client	Age Eligible	VRI Eligible	VRI eligible, 401(k) subset	Age Eligible	VRI Eligible	VRI eligible, 401(k) subset
55-64	68.38%	57.61%	78.69%	32.12%	48.92%	50.30%	40.83%	61.96%	60.04%
65-74	73.08%	66.83%	74.18%	26.67%	46.78%	55.18%	39.48%	66.64%	68.12%
75-	69.52%	54.27%	69.82%	21.28%	46.03%	64.19%	20.85%	52.82%	29.06%

Note: Education is based on attainment. HRS and SCF tabulations use sampling weights.

Table 3-C8. Effect of Imposing VRI Sampling Screens: Fraction with Very Good or Excellent Health by Age

	VRI			HRS			SCF		
Age	Total	Employer-sponsored	Individual client	Age Eligible	VRI Eligible	VRI eligible, 401(k) subset	Age Eligible	VRI Eligible	VRI eligible, 401(k) subset
55-64	75.61%	73.43%	77.70%	43.82%	57.82%	59.73%	19.81%	25.92%	24.77%
65-74	75.35%	74.30%	75.54%	43.69%	58.74%	57.26%	23.67%	32.43%	38.77%
75-	61.13%	74.29%	60.87%	34.85%	51.38%	56.25%	10.96%	8.91%	0.28%

Note: SCF does not have 'Very Good' category, so the fraction captures respondents with Excellent health only. HRS and SCF tabulations use sampling weights.

Table 3-C9. Effect of Imposing VRI Sampling Screens: Fraction Married or Partnered by Age

	VRI			HRS			SCF		
Age	Total	Employer-sponsored	Individual client	Age Eligible	VRI Eligible	VRI eligible, 401(k) subset	Age Eligible	VRI Eligible	VRI eligible, 401(k) subset
55-64	66.05%	73.72%	58.69%	58.88%	72.05%	77.28%	58.45%	71.78%	73.27%
65-74	68.65%	74.82%	67.57%	56.60%	69.95%	79.06%	56.26%	72.70%	78.88%
75-	66.26%	65.72%	66.26%	36.46%	60.74%	80.57%	40.23%	60.82%	97.12%

Note: HRS and SCF tabulations use sampling weights.

Table 3-C10. Effect of Imposing VRI Sampling Screens: Retirement Rate by Age

	VRI			HRS			SCF		
Age	Total	Employer-sponsored	Individual Client	Age Eligible	VRI Eligible	VRI eligible, 401(k) subset	Age Eligible	VRI Eligible	VRI eligible, 401(k) subset
All	55.80%	17.78%	68.52%	63.99%	53.23%	36.70%	56.56%	33.92%	16.87%
55-59	9.43%	4.57%	14.75%	24.42%	19.61%	13.84%	19.88%	7.65%	5.34%
60-64	26.68%	12.39%	38.86%	50.25%	42.05%	34.10%	38.62%	24.56%	15.90%
65-69	62.14%	34.13%	69.91%	76.50%	73.16%	66.15%	59.72%	44.39%	34.15%
70-74	81.23%	57.96%	83.31%	87.18%	85.16%	80.70%	77.06%	67.07%	49.44%
75-100	91.38%	74.29%	91.72%	91.57%	92.95%	90.84%	92.16%	87.37%	69.44%

Note: HRS retirement rate includes respondents with partial retirement. For SCF retirement rate variable 'OCCAT1' in the public version of data is used. Households are defined to be retired if 'OCCAT1=3', which also includes disabled, age +65 and not working, etc. HRS and SCF tabulations use sampling weights.

Appendix 3-D. Estimating Retirement/Wealth Relationship

HRS sample. Table 3-D1 shows how many observations we lose in the HRS by imposing each additional condition on samples used. As we have seen from Table 3.5, the majority of the HRS samples are older than 65. Among those households in which the main breadwinner satisfies the age condition, some are retired while some have dual main breadwinners. In addition, for many households that are not retired, responses for the expected retirement age are missing. [19] All of these conditions account for the small sample size used in the HRS.

LOESS curve and scatter plots including outliers. In Figure 3-D1, we show the estimated relationship between retirement plan and wealth from the VRI (Panel A) and the HRS (Panel B) for the full range.

Estimation with future DB pension and Social Security income included in the normalized wealth. In the LOESS estimation in Section 3.5, expected DB pension and Social Security income are included as a control (Y_i^R). Here, we estimate another version of the model where we define the normalized wealth as the sum of the replacement rate from the annuitizable financial wealth and that from the expected annuity income (Y_i^R). Figure 3-D2 shows the distribution of newly defined normalized wealth and Figure 3-D3 shows the new LOESS estimates. For both figures, Panel A is for the entire sample used in Section 3.5. Panel B is for the employer-sponsored subsets.

Figure 3-D2A shows that the VRI sample still has higher replacement rates, though the gap is less stark than in Figure 3.3A. The VRI has many observations in the range between 1 and 2, while for the HRS, most of the observations have normalized wealth smaller than 1. The

[19] Some breadwinners who are not retired report that they are not currently working, leading to missing responses for expected retirement age. In addition, questions about retirement age are asked only when the respondents said that they plan to retire or stop working.

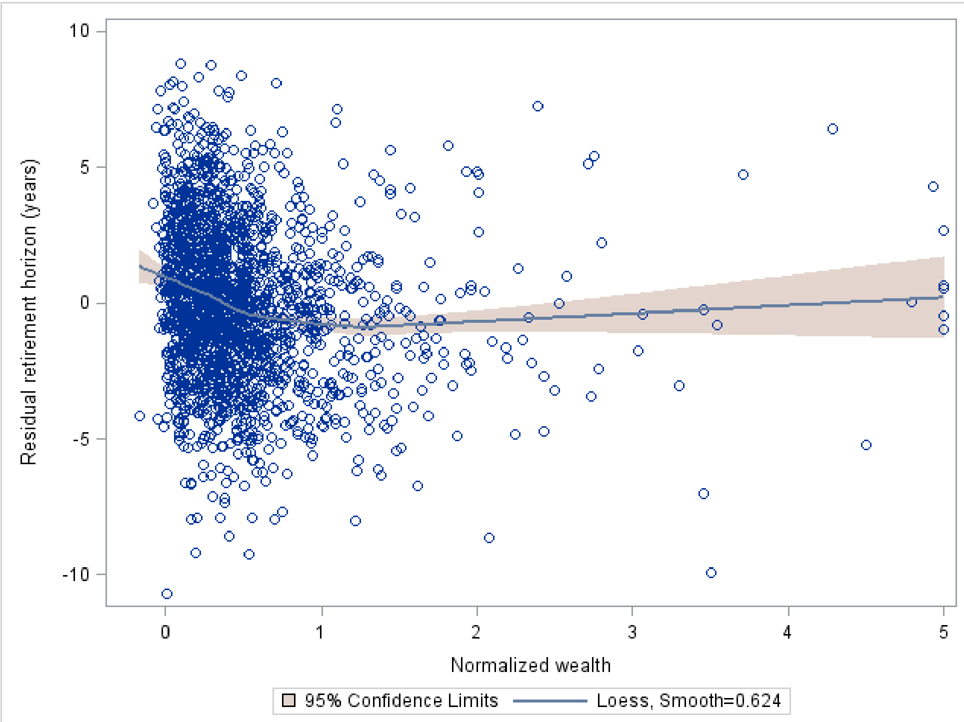
LOESS estimate (Figure 3-D3A) shows basically the same relationship as the baseline model (Figure 3.4A). With the VRI sample, we can estimate a negative and statistically significant relationship for a wider range (between 0 and 2), while the HRS sample shows a steeper slope up to about 0.5 but then becomes flat and statistically insignificant. With the employer-sponsored subset, the distributions of normalized wealth are pretty similar across the VRI and HRS (Figure 3-D2B). Figure 3-D3B shows that conditioning on this subset does not affect the estimated relationship between wealth and retirement plan for the VRI, while for the HRS, the estimates get very noisy due to the small number of observations.

Table 3-D1. HRS Sample Size for Retirement Horizon Analysis: Effect of Each Condition

Condition	Number of observations
(1) None	11,595
(2) Main breadwinner age ≤ 65	5,206
(3) (2) + Main breadwinner not retired, No dual breadwinner	2,442
(4) (3) + Have expected retirement age	1,053

Figure 3-D1. Retirement horizon versus normalized financial wealth: LOESS (full range of data)

A. VRI



B. HRS

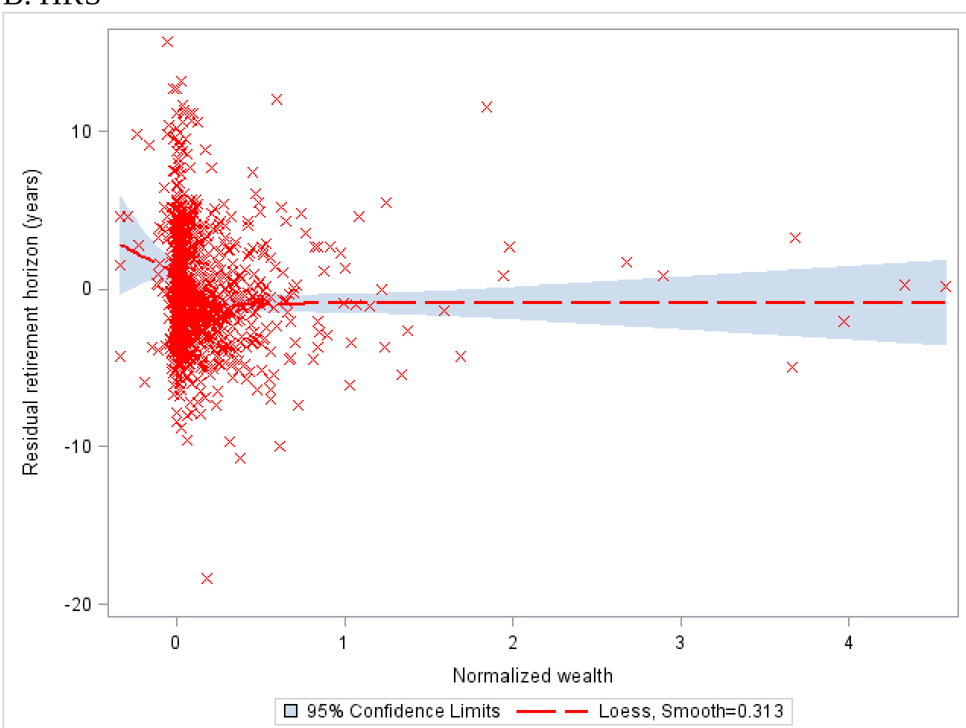
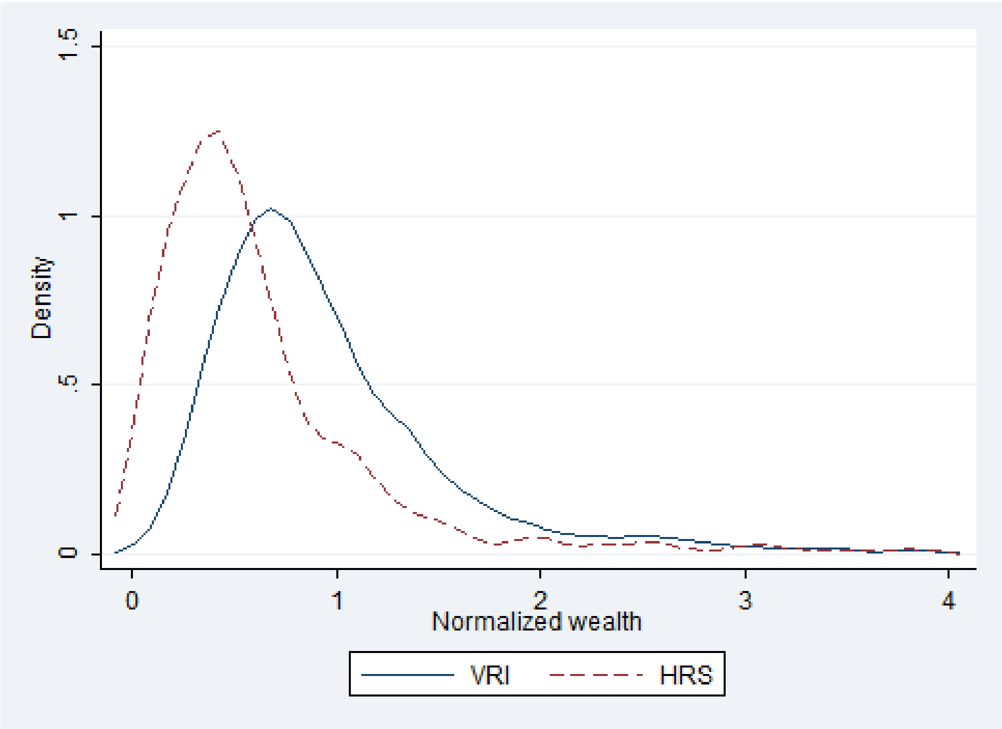


Figure 3-D2. Distribution of normalized financial wealth (including future DB pension and SS income)

A. VRI vs HRS



B. VRI employer-sponsored versus HRS 401(k) subset

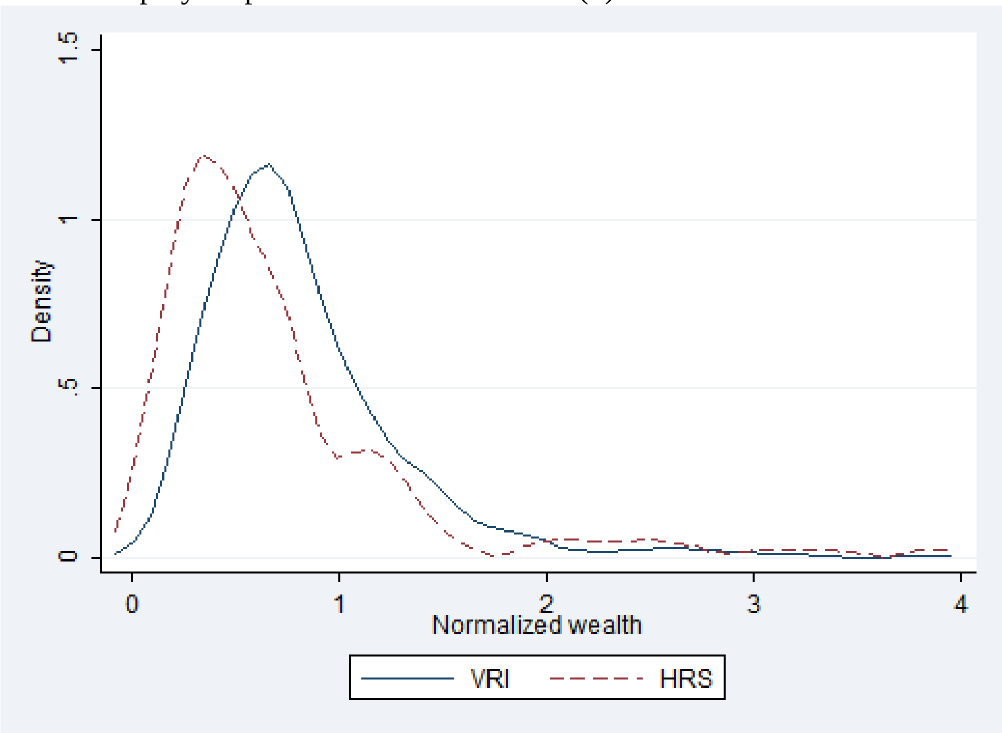
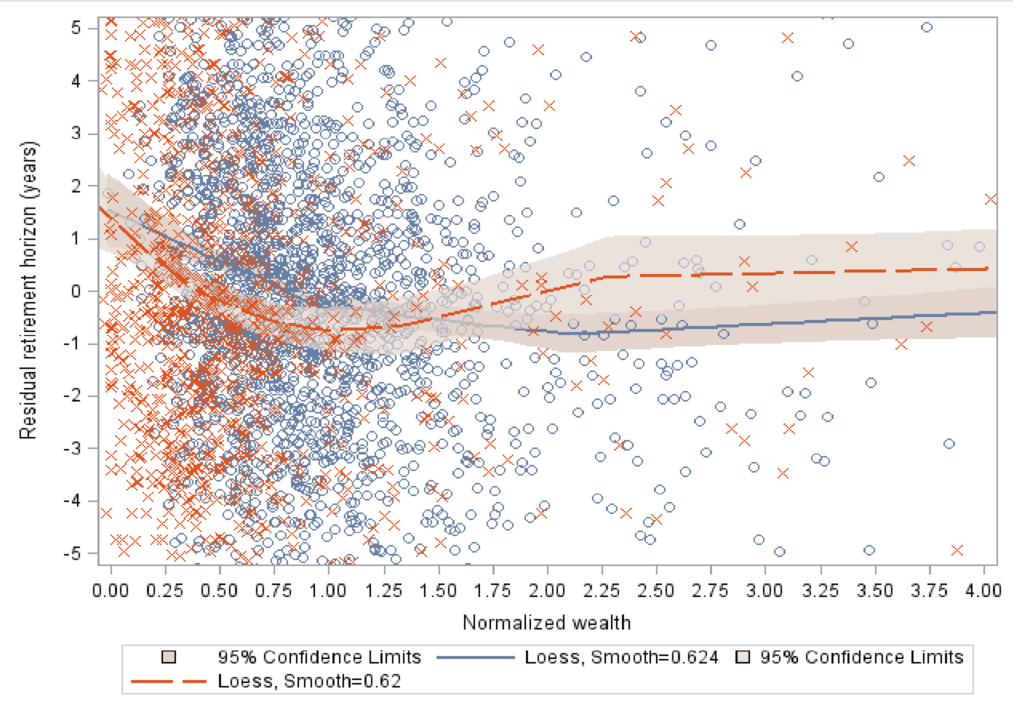


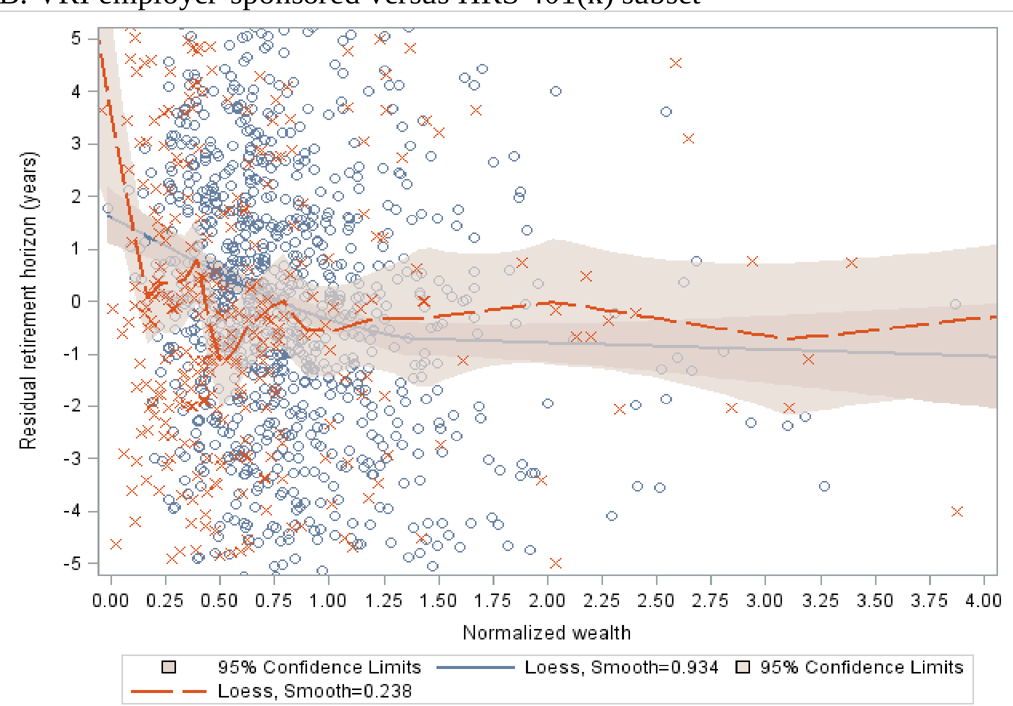
Figure 3-D3. Retirement horizon versus normalized financial wealth: LOESS (Normalized wealth including future DB pension and SS income)

A. VRI vs HRS



Note: x denotes HRS (orange) and o denotes VRI (blue).

B. VRI employer-sponsored versus HRS 401(k) subset



Note: x denotes HRS (orange) and o denotes VRI (blue).