12-18-2018

Household Portfolio Underdiversification and Probability Weighting: Evidence from the Field

Stephen G. Dimmock
Nanyang Technological University

Roy Kouwenberg
Mahidol University and Erasmus University Rotterdam

Olivia S. Mitchell
The Wharton School and the University of Pennsylvania

Kim Peijnenburg
HEC Paris and CEPAR

This paper is part of the NBER's Research Program on the Economics of Aging and the Working Group on Household Portfolios. This project received funding from the TIAA Institute and Wharton School's Pension Research Council/Boettner Center

Household Portfolio Underdiversification and Probability Weighting: Evidence from the Field

Abstract

We test the relation between probability weighting and household portfolio choice in a representative household survey, using custom-designed incentivized lotteries. On average, people display Inverse-S shaped probability weighting, overweighting the small probabilities of tail events. As theory predicts, our Inverse-S measure is positively associated with portfolio underdiversification, which results in significant Sharpe ratio losses. We analyze respondents' individual stock holdings and find that people with higher Inverse-S tend to pick lottery-type stocks and hold positively-skewed equity portfolios. Furthermore, Inverse-S is positively associated with stock market nonparticipation. We find evidence indicating that these choices reflect preferences rather than probability unsophistication.

Keywords

household finance, portfolio underdiversification, probability weighting, rank dependent utility, cumulative prospect theory, salience theory, household portfolio puzzles, stock market participation

Disciplines

Economics

Comments

This paper is part of the NBER's Research Program on the Economics of Aging and the Working Group on Household Portfolios. This project received funding from the TIAA Institute and Wharton School's Pension Research Council/Boettner Center

Household Portfolio Underdiversification and Probability Weighting: Evidence from the Field

Stephen G. Dimmock, Roy Kouwenberg, Olivia S. Mitchell, and Kim Peijnenburg

December 18, 2018

PRC WP2018-9
Pension Research Council Working Paper
Pension Research Council
The Wharton School, University of Pennsylvania
3620 Locust Walk, 3000 SH-DH
Philadelphia, PA 19104-6302
Tel.: 215.573.3414 Fax: 215.573.3418
Email: prc@wharton.upenn.edu
http://www.pensionresearchcouncil.org

This paper is part of the NBER's Research Program on the Economics of Aging and the Working Group on Household Portfolios. For assistance with the survey, the authors gratefully acknowledge Tim Colvin, David Grant, and the American Life Panel team at the RAND Corporation. For comments, we thank Jose Miguel Abito, John Campbell, Nicola Gennaioli, Nishad Kapadia, Alexander Klos, Sonya Lim, Gianpaolo Parise, Valery Polkovnichenko, Meir Statman, Peter Wakker, and Joe Zhang; seminar participants at EDHEC, ESSEC, HEC Paris, IESE Business School, London School of Economics, University of Cambridge, and University of Warwick; and participants at the Financial Intermediation Research Society, SFS Cavalcade, Singapore Symposium, TIAA/PRC Symposium, and Western Finance Association. Yunju Cha and Yong Yu provided outstanding research assistance. This project received funding from the TIAA Institute and Wharton School's Pension Research Council/Boettner Center.
The content is solely the responsibility of the authors and does not represent official views of the TIAA Institute or the Wharton School's Pension Research Council/Boettner Center. Online Appendices are at https://pensionresearchcouncil.wharton.upenn.edu/wp-content/uploads/2018/08/Online_Appendix_2018-08-08.pdf

Household Portfolio Underdiversification and Probability Weighting: Evidence from the Field

Stephen G. Dimmock, Roy Kouwenberg, Olivia S. Mitchell, and Kim Peijnenburg

Abstract

We test the relation between probability weighting and household portfolio choice in a representative household survey, using custom-designed incentivized lotteries. On average, people display Inverse-S shaped probability weighting, overweighting the small probabilities of tail events. As theory predicts, our Inverse-S measure is positively associated with portfolio underdiversification, which results in significant Sharpe ratio losses. We analyze respondents' individual stock holdings and find that people with higher Inverse-S tend to pick lottery-type stocks and hold positively-skewed equity portfolios. Furthermore, Inverse-S is positively associated with stock market nonparticipation. We find evidence indicating that these choices reflect preferences rather than probability unsophistication.

JEL Codes: G11, D81, D14, C83

Keywords: household finance, portfolio underdiversification, probability weighting, rank dependent utility, cumulative prospect theory, salience theory, household portfolio puzzles, stock market participation

Stephen G. Dimmock
Nanyang Technological University
dimmock@ntu.edu.sg

Roy Kouwenberg
Mahidol University and Erasmus University Rotterdam
roy.kou@mahidol.ac.th

Olivia S. Mitchell
The Wharton School of the University of Pennsylvania and NBER
mitchelo@wharton.upenn.edu

Kim Peijnenburg
HEC Paris and CEPR
peijnenburg@hec.fr

People frequently violate the tenets of expected utility theory for low probability events: for example, they simultaneously buy insurance and lottery tickets, overinsure against small losses, and hold underdiversified positions in individual company stocks with high positive skewness hoping to pick the "next Apple."[1] Such seemingly anomalous behaviors are consistent with *probability weighting*: the idea that people use transformed rather than objective probabilities when making decisions. As formalized in prospect theory (Kahneman and Tversky, 1979; Tversky and Kahneman, 1992), rank-dependent utility theory (Quiggin, 1982; Yaari, 1987), and salience theory (Bordalo, Gennaioli, and Shleifer, 2012), people tend to overweight low probability tail events and underweight events from the middle of the probability distribution.

Several theoretical papers show that probability weighting predicts anomalies in observed household portfolio decisions such as underdiversification and the popularity of lottery-type stocks (Barberis and Huang, 2008; Bordalo, Gennaioli, and Shleifer, 2013). For individuals who overweight small probability tail events, the negative skewness of the aggregate stock market makes a well-diversified portfolio less attractive, while the positive skewness of an underdiversified portfolio containing a few individual stocks becomes more attractive.[2]

The empirical literature is less developed, offering mostly indirect evidence using calibrated portfolio choice models (Polkovnichenko, 2005). Obtaining a direct link between probability weighting and portfolio choices is challenging, because individual preferences such as probability weighting are not readily observable. The present paper provides evidence that directly measured probability weighting can explain actual household portfolio decisions, most notably portfolio underdiversification, skewness seeking, and investments in lottery-type stocks.

[1] For further discussion, see the review articles of Fehr-Duda and Epper (2012) and Barberis (2013a).
[2] See Shefrin and Statman (2000), Polkovnichenko (2005), Barberis and Huang (2008), Jin and Zhou (2008), Chapman and Polkovnichenko (2011), De Giorgi and Legg (2012), and He, Kouwenberg, and Zhou (2018). Albuquerque (2012) presents a theoretical foundation for the positive skewness of individual stocks.

To elicit individuals' probability weighting preferences, we designed a purpose-built internet survey module and fielded it in a nationally-representative sample of several thousand respondents in the American Life Panel (ALP). Our module elicits certainty equivalents for a series of binary lotteries adapted from Wakker and Deneffe (1996) and Abdellaoui (2000). The probabilities of winning the lotteries vary from small to large, allowing us to obtain a non-parametric measure of individual respondents' probability weighting behavior, which we term *Inverse-S*. In addition to a fixed participation fee, all respondents had the opportunity to receive real monetary incentives based on their choices (we paid a total of $16,020 to 2,072 of the 2,703 eligible respondents). The survey module also measures subjects' portfolio allocations and collects the names of their five largest individual stockholdings.

Our general population estimates of probability weighting are consistent with those found in earlier studies (Abdellaoui, 2000; Booij, van Praag, and van de Kuilen, 2010; Bruhin, Fehr-Duda, and Epper, 2010). Specifically, we show that most people have inverse-S shaped probability weighting functions implying overweighting of tail events, though there is substantial heterogeneity. On average, when the probability of winning a lottery is only 5%, our subjects are willing to pay *more* for the lottery than its expected value, which is consistent with overweighting the small probability of winning. By contrast, when the probability of winning a lottery is higher (e.g., 50%), our subjects' certainty equivalent is *less* than the expected value of the lottery.

Using our subject-specific variable, *Inverse-S*, we test the theoretical predictions regarding probability weighting and portfolio choice. Specifically, we explore the portfolios of equity holders and measure the fraction of total equity allocated to individual stocks, which Calvet, Campbell, and Sodini (2007, 2009) show is a good proxy for portfolio underdiversification.[3] We

[3] Consistent with Calvet, Campbell, and Sodini (2007, 2009), we find that, conditional on owning individual stocks, half of the respondents held shares in only one or two individual companies, which is consistent with the fraction of the equity portfolio allocated to individual stocks being a reasonable proxy for underdiversification.

find that a one standard deviation increase in *Inverse-S* implies a 12.7 percentage point increase in the fraction of the portfolio allocated to individual stocks. Using subjects' individual stock holdings, we construct an alternative measure of underdiversification: the relative Sharpe ratio loss from investing in individual stocks (as compared to investing in the market portfolio; see Calvet, Campbell, and Sodini, 2007). We find that high *Inverse-S* is associated with large Sharpe ratio losses due to idiosyncratic risk. In particular, our results imply that a one-standard deviation higher *Inverse-S* implies a cost to the average (median) stockholder of $2,504 ($351) per year, as for the same amount of risk the person could have had a higher expected return.

As a robustness test, we estimate parametric measures of probability weighting preferences using the functions proposed by Tversky and Kahneman (1992), Prelec (1998), and Bordalo, Gennaioli, and Shleifer (2012), and we find similar results as with the non-parametric measure. Our module also included a series of questions designed to measure utility function curvature (risk aversion). We create an individual level measure of utility function curvature and show that all results are robust to including this as a control variable, as well as standard demographic and economic control variables.

To address the issue of measurement error, the module recorded the time each subject spent on the elicitation questions and included check questions to assess the internal consistency of the subjects' choices. Our results are robust to excluding subjects who answered the elicitation questions unusually quickly or who made multiple errors on the check questions.

In addition, we find that probability weighting can help explain the *type* of individual stocks people choose. To this end, we asked respondents who own individual stocks to provide the names of their five largest holdings. We then match these names to the CRSP database and construct various measures of the stock characteristics. Consistent with theoretical predictions, respondents with high *Inverse-S* tend to hold lottery-type individual stocks with high positive (expected) skewness. We find similar results in tests of overall portfolio characteristics.

Next, we evaluate whether probability weighting is a component of preferences or a symptom of probability unsophistication (for further discussion see Barberis, 2013a, p. 192). For example, poor quantitative reasoning ability could drive both probability weighting and observed portfolio choices. Based on our summary statistics this seems unlikely, as probability weighting is weakly positively correlated with education, numerical reasoning ability, and financial literacy. Robustness tests show our results are similar if we restrict the sample to subjects who score higher on proxies for probability sophistication, namely, having a college degree and avoiding errors on numerical reasoning questions. The results are also similar if we restrict the sample to subjects who make no errors on financial literacy questions or understand that owning a single company's stock is generally riskier than owning an equity mutual fund. Overall, we conclude that probability weighting reflects preferences rather than probability unsophistication or limited financial knowledge.

We then broaden the sample of survey respondents to consider non-participation in equity markets as well as the type of equity held by those who do participate. The theoretical predictions on non-participation are less clear but generally posit that probability weighting results in non-participation due to first-order risk aversion.[4] Theoretical papers do unequivocally predict that stock market participants with high probability weighting will hold underdiversified individual stock portfolios. To test these predictions, we use a multinomial logit model with four categories: non-participation, mutual funds only, individual stocks only, and both mutual funds and individual stocks. We find that *Inverse-S* is positively associated with non-participation *and* ownership of individual stocks, and thus is negatively associated with owning only mutual funds. This result is

[4] See Epstein and Zin (1990), Segal and Spivak (1990), and Chapman and Polkovnichenko (2011).

directionally inconsistent with probability weighting being a proxy for risk aversion, as subjects make *either* the least risky choice (non-participation) or the riskiest choice (an underdiversified portfolio), thereby mitigating concerns that our measure inadvertently captures risk aversion.

Our paper contributes to the household portfolio choice literature by testing theoretical models of probability weighting and household portfolio choice.[5] Specifically, we are the first to show a relation between directly elicited probability weighting preferences and actual household portfolio decisions. Relatedly, Polkovnichenko (2005) uses stock return data to obtain numerical results in a calibrated model inferring a link between probability weighting and underdiversification. Rieger (2012) and Erner, Klos, and Langer (2013) relate elicited probability weighting metrics to hypothetical financial decisions about structured products in laboratory experiments using university students. In contrast, we relate preferences elicited in the field to people's actual financial decisions. Consistent with the predictions of theory, we show that probability weighting can explain portfolio underdiversification, skewness seeking, and investments in lottery-type stocks, and we further show that probability weighting is related to non-participation in the equity market.

Our paper also contributes to the empirical literature on household portfolio underdiversification.[6] For instance, Kumar (2009) finds that households hold underdiversified portfolios and this behavior is related to the demand for stocks with lottery-like features. Our paper complements these studies, as it explores the underlying preferences driving this demand.

Finally, our work relates to a branch of the asset pricing literature which posits that probability weighting can explain the historically low returns of many securities with positive skewness. Several authors find that stocks with positive expected skewness have unusually low

[5] For example, Shefrin and Statman (2000), Polkovnichenko (2005), Barberis and Huang (2008), Jin and Zhou (2008), Chapman and Polkovnichenko (2011), De Giorgi and Legg (2012), and He, Kouwenberg, and Zhou (2018).
[6] For example, Blume and Friend (1975), Kelly (1995), Calvet, Campbell, and Sodini (2007), Mitton and Vorkink (2007), and Goetzmann and Kumar (2008).

returns (Boyer, Mitton, and Vorkink, 2010; Bali, Cakici, and Whitelaw, 2011; Conrad, Dittmar, and Ghysels, 2013; Conrad, Kapadia, and Xing, 2014). Boyer and Vorkink (2014) and Li, Subrahmanyam, and Yang (2018) find similar results for equity options. Though our paper does not directly address asset pricing implications, our findings do support the preference-based explanation offered in the cited studies. That is, we find a direct link between investors' probability weighting preferences and skewness-seeking behavior.

1. Eliciting Individuals' Probability Weighting and Utility Curvature

1.1. Rank-Dependent Utility and Probability Weighting

A large body of experimental studies finds that individuals frequently make decisions that contradict the predictions of expected utility (Camerer, 1995; Starmer, 2000). In the expected utility model, the utility $U(c_i)$ of each outcome c_i is weighted linearly by its probability p_i:

$$E(U) = \sum_{i=1}^{N} p_i \cdot U(c_i) \ . \qquad (1)$$

However, Allais (1953) demonstrates that linearity in probabilities is often violated. For example, consider the choice between a 100% certainty of receiving $1 million versus a 98% chance of winning $5 million. Most people prefer to receive $1 million with certainty. Next, consider a modification of this choice in which both probabilities are divided by 100: that is, consider the choice between a 1% chance of winning $1 million versus a 0.98% chance of winning $5 million. Now, most people prefer a 0.98% chance of winning $5 million. Such a combination of choices is inconsistent with expected utility: the first preference implies $U(1{,}000{,}000) > 0.98 \times U(5{,}000{,}000)$, while the second preference implies $0.01 \times U(1{,}000{,}000) < 0.0098 \times U(5{,}000{,}000)$.

This phenomenon, known as the Allais paradox, demonstrates that risk preferences can depend non-linearly on probabilities. Many studies replicate this finding, including experiments with large real monetary rewards (Starmer, 2000). Generally, in experiments as well as real world situations, people are risk seeking when the probability of winning is small but risk averse when the probability of winning is large. Furthermore, many people are risk seeking for small probabilities of winning but risk averse for small probabilities of losing. For example, the same person may buy both lottery tickets and insurance (for a review see Fehr-Duda and Epper, 2012).

A large theoretical and empirical literature shows that Allais' findings can be explained by non-expected utility models in which decision-makers transform probabilities with a non-linear weighting function (Starmer, 2000; Fehr-Duda and Epper, 2012). The two most commonly used models are rank-dependent utility (RDU) developed by Quiggin (1982), and cumulative prospect theory (CPT) developed by Tversky and Kahneman (1992). In these models, individuals order the possible outcomes from worst to best ($c_1 < c_2 < \cdots < c_N$) and then assign each outcome a decision weight, π_i, that depends on the cumulative probability of the outcome. For example, the utility functional can be given by:

$$V = \sum_{i=1}^{N} \pi_i \cdot U(c_i) \quad , \tag{2}$$

$$\pi_i = w(P_i) - w(P_{i-1}) = w(p_1 + p_2 + \cdots + p_i) - w(p_1 + p_2 + \cdots + p_{i-1}) \ , \tag{3}$$

where π_i is determined by an increasing weighting function $w(P_i)$, such that $w(0) = 0$ and $w(1) = 1$, and $P_i = p_1 + p_2 + \cdots + p_i$ is the cumulative probability of outcome i.

Figure 1 displays the inverse-S shaped pattern of $w(P_i)$ typically found in experimental studies, in which low probability tail outcomes are substantially overweighted relative to objective probabilities ($\pi_i > p_i$). The weighting function is steep on both the left and the right sides of the figure, which implies overweighting of both extreme good outcomes and extreme bad outcomes. This, in turn, can generate risk seeking towards good outcomes with low probabilities and extreme risk aversion towards bad outcomes with low probabilities.

Probability weighting is similar in CPT and RDU – the theories differ in their treatment of utility curvature (risk aversion) and not probability weighting – except that in CPT the probabilities for loss outcomes ($c_N < \cdots < c_{k+2} < c_{k+1} < 0$) and gain outcomes ($0 < c_k < \cdots < c_2 < c_1$) are transformed by two distinct weighting functions, $w^-(P_i)$ and $w^+(P_i)$. Empirically, the weighting functions for losses and gains tend to have the same inverse-S shaped pattern as in Figure 1 (Tversky and Kahneman, 1992). Therefore, low probability outcomes in both tails are overweighted, similar to rank dependent utility.

More recently, Bordalo, Gennaioli, and Shleifer (2012) propose a model in which probability weighting is determined by the salience of the payoffs, with the contrast between the payoffs determining their salience. In this model, people overweight the probability of salient gains (losses), resulting in risk seeking (averse) behavior. Although in some contexts this model generates different predictions than RDU or CPT, for financial choices the predictions are largely similar. Bordalo, Gennaioli, and Shleifer (2013) show that, relative to expected utility theory, salience theory implies a strong preference for positively skewed securities and reduced demand for a diversified portfolio such as the market index. Accordingly, in this paper we do not seek to distinguish between RDU, CPT, and salience theory.

1.2. Hypotheses

The extant theoretical literature shows that probability weighting affects portfolio choice through two channels: greater sensitivity to skewness and first-order risk aversion. Probability weighting increases sensitivity to skewness, because the investor overweights low probability tail outcomes. As Figure 2 illustrates, portfolios with a few individual stocks have high positive skewness, but diversification reduces skewness and the aggregate stock market has negative skewness (Albuquerque, 2012). As a result, probability weighting makes underdiversified portfolios of individual stocks more attractive (Shefrin and Statman, 2000; Polkovnichenko, 2005;

Barberis and Huang, 2008; Jin and Zhou, 2008) and well-diversified portfolios less attractive (Polkovnichenko, 2005; Chapman and Polkovnichenko, 2011; De Giorgi and Legg, 2012). Thus, theory predicts that higher probability weighting will result in underdiversification.

We illustrate this prediction using a simple calibrated portfolio choice model with probability weighting preferences. In this calibration, people have constant relative risk aversion (CRRA) utility and a Prelec (1998) probability weighting function. They can allocate their portfolios across a positively skewed individual stock, a negatively skewed mutual fund, and a risk-free asset. Our calibration is generally similar to Polkovnichenko (2005). (Details are provided in Online Appendix A.) Figure 3 shows the optimal fraction of equity allocated to the individual stock (a measure of underdiversification) for different levels of probability weighting – denoted *Inverse-S* – and γ, the CRRA parameter. The fraction of equity allocated to the individual stock is strongly increasing in probability weighting. Thus, our simple calibrated portfolio choice model is consistent with prior theoretical papers predicting that people with high *Inverse-S* will hold underdiversified portfolios with high positive skewness.

The calibrated model results show that the allocation of equity is relatively insensitive to γ. This is consistent with the portfolio separation theorem; although γ affects the total allocation to equities, it does not affect the relative portfolio weights between risky securities (i.e., the investor holds constant relative proportions of the mutual fund and the individual stock regardless of γ).

Furthermore, Epstein and Zin (1990), Segal and Spivak (1990), and Chapman and Polkovnichenko (2011) show that probability weighting creates first-order risk aversion – that is, the investor does not become locally risk neutral as the size of a potential investment becomes small. This increased risk aversion reduces demand for equity securities and can lead to non-participation in the equity markets (Polkovnichenko, 2005).

1.3. The Elicitation Procedure

Empirically estimating individual-level measures of probability weighting is complex because preferences are determined by the product of two (usually non-linear) functions: probability weighting and utility. Throughout the paper we will use the less conventional term "utility curvature" to refer to aversion to risk caused by utility curvature, and not the more frequently used term "risk aversion." This is because with probability weighting the curvature of the utility function alone does not fully describe risk aversion – instead, risk averse behavior is the outcome of a combination of utility curvature and probability weighting.

Thus the challenge is to separate the effects of probability weighting from utility function curvature. For elicitation questions with modest rewards, if the subject integrates outcomes with existing wealth as in expected utility theory or RDU, this issue is trivial because the subject's utility function is effectively linear for modest rewards and its curvature can be ignored.[7] This issue is not trivial under behavioral theories that involve narrow framing, however, because the subject evaluates decisions in isolation and utility function curvature can affect even small stake gambles. Prior studies address this issue using two methods. First, parametric methods that assume a specific functional form and then estimate probability weighting and utility curvature parameters (Tanaka, Camerer, and Nguyen, 2010; Erner, Klos, and Langer, 2013). The disadvantages of this approach are the need to commit to a specific functional form and the estimation error in the individual level parameter estimates. Second, non-parametric methods that do not assume a functional form but require chaining, so that the choices offered to a subject depend upon her prior choices (Wakker and Deneffe, 1996; Abdellaoui, 2000; van de Kuilen and Wakker, 2011). The disadvantage of this second approach is that, as Abdellaoui (2000, p. 1511) notes "...error propagation in the trade-off

[7] This does not mean that individuals are effectively risk neutral for small gambles, however, as probability weighting alone generates first-order risk aversion (Yaari, 1987; Segal and Spivak, 1990).

method can produce `noisy' probability weighting functions" (e.g., a response error in the first question affects the choices offered in all subsequent questions).

Our solution to separate probability weighting from utility curvature is to use a non-parametric approach and limit the need for chaining. Our survey questions are adapted from Wakker and Deneffe (1996) and Abdellaoui (2000), albeit with some modifications that reduce error propagation and the time required to complete the questions due to the constraints of a general population survey (rather than a classroom experiment).[8] We designed and fielded a customized module in the American Life Panel (ALP) survey presenting subjects with 10 multi-round questions. The first four questions measure utility curvature and the remaining six measure probability weighting. Each question asks subjects to choose between two options: A or B (see Figure 4). There are three rounds per question, and based on each subject's choice in a given round, one option in the subsequent round is changed to become either more or less attractive. As a starting point for each question, we use the answer of a risk neutral expected utility maximizer. Hence the choices offered to subjects are determined only by their prior answers within the rounds of a single question, rather than across different questions.

To illustrate, Figure 4 shows the first round of the first question, intended to measure utility curvature. Option A offers a 33% chance of winning \$12 and a 67% chance of winning \$3, while Option B initially offers a 33% chance of winning \$18 and a 67% chance of winning \$0. Accordingly, both options have an expected value of \$6 and offer the same chance of winning the larger payoff (33%), but Option B is riskier (Option B is a mean-preserving spread of Option A). If the subject selects the safer Option A, then Option B is made more attractive by increasing the

[8] We first piloted four different designs of the elicitation method in a sample of 207 ALP respondents, comparing the method of Abdellaoui (2000) with the midweight method of van de Kuilen and Wakker (2011), while using two different question presentation formats (choice lists and multiple pairwise choices). For our main survey, we chose the question format that the respondents found clear, minimized mistakes, and led to lower average response times. Online Appendix B provides further details of the elicitation method. We do not include the pilot sample responses in our empirical tests and the subjects for the pilot were not included in the sample for the main survey.

winning amount to $21. If, instead, the subject chooses Option B, then Option B is made less attractive by decreasing the winning amount to $16. This process continues for three rounds, until the subject's indifference point is closely approximated. For each question, the subject is then presented with a fourth choice used only to evaluate consistency with prior choices.

Panel A of Table 1 shows the structure of the four sets of questions designed to measure utility curvature. In all four questions, the probability of winning the large prize is fixed at 33% for both Option A and B. Thus, the effect of probability weighting is largely cancelled out in the comparison between Options A and B, as the probability of winning is the same. Furthermore, we use a 1/3 probability of winning as, on average, this probability is neither under- nor overweighted (Tversky and Fox, 1995). We ask four sets of questions instead of one to obtain a more accurate measure of utility curvature and minimize the effect of measurement error.

We next present each subject with six questions designed to measure probability weighting. The goal is to elicit the certainty equivalent of Option A, which is a risky choice with two possible outcomes. Figure 5 depicts the first round of one of the questions: Option A offers a fixed large payoff of $42 with probability p = 5% and a small payoff of $6 with probability 95%, while Option B offers a sure amount of $8. If the subject chooses risky Option A, then in the second round the sure amount for Option B is increased to $9. If the subject instead chooses Option B, then in the second round the sure amount is reduced to $7. This process is repeated for three rounds until the certainty equivalent for Option A is closely approximated, as illustrated by the decision tree in Figure 6. We then compare the certainty equivalent to the expected value of the risky gamble so as to estimate the percentage risk premium.[9] In the remaining five sets of probability weighting

[9] For the four sets of utility curvature questions, the certainty equivalent is not known as the respondent compares two lotteries. For these questions, we define the % risk premium as the percentage difference between the respondent's elicited indifference value and the indifference value of a risk neutral decision maker.

questions, the probabilities, *p*, of winning the large prize in Option A are 12%, 25%, 50%, 75%, and 88%. Panel B of Table 1 shows the structure of the six sets of probability weighting questions.

We also include consistency checks of subjects' choices, as elicited preferences likely contain measurement error (see Harless and Camerer, 1994; Hey and Orme, 1994). After the subject has completed three rounds of the question, we ask a question of which only one response is consistent with previous choices, as the sure amount falls outside the person's indifference bounds. (Details are provided in Online Appendix B.)

The subjects in our survey module could win real rewards based on their choices. This is important, as prior studies show that real rewards produce more reliable estimates of preferences (Smith, 1976). At the beginning of the survey, all subjects are told that one of their choices would be randomly selected and played for real money. We paid a total of $16,020 in real incentives to 2,072 of the 2,703 eligible subjects who completed the survey. The American Life Panel (ALP) was responsible for determining and making the incentive payments, and subjects in the ALP regularly participate in and receive payments from the ALP surveys. The involvement of the ALP should minimize subjects' potential concerns about the credibility of the incentives.

An advantage of our experimental survey approach is that we can explicitly state the probabilities, ensuring the subjects know the precise probabilities of all outcomes. This allows us to measure *preferences* towards probabilities rather than *beliefs* about probabilities; in contrast, it is extremely difficult to disentangle preferences and beliefs regarding natural events. For instance, the popularity of actuarially unfair extended warranties could result from either probability weighting or overestimation of the probability of malfunction (Abito and Salant, 2018).

1.4. The Probability Weighting Measure

Using the six indifference values elicited from the probability weighting questions described above, we create a probability weighting measure for each individual. First, we convert the indifference values into percentage premiums relative to the expected value of the risky gamble (Option A). For example, consider the 5% probability weighting question. Suppose we approximate that a subject is indifferent between Option A [5%, $42; 95%, $6] and Option B [100%, $8.25]. The expected value of Option A is $7.80, implying a percentage risk premium for question $PW_{5\%}$ of: $(7.80 - 8.25)/7.80 = -5.8\%$. In this case, the premium is negative as the subject overweights the low probability of winning a large prize and demands a certainty equivalent greater than the expected value of the risky gamble.

The risk premiums are summarized in the final column of Panel B in Table 1. On average, for high probabilities, people demand large positive risk premiums. For small probabilities (5% and 12%), however, people are willing to pay more than the expected value to own the lottery. This pattern is consistent with overweighting of small probabilities. In contrast, this pattern is inconsistent with any model of expected utility, including models that incorporate skewness preferences (Quiggin, 1993).

Using these premiums, we create our non-parametric probability weighting variable, *Inverse-S*, as follows:

$$Inverse\text{-}S = (PW_{88\%} + PW_{75\%} + PW_{50\%}) - (PW_{25\%} + PW_{12\%} + PW_{5\%}). \quad (4)$$

In the experimental literature, individuals switch from over- to underweighting probabilities in the range between 25% and 50% (where the probability weighting function crosses the diagonal in Figure 1). Note that, however, a positive risk premium for the 25% question does not necessarily imply that the 25% probability is underweighted. Instead, the effects of utility curvature may fully offset the effects of probability weighting, resulting in a risk averse choice. Our measure is thus simply the premiums in the overweighting range less the premiums in the underweighting range. Higher values indicate a more pronounced *Inverse-S* shape for the probability weighting function.

This measure is parsimonious and it allows us to avoid assuming a specific functional form for probability weighting. If individuals frame narrowly and utility function curvature affects the responses, taking the difference between the percentage premiums reduces the influence of curvature, because curvature affects all premiums similarly and is thus largely differenced out of the measure. The cost of the tradeoff we have made in our survey design – limiting chaining to avoid measurement error – is that it is theoretically possible for utility curvature to influence our measure of probability weighting. In practice, however, this possibility does not appear to affect the measure. The summary statistics in the next section show that the correlation between *Inverse-S* and our measure of utility curvature is small (ρ = 0.09), and our empirical results are theoretically inconsistent with *Inverse-S* measuring utility curvature. Nevertheless, to ensure that *Inverse-S* does not inadvertently measure utility curvature, in robustness tests we jointly estimate utility curvature and probability weighting parameters using a parametric model.

Specifically, we jointly estimate utility curvature using CRRA utility and the probability weighting function proposed by Prelec (1998, Eq. 3.1). The Prelec function has clear axiomatic foundations and is well suited for very small and very large probabilities. The curve features a fixed intersection point at $p = 1/e = 0.37$, which is consistent with experimental findings.

As additional robustness tests, we also estimate the parameters using the salience function proposed by Bordalo, Gennaioli, and Shleifer (2012, Eq. 5) and the probability weighting function proposed by Tversky and Kahneman (1992, Eq. 6). The salience function provides an intuitive psychological foundation for why probability weighting occurs and Bordalo, Gennaioli, and Shleifer (2013) show that salience theory predicts portfolio underdiversification. The Tversky and Kahneman (1992) function is commonly used in the finance literature.[10] Online Appendix C provides details about the estimation of the three parametric functions.

[10] Although widely used in the finance literature, the Tversky and Kahneman (1992) function generates an artificial negative correlation between the utility curvature parameter and the probability weighting parameter (Fehr-Duda and

2. Data and Variables

2.1. Data Sources: American Life Panel Survey and CRSP

We fielded our survey module in the RAND American Life Panel[11] from June 20 to July 19, 2017. The ALP includes several thousand households that regularly answer Internet surveys. To limit selection bias, households lacking Internet access at the recruiting stage are provided with a laptop and wireless service. To ensure that the sample is representative of the U.S. population, we use survey weights provided by the ALP for all analyses and summary statistics reported in this paper. In addition to the probability weighting variables, our module also collects information on portfolio choice and some control variables. Other controls, such as demographic and economic characteristics, are available from earlier survey modules. The ALP invited 3,397 panel members and closed the survey when 2,701 completed the survey, resulting in a completion rate of 79.5%.

Respondents who indicated that they hold individual stocks are asked to list the names (or tickers) of their five largest holdings. We match these names or tickers by hand to the CRSP daily stock return database,[12] and we then construct various measures of stock characteristics using daily return data from July 1, 2016 to June 30, 2017. We select this specific period since our survey was fielded from June 20 to July 19, 2017. Table 2 provides summary statistics of the key variables (Appendix Table A1 defines the variables).

2.2. Dependent Variables

Fraction of Equity in Individual Stocks is the fraction of the respondent's total equity portfolio invested in individual stocks, conditional upon non-zero equity ownership. The average fraction allocated to individual stocks is 45%. Calvet, Campbell, and Sodini (2007, 2009) show

Epper, 2012). For this reason, we do not jointly estimate the utility curvature parameter along with the Tversky and Kahneman (1992) probability weighting parameter.

[11] For further information about the ALP see Online Appendix D and https://www.rand.org/labor/alp.html.

[12] In our tests, we use only U.S. based common stocks. We are unable to match 12.1% of the reported holdings because the holding was a foreign or private company, or because the reported name was ambiguous or unmatchable.

that this fraction is a good proxy for portfolio underdiversification. In addition, for the subsample of individual stock owners, we observe the number of individual companies that they own. We find that, conditional on owning individual stocks, half of the respondents held shares in only one or two individual companies, which is consistent with the fraction of the equity portfolio allocated to individual stocks being a reasonable proxy for underdiversification.

As an alternative measure of portfolio underdiversification, we calculate the *Relative Sharpe Ratio Loss* (*RSRL*) of each respondent (following Campbell, Calvet, and Sodini, 2007, Eq. 7). We assume that the investor's mutual fund holdings are in a market index fund (beta of one and no idiosyncratic risk) and calculate the *RSRL* as follows:

$$RSRL_i = 1 - \frac{\mu_i / \sigma_i}{\mu_M / \sigma_M} = 1 - \frac{\beta_i \cdot \sigma_M}{\sigma_i}, \quad (6)$$

where μ_i (μ_m) is the risk premium of the investor's portfolio (market portfolio), σ_i (σ_M) is the standard deviation of the investor's portfolio (market portfolio), and β_i is the beta of the investor's entire portfolio. One caveat is that we do not know the exact amount invested in each individual stock; we know only the total amount invested in individual stocks and the total amount invested in equity mutual funds. Hence we assume that the investor holds an equally weighted portfolio of individual stocks. An equally weighted individual stock portfolio generates out-of-sample diversification benefits similar to that of optimal strategies (DeMiguel, Garlappi, and Uppal, 2009). Therefore, our underdiversification measures are downward biased resulting in conservative regression estimates. The investor's *RSRL* will equal zero if he holds a fully diversified portfolio while larger values indicate underdiversification.

We also generate several stock level measures of (expected) skewness using the CRSP daily stock return data. We create these measures at the individual stock level and at the portfolio level using the equal-weighted daily returns of the investor's stockholdings. *Total Skewness* is the skewness of daily stock returns. Following Kumar (2009), *Idiosyncratic Skewness* is the skewness of the residuals from a two-factor model that includes the market risk premium, *RMRF*, and its square, $RMRF^2$. We include the square of the market risk premium to remove loading on systematic skewness. *Max. One-Day Return* is the maximum one-day return over the period, which Bali, Cakici, and Whitelaw (2011) argue is a good proxy for investors' beliefs about lottery-like payoffs. *Idiosyncratic* σ is the annualized standard deviation of the residuals from a Fama and French (2015) five-factor model. *Stock* β is the average market beta of the investor's stock holdings. For respondents who own multiple stocks the summary statistics in Table 2 are calculated by first averaging across stocks for that respondent and then averaging across respondents.

The final three dependent variables in Table 2 are summarized for the entire sample, including subjects who do not own equities. *Mutual Funds Only* is an indicator variable equal to one for the 8.3% of the respondents who own only equity mutual funds and no individual stocks. *Individual Stocks Only* is an indicator variable equal to one for the 7.0% of the sample whose equity ownership consists exclusively of individual company stocks and no equity mutual funds. *Both Mutual Funds and Individual Stocks* is an indicator variable equal to one for the 8.6% of the sample who own both equity mutual funds and individual stocks.[13]

2.3. Control Variables

All of the empirical tests control for demographic and economic characteristics including age, sex, race, ethnicity, marital status, number of household members, education, employment

[13] Our sample had a lower equity participation rate than that reported in some other studies as we exclude equity ownership in 401(k) and other tax deferred plans. Such equity holdings may not reflect active choices, due to the U.S. Department of Labor's acceptance of target date funds as an investment default. For more on target date funds and 401(k) plan investment options, see Mitchell and Utkus (2012). Further, this largely avoids underdiversification due to employee stock ownership, because employee ownership of publicly-traded companies occurs primarily through tax deferred plans such as 401(k) and employee stock ownership plans (Curcuru, Heaton, Lucas, and Moore, 2010).

status, family income, and financial wealth. Including these variables controls for the potential confounding effects they might have on household portfolio choice.[14]

Our ALP survey module also included additional questions to measure utility curvature, optimism, financial literacy, numeracy, and trust.[15] These variables mitigate against the potential omitted variable bias that could occur from factors that are conceptually similar to probability weighting. For example, utility curvature could be highly correlated with probability weighting. Thus, in the regressions, we control for utility curvature to ensure that our probability weighting variable captures a component of preferences that is distinct from utility curvature. Our measure of utility curvature is the average of the risk premiums from the four utility curvature questions summarized in Panel A of Table 1.

Optimistic beliefs could influence the overweighting of small probabilities (i.e., optimists may have upwardly-biased beliefs about the probability that lotteries resolve in their favor). Accordingly, we follow Puri and Robinson (2007) and include a question assessing individuals' subjective life expectancies, and we measure optimism by comparing subjective and objective life expectancies (where the latter are derived from age/sex population mortality tables). We also control for financial literacy, which prior studies show has a strong association with financial decisions (Lusardi and Mitchell, 2007, 2014; van Rooij, Lusardi, and Alessie, 2011). To ensure that overweighting of small probabilities is not simply a proxy for low financial literacy, our survey module also includes the "Big Three" financial literacy questions developed by Lusardi and Mitchell (2007) for the Health and Retirement Study (HRS). Our index of financial literacy is the number of correct responses to these questions. The module also includes three questions to assess numeracy based on questions from the HRS and the English Longitudinal Study of Ageing, along

[14] Six control variables have missing values, which we impute using group median imputation. Groups are based on gender, education and age. For these six variables, on average six percent of the observations are missing. In all regressions that include these controls, we include dummies for observations for which we imputed missing data.
[15] Online Appendix D provides the exact wording of the numeracy, financial literacy, trust, and optimism questions.

with the trust question from the World Values Survey, as Guiso, Sapienza, and Zingales (2008) report a relation between trust and portfolio choice.

2.4. Probability Weighting

Panel B of Table 1 summarizes the responses to the six probability weighting questions from the ALP survey module. On average, subjects prove to be risk seeking for low probability questions with p = 0.05 and p = 0.12; indeed, consistent with the overweighting of small probabilities, the average risk premiums are negative (-7.1% and -2.3%, respectively). For these questions, the required positive risk premium due to utility curvature is more than offset by the risk seeking due to probability weighting. For the p = 0.25 question, the average risk premium is 4.6%. At larger probabilities, p = 0.5, 0.75 and 0.88, the average risk premiums increase to 15.1%, 22.8%, and 28.2%, respectively. Overall, the pattern in the average risk premiums is consistent with *Inverse-S*-shaped probability weighting: overweighting of small probabilities and underweighting of high probabilities.

Panel A of Table 3 summarizes the non-parametric probability weighting measure, *Inverse-S*. Consistent with inverse-S shaped probability weighting in the general population, on average the sum of the risk premiums for the three high probability questions exceeds the sum of the risk premiums for the three low probability questions by 71 percentage points. Our probability weighting variable, *Inverse-S*, is positive for 81% of the respondents, indicating an inverse-S shaped probability weighting function,[16] which is consistent with the results from laboratory experiments using students (Abdellaoui, 2000; Bruhin, Fehr-Duda, and Epper, 2010). Panel A also shows there is substantial heterogeneity in probability weighting, which has important implications for the finance literature as it may help explain the observed large heterogeneity in portfolio

[16] Similarly, when we fit the Prelec (1998) weighting function jointly with a CRRA power utility function using all ten questions, the majority (73%) of the respondents exhibit an inverse-S shaped function (see Online Appendix C).

allocations. The correlations between our *Inverse-S* measure and the Tversky and Kahneman (1992), Prelec (1998), and Bordalo, Gennaioli, and Shleifer (2013) probability weighting measures are 0.59, 0.75, and 0.78, respectively (see Online Appendix C for summary statistics of the parametric measures of probability weighting).

Panel B of Table 3 shows the pairwise correlations between *Inverse-S* and education, utility curvature, numeracy, financial literacy, optimism, and trust. Although not the main focus of our paper, these correlations help illustrate the relation between our *Inverse-S* measure and respondent characteristics. The correlation between utility curvature and *Inverse-S* is low and positive ($r = 0.092$), with utility curvature explaining less than 1% (R^2) of the variation in *Inverse-S*. To place this small correlation in perspective, the average correlation among the risk premiums of the four utility curvature questions in Panel A of Table 1 is $r = 0.70$ (demonstrating strong internal consistency). Accordingly, *Inverse-S* and utility curvature appear to be separate components of preferences.

The correlations in Table 3 also provide evidence on the relation between *Inverse-S* and proxies for intelligence. Panel B shows that *Inverse-S* is positively correlated with education, numeracy, and financial literacy, although the magnitudes are small. Thus there is no evidence that probability weighting is greater for individuals who are less intelligent or less educated; this is consistent with Booij, van Praag, and van de Kuilen (2010) who also find no relation between education and probability weighting in the general population.

Optimism could potentially lead to overweighting the probability of winning the lotteries. Yet this would decrease the risk premiums for all questions instead of generating risk seeking for low probabilities and risk aversion for high probabilities. Because we construct *Inverse-S* as the difference between risk premiums, any influence from optimism should be approximately differenced out. Indeed, the correlation between *Inverse-S* and optimism is not significant.

3. Probability Weighting and Household Portfolio Choice

Next, we test the relation between probability weighting and household portfolio choice decisions. For ease of interpretation, we standardize the *Inverse-S* variable so it has a mean of zero and a standard deviation of one. Following Dimmock, Kouwenberg, Mitchell, and Peijnenburg (2016), all specifications include controls for age, age squared, education, log(family income), log(financial wealth), sex, White, Hispanic, log(number of household members), and employed. Our baseline specification also includes controls for utility curvature, numeracy, financial literacy, optimism, and trust.[17] For all specifications, we calculate *t*-statistics using robust standard errors.

3.1. Probability Weighting and Equity Portfolio Underdiversification

Table 4 shows the results of Tobit regressions in which the dependent variable is a measure of portfolio underdiversification. In Panel A, the dependent variable is *Fraction of Equity in Individual Stocks*. In Panel B, the dependent variable is the *Relative Sharpe Ratio Loss* variable of Calvet, Campbell, and Sodini (2007). In both panels, the sample includes only those subjects with non-zero equity holdings. Column (1) includes no additional control variables; column (2) adds the economic and demographic controls; column (3) adds the utility curvature control; and column (4) adds the numeracy, financial literacy, optimism, and trust controls.

As noted above, theoretical models predict that probability weighting will make underdiversified portfolios more attractive due to their positive skewness (Shefrin and Statman, 2000; Polkovnichenko, 2005; Barberis and Huang, 2008; Jin and Zhou, 2008). Panel A confirms this empirically, showing a significant and positive relation between *Inverse-S* and the fraction of equity holdings allocated to individual stocks. The results are similar in all four columns and there

[17] Dimmock et al. (2016) find that ambiguity aversion relates to households' portfolio choices. In the present case, our elicitation questions rule out ambiguity because all probabilities are known. For approximately half of our sample, we have the measure of ambiguity aversion from the Dimmock et al. (2016) study, fielded in the ALP in March 2012, five years prior to our study. The correlation between *Inverse-S* and ambiguity aversion is only 0.057. In robustness tests reported in Online Appendix E, we show that the coefficient on *Inverse-S* remains positive and significant if ambiguity aversion is included as a control variable.

is little change as additional control variables are included. The coefficient reported in column (4) implies that a one standard deviation increase in *Inverse-S* results in a 12.7 percentage point increase in the fraction of the portfolio allocated to individual stocks (a 28.2% increase relative to the baseline allocation of 45.0 percentage points). Consistent with the portfolio separation theorem, the utility curvature parameter is not related to the fraction of equity allocated to individual stocks.

Panel B shows a significant positive relation between *Inverse-S* and *Relative Sharpe Ratio Loss*. Individuals who overweight small probability tail events hold portfolios with lower Sharpe ratios than could have been obtained with similar levels of systematic risk. The coefficient reported in column (4) implies that a one standard deviation increase in *Inverse-S* results in a 4.3% lower Sharpe ratio, relative to the market index. To interpret the economic magnitude of these results, we use the dollar return loss measure of Calvet, Campbell, and Sodini (2007, Eq. 11). Our results imply that, for a one-standard deviation increase in *Inverse-S,* the average (median) stockholder loses $2,504 ($351) per year.[18]

The results in Panel B are generally similar to those in Panel A, though the sample size is smaller because some respondents do not provide stock identifiers or the identifiers cannot be matched to specific individual stocks.[19] Given the similarity of the results, and because the two proxies for underdiversification have a correlation of 0.90, in the remainder of the paper we report results only for the *Fraction of Equity in Individual Stocks*.

[18] The dollar return loss is the additional expected dollar return an investor could have received given her overall level of risk. It is calculated by fixing the investor's overall portfolio risk, but replacing the (uncompensated) idiosyncratic risk with (compensated) systematic risk.
[19] In particular, 40 respondents did not report the name or ticker of any of their holdings and 56 respondents gave names or tickers that were not domestic common stocks or could not be matched to a single security.

3.2. Alternative Measures of Probability Weighting Preferences

Our main analyses use a parsimonious non-parametric measure for the *Inverse-S* parameter.[20] As a robustness test, we estimate three alternative versions of the baseline specification in which we replace *Inverse-S* with a parametrically estimated probability weighting measure. First, we use the function proposed by Prelec (1998, Eq. 3.1) because it has clear axiomatic foundations and is widely used in the decision sciences literature. In this specification, we use a parametric measure of utility curvature that is jointly estimated along with the probability weighting parameter. Second, we use the function proposed by Bordalo, Gennaioli, and Shleifer (2012, Eq. 5) in their model of salience because it provides a clear and intuitive explanation for why probability weighting occurs. Third, we use the function proposed by Tversky and Kahneman (1992, Eq. 6) because it is well-known and frequently used in finance and economics research.

Results are presented in Panel A of Table 5. All three of the parametric measures are defined so that higher values indicate a more pronounced inverse-S shape, and we standardize these variables to have a mean of zero and standard deviation of one. For all three measures, the results are similar to those in the main specification. Importantly, the Prelec (1998) probability weighting parameter is jointly estimated along with utility function curvature, and hence our conclusions are robust to using this alternative method to separate probability weighting from utility curvature.

3.3. Measurement Error in Preference Elicitation

Harless and Camerer (1994) and Hey and Orme (1994) show that subjects often give inconsistent responses to questions designed to elicit preferences. If such errors are pure noise, this will reduce the power of tests but not introduce bias. If, however, errors in elicited preference are

[20] To demonstrate that the results are not driven by outliers, Online Appendix Table E.1 reports results for three alternative measures of *Inverse-S*: a rank transformation for which zero indicates the lowest value of *Inverse-S* and one the highest, an indicator variable equal to one if the subject's *Inverse-S* value is above the median, and an indicator variable equal to one if the subject's *Inverse-S* value is above 25%. In all three specifications there is a positive and significant relation between *Inverse-S* and the fraction of equity allocated to individual stocks.

correlated with errors in actual decisions (e.g., underdiversification), this could affect inferences. Our ALP module includes several features that allow us to address this issue. First, it includes the check questions described earlier to test the internal consistency of subjects' choices. Second, the module recorded the time subjects spent on each question, allowing us to identify subjects who answered the questions unusually quickly. Panel B of Table 5 reports results for two restricted samples: one excludes subjects who made more than three mistakes on the check questions, and the other omits those who spent less than 90 seconds on the probability weighting questions. Results are similar to those for the full sample, suggesting that our findings are not driven by measurement error in elicited preferences or by individuals who did not understand the questions.

4. Probability Weighting and Individual Stock Characteristics

Probability weighting has implications not just for the choice between mutual funds and individual stocks, but also for the *type* of individual stocks an investor chooses. Investors who overweight the probabilities of tail events should select stocks with high positive skewness, but they will not exhibit a preference for high systematic risk (Barberis and Huang, 2008; Boyer, Mitton, and Vorkink, 2010). Positively skewed stocks are appealing because the investor has a chance, albeit a small one, of becoming rich if that company becomes the "next Apple."

Our survey module asks subjects who own individual stocks to list the names (or tickers) of their five largest individual stock holdings. The five largest holdings encompass the entire portfolio of most individual stockholders in the sample; about half hold only one or two stocks, and 75% hold five or fewer. As described in Section 2.2., we match these stocks to the CRSP daily stock return database and construct various stock characteristics that measure skewness: *Total Skewness, Idiosyncratic Skewness, Max. One-Day Return,* and *Idiosyncratic σ*. We include *Idiosyncratic σ* because it is a proxy for expected positive skewness (Boyer, Mitton, and Vorkink, 2010), and not because probability weighting implies a preference for idiosyncratic risk itself. We also calculate the market beta, *Stock β*, as a measure of systematic risk.

Table 6 shows regression estimates for the five dependent variables described above. The key independent variable is *Inverse-S*; the sample includes only subjects with individual stockholdings; and all models include the full set of controls. In Panel A, the unit of observation is a stockholding (e.g., there are three observations for a respondent who holds three stocks) and standard errors are clustered by respondent. In this panel, the focus is on the characteristics of the specific stocks selected. In Panel B, the unit of observation is the investor's entire equity portfolio, and the dependent variables are characteristics calculated from the returns of an equally-weighted portfolio of the investor's stockholdings combined with her equity mutual fund holdings.[21] In this panel, the focus is on the characteristics of the investor's overall equity portfolio.

Columns (1) to (3) show that *Inverse-S* is significantly and positively related to *Total Skewness*, *Idiosyncratic Skewness*, and *Max. One-Day Return*. Investors with higher probability weighting choose lottery-type stocks that have high expected positive skewness. Column (4) of Panel A shows that *Inverse-S* has a positive and significant relation (at the 10% level) with idiosyncratic risk (a proxy for expected skewness); however this relation is not significant in the portfolio level results shown in Panel B.

Column (5) shows that the relation between *Inverse-S* and systematic risk, measured by *Stock β*, is neither statistically nor economically significant. Thus, the overall pattern of results in Table 6 indicates that investors with high *Inverse-S* choose to hold portfolios with high expected positive skewness but not higher systematic risk. Importantly, this pattern is precisely what is implied by probability weighting. It is not, however, an obvious implication of alternative explanations. For example, if *Inverse-S* inadvertently measured risk seeking preferences (utility

[21] Although we have information on the total amount invested in individual stocks and the total amount invested in stock mutual funds, we do not have data on the amount in each separate individual stock.

curvature), it would imply higher positive skewness and higher systematic risk, which is not what we find.

These results relate to two streams of the literature that argue probability weighting explains observed financial market behavior. First, although our data do not allow us to directly test the relation between probability weighting and asset pricing, our results are consistent with studies of positive skewness and asset pricing. For instance, Boyer, Mitton, and Vorkink (2010), Bali, Cakici, and Whitelaw (2011), Conrad, Dittmar, and Ghysels (2013), Conrad, Kapadia, and Xing (2014), and Barberis, Mukherjee, and Wang (2016) show that stocks with positive expected skewness have abnormally low returns.[22] Barberis and Huang (2008) argue that probability weighting can cause positively skewed securities to have low returns. Our results support the findings of these asset pricing studies by providing direct evidence that investors who overweight small probabilities exhibit a preference for positively skewed securities. Second, our results are consistent with Henderson and Pearson (2011) and Li, Subrahmanyam, and Yang (2018) who argue that financial institutions design products that cater to investors' probability weighting preferences. These products are popular despite having large negative abnormal returns.

5. Preference, Probability Unsophistication, or Financial Knowledge?

Thus far, we have interpreted probability weighting as a component of *preferences* rather than a misunderstanding of the underlying probabilities. In other words, we posit that subjects understand the underlying probabilities, but use weighted rather than objective probabilities for decision making. Indeed, our elicitation procedure is designed to ensure that the subjects know the exact objective probabilities. In this section, we consider two closely-related alternative explanations based on miscalibration of the underlying probabilities rather than on preferences: (1) Probability unsophistication – that some individuals have difficulty with probabilistic

[22] Relatedly, Wang (2017) shows undervaluation of securities with negative expected skewness.

reasoning, and this difficulty affects both their elicited *Inverse-S* values and their portfolio choices; and (2) Limited financial knowledge – that, for some reason, *Inverse-S* is correlated with a lack of financial knowledge. For these alternative explanations, probability weighting and underdiversification represent clear mistakes. That is, if high *Inverse-S* respondents were educated about probabilistic reasoning or financial markets, they would make different choices. With preferences, on the other hand, such interventions would not result in different choices.

5.1. Preference or Probability Unsophistication

The first alternative explanation is based on probability unsophistication. For example, subjects with limited quantitative reasoning skills may have difficulty evaluating questions involving probabilities, and such cognitive limitations could also cause investment errors. This explanation appears unlikely based on the summary statistics in Panel B of Table 3, which show that *Inverse-S* has a small but significantly *positive* correlation with education, numeracy, and financial literacy. Nevertheless, we perform additional tests using two restricted samples. In column (1) of Table 7, the sample includes only subjects with a college degree (undergraduate or graduate). In column (2), the sample includes only subjects who correctly answer all three of the numeracy questions. In both columns, *Inverse-S* is significantly positively related to portfolio underdiversification, suggesting that *Inverse-S* does not reflect poor quantitative reasoning.

5.2. Preference or Limited Financial Knowledge

The second alternative explanation is that *Inverse-S* may be correlated with a lack of financial knowledge. For example, some subjects may simply be unaware of the benefits of diversification.[23] A priori, however, it is not obvious why a lack of financial knowledge would be correlated with *Inverse-S*. Indeed, a key advantage of eliciting probability weighting preferences

[23] For instance, von Gaudecker (2015) finds that underdiversification is related to low financial literacy.

using lotteries instead of natural events is that we can clearly and unambiguously define the relevant probabilities, limiting the scope for beliefs to affect subjects' responses (for further discussion see Barberis, 2013b, p. 614).

We test this alternative explanation using two restricted samples. In column (3) of Table 7, the sample includes only subjects who answer all three financial literacy questions correctly. In column (4), the sample includes only subjects who correctly answer the question "Please tell us whether this statement is true or false. `Buying a stock mutual fund usually provides a safer return than a single company stock.'" In the latter sample, subjects correctly state that a mutual fund is usually safer than an individual stock. The results show that *Inverse-S* is positively associated with portfolio underdiversification, even for investors who understand the risks associated with underdiversification. Subjects who overweight small probabilities choose to hold individual stocks despite knowing they are riskier than mutual funds.

Our results are consistent with experimental studies that find people are unwilling to change choices violating the independence axiom even after the axiom is explained to them (MacCrimmon, 1968; Slovic and Tversky, 1974). In other words, the finding that the relation between *Inverse-S* and underdiversification is due to preferences toward probabilities rather than probabilistic unsophistication illuminates the discussion about whether probability weighting is a "mistake" in the sense that people would make different choices if they understood decision theory (Fehr-Duda and Epper, 2012; Barberis, 2013a,b). Of course, probability weighting can still be considered a mistake in the sense that it constitutes a violation of the independence axiom, but this is a fundamentally different type of mistake that is more difficult to change.

6. Probability Weighting and Participation in Mutual Funds and Individual Stocks

Next we broaden the analysis to consider non-participation in equity markets, as well as the choice between individual stocks versus stock mutual funds by those who do participate. For these tests, the theoretical predictions are less clear compared to the tests discussed above. If an investor's choice set includes only the risk-free asset and a mutual fund (or market index), prior studies show that probability weighting can cause non-participation due to first-order risk aversion[24] (Chapman and Polkovnichenko, 2011; De Giorgi and Legg, 2012; He, Kouwenberg, and Zhou, 2018). When an individual stock is added to the choice set, however, the predictions are less clear. On the one hand, probability weighting implies first-order risk aversion, which makes any equity investment, including individual stocks, less attractive. On the other hand, probability weighting implies a preference for positive skewness, which makes individual stocks more attractive. Thus, probability weighting can result in non-participation or portfolio underdiversification, depending on the subject's beliefs about the risks and skewness of individual stocks. Hence the net effect of probability weighting is an empirical question.

Table 8 reports the results of multinomial logit models in which the dependent variable takes one of four values: *Non-Participation*, *Mutual Funds Only*, *Individual Stocks Only*, and *Both Mutual Funds and Individual Stocks*. Classic financial theory predicts that individuals should (1) participate in the equity market and (2) hold a well-diversified portfolio. In other words, the rational benchmark is to invest in mutual funds; both non-participation and underdiversification are possible behavioral deviations from rationality due to probability weighting. Accordingly, *Mutual Funds Only* serves as a natural basis of comparison and we use it as the excluded or reference category in the multinomial model.

The results show that subjects with higher *Inverse-S* are more likely to choose either non-participation or individual stock ownership, and are thus less likely to own only mutual funds. The economic magnitudes implied by the coefficient estimates are large. For instance, the coefficient

[24] Epstein and Zin (1990), Segal and Spivak (1990), and Chapman and Polkovnichenko (2011) show that the probability weighting in rank-dependent utility implies first-order risk aversion (i.e., that the investor does not become locally risk neutral as the size of a potential investment becomes small).

in column (1) implies that a one standard deviation increase in *Inverse-S* raises the probability of choosing *Non-Participation* instead of *Mutual Funds Only* by one-third ($e^{0.290} = 1.34$). Likewise, a one standard deviation increase in *Inverse-S* raises the probability of choosing *Individual Stocks Only* by 39.8%, and choosing *Both Mutual Funds and Individual Stocks* by 31.1%.

The interpretation of the multinomial logit results comes with a caveat, however, as theoretically determining whether high *Inverse-S* results in non-participation or underdiversification depends on the subject's beliefs about expected equity returns, risk, and individual stock skewness (He, Kouwenberg, and Zhou, 2018). As we lack data on beliefs about return distributions, we cannot disentangle why some high *Inverse-S* subjects choose not to participate in the stock market while others buy positively-skewed individual stocks.

We emphasize that the pattern of results in Table 8 is broadly consistent with the theoretical predictions of probability weighting, while it is inconsistent with most alternative interpretations. For example, if *Inverse-S* inadvertently measured utility curvature, it would be positively related to non-participation but negatively related to underdiversification. Alternatively, if *Inverse-S* inadvertently measured optimism, it would be negatively related to non-participation. Instead, however, *Inverse-S* is positively related to both non-participation and underdiversification.

7. Conclusion

Our paper is the first empirical study to provide *direct* evidence linking probability weighting and portfolio underdiversification. We measure probability weighting in an incentivized survey module fielded in a large and nationally representative sample of the U.S. population. Using our *Inverse-S* measure, we demonstrate that most individuals exhibit probability weighting – they overweight low probability tail events – though there is also substantial heterogeneity. We find that higher probability weighting is associated with portfolio underdiversification, consistent with theoretical predictions. We also find that investors with higher *Inverse-S* tend to hold lottery-type stocks and invest in positively-skewed equity portfolios. Furthermore, people that overweight small probabilities are less likely to participate in the equity market at all, and if they do participate, they invest in individual stocks instead of mutual funds. This finding is directionally inconsistent with *Inverse-S* being a proxy for utility curvature (risk aversion). Finally, we find evidence consistent with probability weighting being a component of preferences, rather than the result of probability unsophistication or lack of financial knowledge.

The implied economic magnitudes of our results are large; a one-standard deviation higher *Inverse-S* implies a cost to the average (median) stockholder of $2,504 ($351) per year. Furthermore, probability weighting increases the dispersion of portfolio returns, pushing people to either not participate or hold positively skewed portfolios. This will lead to increased heterogeneity in realized investment returns, which potentially exacerbates wealth inequality.[25]

[25] See for instance, Bach, Calvet, and Sodini, (2017); Lusardi, Michaud, and Mitchell (2017); Campbell, Ramadorai, and Ranish (2018); and Fagereng, Guiso, Malacrino, and Pistaferri (2018).

References

Abdellaoui, Mohammed. 2000. Parameter-Free Elicitation of Utility and Probability Weighting Functions. *Management Science* 46, 1497-1512.

Abito, Jose Miguel, and Yuval Salant. 2018. The Effect of Product Misperception on Economic Outcomes: Evidence from the Extended Warranty Market. *Review of Economic Studies*, forthcoming.

Albuquerque, Rui. 2012. Skewness in Stock Returns: Reconciling the Evidence on Firm versus Aggregate Returns. *Review of Financial Studies* 25, 1630-1673.

Allais, Maurice. 1953. Le Comportement de L'Homme Rationnel Devant le Risque: Critique des Postulats et Axiomes de L'Ecole Américaine. *Econometrica* 21, 269-290.

Bach, Laurent, Laurent E. Calvet, and Paolo Sodini. 2017. Rich Pickings? Risk, Return, and Skill in the Portfolios of the Wealthy, Working paper, Stockholm School of Economics.

Bali, Turan G., Nusret Cakici, and Robert Whitelaw. 2011. Maxing Out: Stocks as Lotteries and the Cross-Section of Expected Returns. *Journal of Financial Economics* 99, 427-446.

Barberis, Nicholas C. 2013a. Thirty Years of Prospect Theory in Economics: A Review and Assessment. *Journal of Economic Perspectives* 27, 173-196.

Barberis, Nicholas C. 2013b. The Psychology of Tail Events: Progress and Challenges. *American Economic Review* 103, 611-616.

Barberis, Nicholas C., and Ming Huang. 2008. Stocks as Lotteries: The Implications of Probability Weighting for Security Prices. *American Economic Review* 98, 2066-2100.

Barberis, Nicholas C., Abhiroop Mukherjee, and Baolin Wang. 2016. Prospect Theory and Stock Returns: An Empirical Test. *Review of Financial Studies* 29, 3068-3107.

Blume, Marshall E., and Irwin Friend. 1975. The Asset Structure of Individual Portfolios and Some Implications for Utility Functions. *Journal of Finance* 30, 585-603.

Booij, Adam S., Bernard M.S. van Praag, and Gijs van de Kuilen. 2010. A Parametric Analysis of Prospect Theory's Functionals for the General Population. *Theory and Decision* 68, 115-148.

Bordalo, Pedro, Nicola Gennaioli, and Andrei Shleifer. 2012. Salience Theory of Choice under Risk. *Quarterly Journal of Economics* 127, 1243-1285.

Bordalo, Pedro, Nicola Gennaioli, and Andrei Shleifer. 2013. Salience and Asset Prices. *American Economic Review* 103, 623-628

Boyer, Brian, Todd Mitton, and Keith Vorkink. 2010. Expected Idiosyncratic Skewness. *Review of Financial Studies* 23, 169-202.

Boyer, Brian, and Keith Vorkink. 2014. Stock Options as Lotteries. *Journal of Finance* 69, 1485-1527.

Bruhin, Adrian, Helga Fehr-Duda, and Thomas Epper. 2010. Risk and Rationality: Uncovering Heterogeneity in Probability Distortion. *Econometrica* 78, 1375-1412.

Calvet, Laurent E., John Y. Campbell, and Paolo Sodini. 2007. Down or Out: Assessing the Welfare Costs of Household Investment Mistakes. *Journal of Political Economy* 115, 707-474.

Calvet, Laurent E., John Y. Campbell, and Paolo Sodini. 2009. Measuring the Financial Sophistication of Households. *American Economic Review* 99, 393-398

Camerer, Colin. 1995. Individual Decision Making, In: J. Kagel and A. Roth, eds., *Handbook of Experimental Economics* Princeton: Princeton University Press: 587-703.

Campbell, John Y., Tarun Ramadorai, and Benjamin Ranish. 2018. Do the Rich Get Richer in the Stock Market: Evidence from India. *American Economic Review: Insights*, forthcoming.

Chapman, David A., and Valery Polkovnichenko. 2011. Risk Attitudes Towards Small and Large Bets in the Presence of Background Risk. *Review of Finance* 15, 909-927.

Conrad, Jennifer, Robert F. Dittmar, and Eric Ghysels. 2013. Ex Ante Skewness and Expected Stock Returns. *Journal of Finance* 68, 85-124.

Conrad, Jennifer, Nishad Kapadia, and Yuhang Xing. 2014. Death and Jackpots: Why Do Individual Investors Hold Overpriced Stocks? *Journal of Financial Economics* 113, 455-475.

Curcuru, Stephanie, John Heaton, Deborah Lucas, and Damien Moore. 2010. Heterogeneity and Portfolio Choice: Theory and Evidence. In: Y. Ait-Sahalia and L.P. Hansen, editors*, Handbook of Financial Econometrics: Tools and Techniques*, Elsevier, 337-382.

De Giorgi, Enrico G., and Shane Legg. 2012. Dynamic Portfolio Choice and Asset Pricing with Narrow Framing and Probability Weighting. *Journal of Economic Dynamics and Controls* 36, 951-972.

DeMiguel, Victor, Lorenzo Garlappi, and Raman Uppal. 2009. Optimal Versus Naïve Diversification: How Inefficient is the 1/*N* Strategy? *Review of Financial Studies* 22, 1915-1953.

Dimmock, Stephen G., Roy Kouwenberg, Olivia S. Mitchell, and Kim Peijnenburg. 2016. Ambiguity Aversion and Household Portfolio Choice Puzzles: Empirical Evidence. *Journal of Financial Economics* 119, 559-577.

Epstein, Larry G., and Stanley E. Zin. 1990. 'First-Order' Risk Aversion and the Equity Premium Puzzle. *Journal of Monetary Economics* 26, 387-407.

Erner, Carsten, Alexander Klos, and Thomas Langer. 2013. Can Prospect Theory be Used to Predict an Investor's Willingness to Pay? *Journal of Banking and Finance* 37, 1960-1973.

Fagereng, Andreas, Luigi Guiso, Davide Malacrino, and Luigi Pistaferri. 2018. Heterogeneity and Persistence in Returns to Wealth. NBER working paper 22822.

Fama, Eugene F., and Kenneth R. French. 2015. A Five-Factor Asset Pricing Model. *Journal of Financial Economics* 116, 1-22.

Fehr-Duda, Helga, and Thomas Epper. 2012. Probability and Risk: Foundations and Economic Implications of Probability-Dependent Risk Preferences. *Annual Review of Economics* 4, 567-593.

Goetzmann, William N., and Alok Kumar. 2008. Equity Portfolio Diversification. *Review of Finance* 12, 433-463.

Guiso, Luigi, Paola Sapienza, and Luigi Zingales. 2008. Trusting the Stock Market. *Journal of Finance* 63, 2557-2600.

Harless, David W., and Colin F. Camerer. 1994. The Predictive Utility of Generalized Expected Utility Theories. *Econometrica* 62, 1251-1289.

He, Xue Dong, Roy Kouwenberg, and Xun Yu Zhou. 2018. Inverse S-Shaped Probability Weighting and Its Impact on Investment. *Mathematical Control & Related Fields* 8, 679-706.

Henderson, Brian J., and Neal D. Pearson. 2011. The Dark Side of Financial Innovation: A Case Study of the Pricing of a Retail Financial Product. *Journal of Financial Economics* 100, 227-247.

Hey, John D., and Chris Orme. 1994. Investigating Generalizations of Expected Utility Theory Using Experimental Data. *Econometrica* 62, 1291-1326.

Jin, Hanqing, and Xun Yu Zhou. 2008. Behavioral Portfolio Selection in Continuous Time. *Mathematical Finance* 18, 385-426.

Kahneman, Daniel, and Amos Tversky. 1979. Prospect Theory: An Analysis of Decisions Under Risk. *Econometrica* 47, 263-291.

Kelly, Morgan. 1995. All Their Eggs in One Basket: Portfolio Diversification of US Households. *Journal of Economic Behavior and Organization* 27, 87-96.

Kumar, Alok. 2009. Who Gambles in the Stock Market? *Journal of Finance* 64, 1889-1933.

Li, Xindan, Avanidhar Subrahmanyam, and Xuewei Yang. 2018. Can Financial Innovation Succeed by Catering to Behavioral Preferences? Evidence from a Callable Options Market. *Journal of Financial Economics* 128, 38-65.

Lusardi, Annamaria, Pierre-Carl Michaud, and Olivia S. Mitchell. 2017. Optimal Financial Knowledge and Wealth Inequality. *Journal of Political Economy* 125, 431-477.

Lusardi, Annamaria, and Olivia S. Mitchell. 2007. Baby Boomer Retirement Security: The Roles of Planning, Financial Literacy, and Housing Wealth. *Journal of Monetary Economics* 54, 205-224.

Lusardi, Annamaria, and Olivia S. Mitchell. 2014. The Economic Importance of Financial Literacy: Theory and Evidence. *Journal of Economic Literature* 52, 5-44.

MacCrimmon, Kenneth. 1968. Descriptive and Normative Implications of the Decision Theory Postulates. *Risk and Uncertainty* 3, 3-32.

Mitchell, Olivia S., and Steve P. Utkus. 2012. Target-Date Funds in 401(k) Retirement Plans. NBER working paper 17911.

Mitton, Todd, and Keith Vorkink. 2007. Equilibrium Underdiversification and the Preference for Skewness. *Review of Financial Studies* 20, 1255-1288.

Polkovnichenko, Valery. 2005. Household Portfolio Diversification: A Case for Rank-Dependent Preferences. *Review of Financial Studies* 18, 1467-1502.

Prelec, Drazen. 1998. The Probability Weighting Function. *Econometrica* 66, 497-527.

Puri, Manju, and David T. Robinson. 2007. Optimism and Economic Choice. *Journal of Financial Economics* 86, 71-99.

Quiggin, John. 1982. A Theory of Anticipated Utility. *Journal of Economic Behavior and Organization* 3, 323-343.

Quiggin, John. 1993. *Generalized Expected Utility Theory: The Rank Dependent Model*. Kluwer: Norwell, MA, USA.

Rieger, Marc O. 2012. Why Do Investors Buy Bad Financial Products? Probability Misestimation and Preferences in Financial Investment Decision. *Journal of Behavioral Finance* 13, 108-118.

Segal, Uzi, and Avia Spivak. 1990. First Order versus Second Order Risk Aversion. *Journal of Economic Theory* 51, 111-125.

Shefrin, Hersh, and Meir Statman. 2000. Behavioral Portfolio Theory. *Journal of Financial and Quantitative Analysis* 35, 127-151.

Slovic, Paul, and Amos Tversky. 1974. Who Accepts Savage's Axiom? *Systems Research and Behavioral Science* 19, 368-373.

Starmer, Chris. 2000. Developments in Non-Expected Utility Theory: The Hunt for a Descriptive Theory of Choice under Risk. *Journal of Economic Literature* 38, 332-382.

Smith, Vernon L. 1976. Experimental Economics: Induced Value Theory. *American Economic Review* 66, 274-279.

Tanaka, Tomomi, Colin F. Camerer, and Quang Nguyen. 2010. Risk and Time Preferences: Linking Experimental and Household Survey Data from Vietnam. *American Economic Review* 100, 557-571.

Tversky, Amos, and Craig R. Fox. 1995. Weighting Risk and Uncertainty. *Psychological Review* 102, 269-283.

Tversky, Amos, and Daniel Kahneman. 1992. Advances in Prospect Theory: Cumulative Representation of Uncertainty. *Journal of Risk and Uncertainty* 5, 297-323.

van de Kuilen, Gijs, and Peter P. Wakker. 2011. The Midweight Method to Measure Attitudes Toward Risk and Ambiguity. *Management Science* 57, 582-599.

van Rooij, Maarten, Annamaria Lusardi, and Rob Alessie. 2011. Financial Literacy and Stock Market Participation. *Journal of Financial Economics* 101, 449-472.

von Gaudecker, Hans-Martin. 2015. How Does Household Portfolio Diversification Vary with Financial Literacy and Financial Advice? *Journal of Finance* 70, 489-507.

Yaari, Menahem E. 1987. The Dual Theory of Choice under Risk. *Econometrica* 55, 95-115.

Wakker, Peter P., and Daniel Deneffe. 1996. Eliciting von Neumann-Morgenstern Utilities when Probabilities are Distorted or Unknown. *Management Science* 42, 1131-1150.

Wang, Baolian. 2017. Probability Weighting and Asset Prices: Evidence from Mergers and Acquisitions. Working paper, Fordham University.

Table 1: Questions to Elicit Utility Curvature and Probability Weighting

This table shows the questions used to elicit utility curvature and probability weighting. Panel A shows the four questions used to elicit utility curvature and Panel B shows the six questions used to elicit probability weighting. All results use ALP survey weights.

Panel A: Utility Curvature Questions

	Option A		Option B		Estimates of $X in Data	
	Probability	Amount	Probability	Amount	Mean	Risk Premium %
Questions $RA_{\$12}$	33%	$12	33%	$X	21.4	18.5%
	67%	$3	67%	$0		
Questions $RA_{\$18}$	33%	$18	33%	$X	27.5	14.3%
	67%	$3	67%	$0		
Questions $RA_{\$24}$	33%	$24	33%	$X	34.8	15.6%
	67%	$3	67%	$0		
Questions $RA_{\$30}$	33%	$30	33%	$X	42.1	16.6%
	67%	$3	67%	$0		

Panel B: Probability Weighting Questions

	Option A		Option B		Estimates of $X in Data	
	Probability	Amount	Probability	Amount	Mean	Risk Premium %
Questions $PW_{5\%}$	5%	$42	100%	$X	8.4	-7.1%
	95%	$6				
Questions $PW_{12\%}$	12%	$42	100%	$X	10.6	-2.3%
	88%	$6				
Questions $PW_{25\%}$	25%	$42	100%	$X	14.3	4.6%
	75%	$6				
Questions $PW_{50\%}$	50%	$42	100%	$X	20.4	15.1%
	50%	$6				
Questions $PW_{75\%}$	75%	$42	100%	$X	25.5	22.8%
	25%	$6				
Questions $PW_{88\%}$	88%	$42	100%	$X	27.0	28.2%
	12%	$6				

Table 2: Summary Statistics for Outcome and Control Variables

This table reports summary statistics for the variables used in our study. Variable definitions appear in Appendix Table A1. The individual stock characteristics (*Relative Sharpe Ratio Loss, Total Skewness, Idiosyncratic Skewness, Max. One-Day Return, Idiosyncratic* σ, and *Stock* β) are shown only for respondents who own individual stocks. All results use ALP survey weights. The number of ALP respondents is $N = 2,671$.

	Equity Owners			All Respondents		
Variable	Mean	Median	Std	Mean	Median	Std
Outcome variables						
Fraction of Equity in Individual Stocks	0.45	0.50	0.41			
Relative Sharpe Ratio Loss	0.19	0.08	0.23			
Total Skewness	-0.00	-0.02	0.79			
Idiosyncratic Skewness	-0.03	0.00	0.99			
Max. One-Day Return	0.07	0.05	0.05			
Idiosyncratic σ	0.18	0.15	0.12			
Stock β	0.99	0.97	0.25			
Mutual Funds Only	0.35	0.00	0.48	0.08	0.00	0.28
Individual Stocks Only	0.29	0.00	0.45	0.07	0.00	0.25
Both Mutual Funds and Individual Stocks	0.36	0.00	0.48	0.09	0.00	0.28
Control variables						
Age	52.26	54.00	17.18	47.84	47.00	16.51
Female	0.44	0.00	0.50	0.52	1.00	0.50
Married	0.66	1.00	0.47	0.59	1.00	0.49
White	0.89	1.00	0.31	0.76	1.00	0.43
Hispanic	0.07	0.00	0.26	0.19	0.00	0.39
Number of Household members	1.08	1.00	1.23	1.36	1.00	1.52
Employed	0.50	0.00	0.50	0.54	1.00	0.50
Family Income (in $1000)	100.93	87.50	58.23	71.34	55.00	53.36
Financial Wealth (in $1000)	310.53	43.00	2956.16	88.00	0.60	1353.56
No College Degree	0.43	0.00	0.50	0.60	1.00	0.49
Bachelor or Associate Degree	0.33	0.00	0.47	0.27	0.00	0.44
Master or Higher Degree	0.24	0.00	0.43	0.13	0.00	0.34
Utility Curvature	0.16	0.12	0.23	0.16	0.13	0.24
Optimism	1.74	1.73	8.13	0.42	0.57	9.81
Financial Literacy	2.61	3.00	0.65	2.18	2.00	0.94
Numeracy	2.66	3.00	0.62	2.39	3.00	0.83
Trust	1.97	2.00	1.34	1.71	2.00	1.36

Table 3: Probability Weighting in the U.S. Population

This table shows summary statistics on probability weighting in the U.S. population measured using our American Life Panel (ALP) survey module. Panel A summarizes the *Inverse-S* measure. Panel B shows the pairwise correlations between *Inverse-S* and variables measuring utility curvature, financial literacy, numeracy, education, optimism, and trust. Education is a categorical variable ranging from 1 to 14, with higher values indicating greater education. Panel C shows the percentage of respondents who passed the consistency check round for each of the six probability weighting questions. The sample size is N = 2,671. All results use ALP survey weights. The symbols *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Panel A: Summary statistics Inverse-S measure

Measure	Mean	Standard Deviation	Minimum	Median	Maximum
Inverse-S	0.708	0.799	-1.809	0.731	2.955

Panel B: Bivariate correlations with Inverse-S measure

Variable	Correlation
Utility Curvature	0.092***
Education	0.090***
Numeracy	0.109***
Financial Literacy	0.125***
Optimism	0.012
Trust	0.041**

Panel C: Summary statistics consistency checks

Question	Consistent	Inconsistent
5% Question	71.6%	28.4%
12% Question	73.4%	26.6%
25% Question	77.5%	22.5%
50% Question	71.8%	28.2%
75% Question	71.3%	28.7%
88% Question	75.5%	24.5%

Table 4: Probability Weighting and Underdiversification

This table reports Tobit regression results in which the dependent variables are proxies for underdiversification. In Panel A, the dependent variable is *Fraction of Equity in Individual Stocks*. In Panel B, the dependent variable is the *Relative Sharpe Ratio Loss*. This dependent variable is calculated using daily returns over the period July 1, 2016 to June 30, 2017. In both panels, the key independent variable is *Inverse-S*. Column (1) includes a constant. Column (2) includes a constant, missing data dummies, and controls for age, age-squared divided by one thousand, female, married, white, Hispanic, number of household members, employment status, education, (ln) family income, and (ln) financial wealth. Column (3) includes the same controls and constant as in column (2) plus a control for utility curvature. Column (4) includes the same controls and constant as in column (3) plus controls for numeracy, financial literacy, optimism, and trust. All results use ALP survey weights. The symbols *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Panel A: Fraction of Equity in Individual Stocks

	(1)	(2)	(3)	(4)
Inverse-S	0.136**	0.121**	0.122**	0.127**
	(2.282)	(2.473)	(2.471)	(2.454)
Utility Curvature			-0.022	-0.013
			(-0.101)	(-0.059)
Optimism				-0.012
				(-1.588)
Financial Literacy				-0.220**
				(-2.392)
Numeracy				0.127
				(1.327)
Trust				0.014
				(0.324)
Control variables	no	yes	yes	yes
Observations	741	741	741	741
Adj. R^2	0.010	0.038	0.038	0.050

Panel B: Relative Sharpe Ratio Loss

	(1)	(2)	(3)	(4)
Inverse-S	0.047**	0.042**	0.043**	0.043**
	(2.168)	(2.219)	(2.296)	(2.287)
Utility Curvature			-0.053	-0.042
			(-0.658)	(-0.536)
Optimism				-0.004
				(-1.485)
Financial Literacy				-0.060*
				(-1.887)
Numeracy				0.021
				(0.539)
Trust				0.000
				(0.003)
Control variables	no	yes	yes	yes
Observations	645	645	645	645
Adj. R^2	0.021	0.114	0.119	0.140

Table 5: Robustness: Alternative *Inverse-S* Measures and Measurement Error

This table reports Tobit regression results in which the dependent variable is *Fraction of Equity in Individual Stocks*. In Panel A, the key independent variables are three parametric alternatives to our *Inverse-S* measure: *Prelec Inverse-S*, *Salience Theory Inverse-S*, and *Tversky and Kahneman Inverse-S*. In column (1), the probability weighting measure, *Prelec Inverse-S*, and utility curvature parameter are jointly estimated assuming the functional form for probability weighting in Prelec (1998, Eq. 3.1) and CRRA utility. In column (2), *Salience Theory Inverse-S* is estimated assuming the salience function in Bordalo, Gennaioli, and Shleifer (2012, p. 1250) and we include our baseline non-parametric utility curvature measure. In column (3), *Tversky and Kahneman Inverse-S* is estimated assuming the functional form for probability weighting in Tversky and Kahneman (1992, Eq. 6) and we include our baseline non-parametric utility curvature measure. Details are in Online Appendix C. In Panel B, the key independent variable is *Inverse-S*. Column (1) excludes respondents who made more than 3 errors on the consistency check questions. Column (2) excludes respondents who spend less than 90 seconds on the probability weighting questions. All models include a constant, missing data dummies, and controls for age, age-squared divided by one thousand, female, married, white, Hispanic, number of household members, employment status, education, (ln) family income, (ln) financial wealth, numeracy, financial literacy, trust, utility curvature, and optimism. All results use ALP survey weights. The symbols *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Panel A: Alternative Inverse-S Measures

	Prelec Inverse-S	*Salience Theory Inverse-S*	*Tversky and Kahneman Inverse-S*
	(1)	(2)	(3)
Alternative Inverse-S	0.135**	0.084*	0.147**
	(2.194)	(1.704)	(2.302)
Full Controls	yes	yes	yes
Observations	734	741	734
Adj. R^2	0.047	0.045	0.051

Panel B: Robustness to Measurement Error

	Exclude Respondents More Than 3 Errors	Exclude Respondents Less Than 90 Seconds
	(1)	(2)
Inverse-S	0.155**	0.120**
	(2.532)	(2.241)
Full Controls	yes	yes
Observations	674	724
Adj. R^2	0.053	0.054

Table 6: Probability Weighting and the Characteristics of Individual Stock Holdings

This table reports the coefficients of OLS regressions. The key independent variable is *Inverse-S*. The dependent variables are generated using the characteristics of the stocks held by the subjects, and they are calculated using daily returns over the period July 1, 2016 to June 30, 2017. In Panel A, the analyses are at the stock level and standard errors are clustered at the respondent level. In Panel B, the analyses are at the portfolio level combining both mutual fund and individual stock allocations. Mutual funds are assumed to have similar Sharpe ratios. Individual stock allocations are assumed to be equally weighted and combined with mutual fund allocations using the reported amounts allocated to each category. In column (1), the dependent variable *Total Skewness* is the skewness of daily returns. In column (2), the dependent variable *Idiosyncratic Skewness* is the skewness of the residuals from a two factor model ($RMRF$ and $RMRF^2$). In column (3), the dependent variable *Max. One-Day Return* is the maximum one-day return. In column (4), the dependent variable *Idiosyncratic* σ is the annualized standard deviation of the residuals from the Fama-French five-factor model. In column (5), the dependent variable *Stock* β is the market beta of the investor's stock holdings. All models include a constant, missing data dummies, and controls for age, age-squared divided by one thousand, female, married, white, Hispanic, number of household members, employment status, education, (ln) family income, (ln) financial wealth, numeracy, financial literacy, trust, utility curvature, and optimism. All results use ALP survey weights. The symbols *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Panel A: Analysis at the stock level

	Total Skewness	Idiosyncratic Skewness	Max. One-Day Return	Idiosyncratic σ	Stock β
	(1)	(2)	(3)	(4)	(5)
Inverse-S	0.111**	0.144***	0.006**	0.012*	0.015
	(2.524)	(2.742)	(2.297)	(1.767)	(0.984)
Full Controls	yes	yes	yes	yes	yes
Observations	1,174	1,174	1,174	1,174	1,174
Adj. R^2	0.071	0.070	0.049	0.037	0.077

Panel B: Analysis at the portfolio level

	Total Skewness	Idiosyncratic Skewness	Max. One-Day Return	Idiosyncratic σ	Stock β
	(1)	(2)	(3)	(4)	(5)
Inverse-S	0.098**	0.167***	0.005*	0.009	0.014
	(2.094)	(2.702)	(1.816)	(1.372)	(0.916)
Full Controls	yes	yes	yes	yes	yes
Observations	439	439	439	439	439
Adj. R^2	0.078	0.068	0.023	0.009	0.096

Table 7: Preference, Probability Unsophistication, or Financial Knowledge

This table reports Tobit regression results in which the dependent variable is *Fraction of Equity in Individual Stocks*. The key independent variable is *Inverse-S*. Column (1) includes only respondents that have a college degree, column (2) includes only respondents that answer all three numeracy questions correctly, column (3) only includes respondents that answer all three financial literacy questions correctly, and column (4) only includes respondents who correctly answer the question "Buying a stock mutual fund usually provides a safer return than a single company stock." All models include a constant, missing data dummies, and controls for age, age-squared divided by one thousand, female, married, white, Hispanic, number of household members, employment status, education, (ln) family income, (ln) financial wealth, numeracy, financial literacy, trust, utility curvature, and optimism. All results use ALP survey weights. The symbols *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

	Highly Educated Subsample	High Numeracy Subsample	High Financial Literacy Subsample	Know Stocks Riskier Than Mutual Funds Subsample
	(1)	(2)	(3)	(4)
Inverse-S	0.116*	0.092*	0.148**	0.114**
	(1.824)	(1.688)	(2.396)	(2.065)
Full Controls	yes	yes	yes	yes
Observations	584	567	577	634
Adj. R^2	0.044	0.078	0.075	0.062

Table 8: Participation in Mutual Funds, Individual Stocks, and Both

This table reports the coefficients of a multinomial logit regression for *Non-Participation*, *Individual Stocks Only*, and *Both Mutual Funds and Individual Stocks*. The excluded category is *Mutual Funds Only*. In column (1), the dependent variable equals one if the respondent does not participate in the stock market. In column (2), the dependent variable equals one if the respondent invests only in individual stocks. In column (3), the dependent variable equals one if the respondent invests in both mutual funds and individual stocks. The key independent variable is *Inverse-S*. The model includes a constant, missing data dummies, and controls for age, age-squared divided by one thousand, female, married, white, Hispanic, number of household members, employment status, education, (ln) family income, (ln) financial wealth, numeracy, financial literacy, trust, utility curvature, and optimism. All results use ALP survey weights. The symbols *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

	Non-Participation	Individual Stocks Only	Both Mutual Funds and Individual Stocks
	(1)	(2)	(3)
Inverse-S	0.290***	0.335**	0.271*
	(2.693)	(2.395)	(1.930)
Full Controls		yes	
Observations		2,671	
Adj. R^2		0.158	

Figure 1: Probability Weighting Function

This figure shows an example of a probability weighting function $w(P)$. P_i is the cumulative probability of outcome i and π_i is the decision weight.

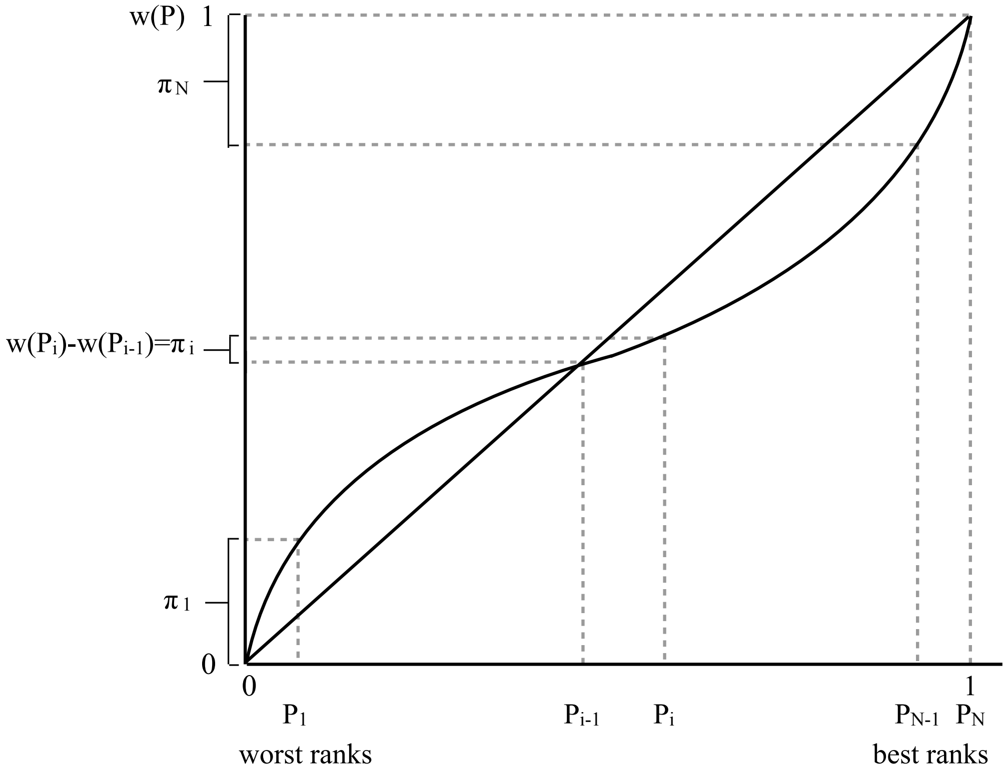

Figure 2: Standard Deviation and Skewness Against Number of Stocks

This figures shows the annualized standard deviation and skewness as a function of the number of stocks. To create the figure, we randomly select N stocks from the set of CRSP domestic common stocks to form an equally weighted portfolio. We then find the (annualized) standard deviation and skewness of this equally weighted portfolio using daily returns over the period July 2016 to June 2017. We repeat this procedure 1,000 times and plot the average portfolio statistics for each N.

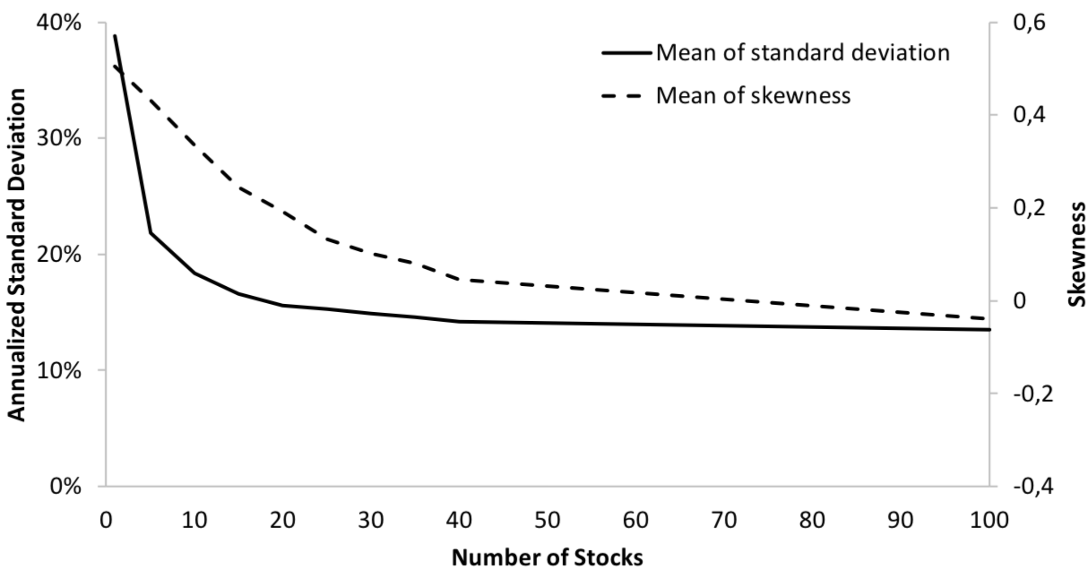

Figure 3: Optimal Fraction of Equity in Individual Stocks

The figure displays the average optimal individual stock holdings as a % of total assets invested in equity. The investor chooses her optimal investment in a negatively skewed mutual fund, a positively skewed individual stock (portfolio), and a risk free asset. We model utility curvature using CRRA preferences with parameter γ. We assume the probability weighting function specified in Prelec (1998, Eq. 3.1). For details see Online Appendix A.

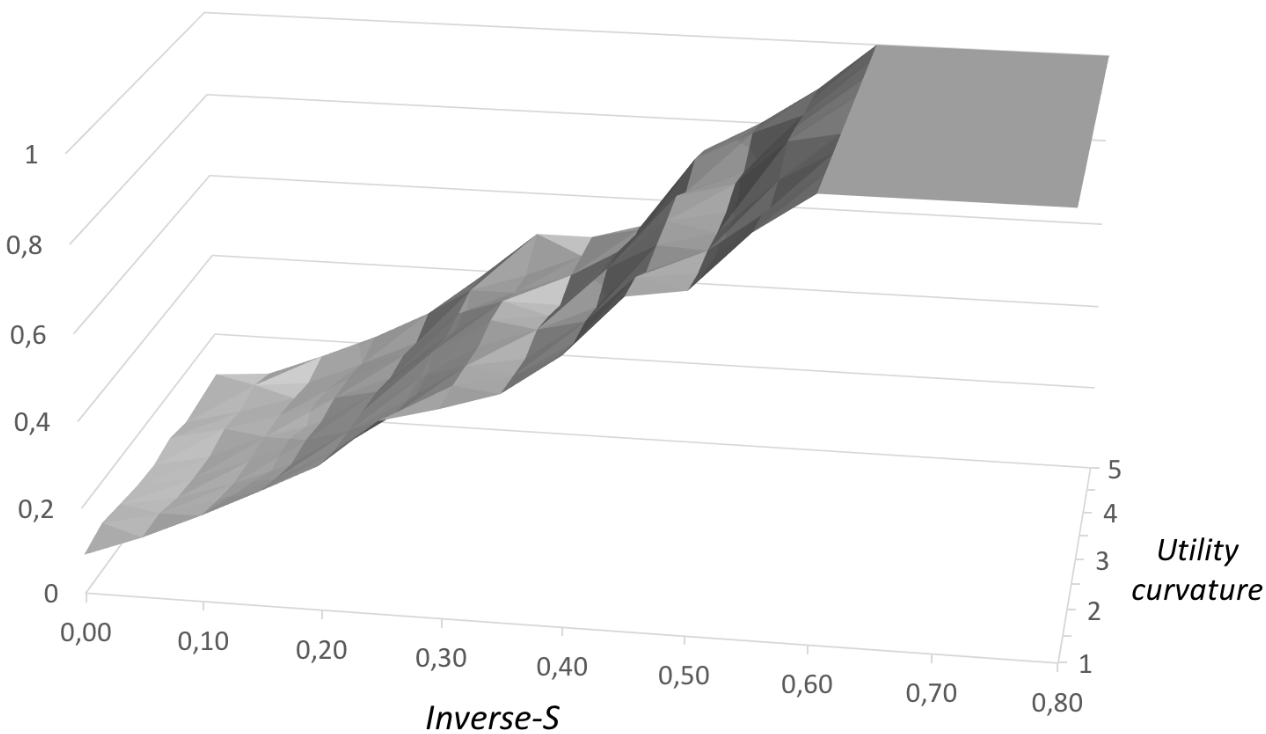

Figure 4: Example of a Question to Elicit Utility Curvature

The payoff of Option A and Option B is determined by a draw of one ball from a box with 100 balls. Each ball in the box is either purple or orange. One ball will be drawn randomly from the box and its color determines the payoff you can win. For Option A, you win $12 if the ball drawn is purple (33% chance) and $3 if the ball drawn is orange (67% chance). For option B, you win $18 if the ball drawn is purple (33% chance) and $0 if the ball drawn is orange (67%).

Option A	Option B
○ 33% chance of winning $12 67% chance of winning $3	○ 33% chance of winning $18 67% chance of winning $0

Figure 5: Example of a Question to Elicit *Inverse-S*

The payoff of Option A and Option B is determined by a draw of one ball from a box with 100 balls. Each ball in the box is either purple or orange. One ball will be drawn randomly from the box and its color determines the payoff you can win. For Option A, you win $42 if the ball drawn is purple (5% chance) and $6 if the ball drawn is orange (95% chance). For option B, you win $8 for sure (100% chance).

Option A	Option B
○ 5% chance of winning $42 95% chance of winning $6	○ 100% chance of winning $8

Figure 6: Example of Question Rounds for a Probability Weighting Question

This figure shows an example of three rounds for a probability weighting question.

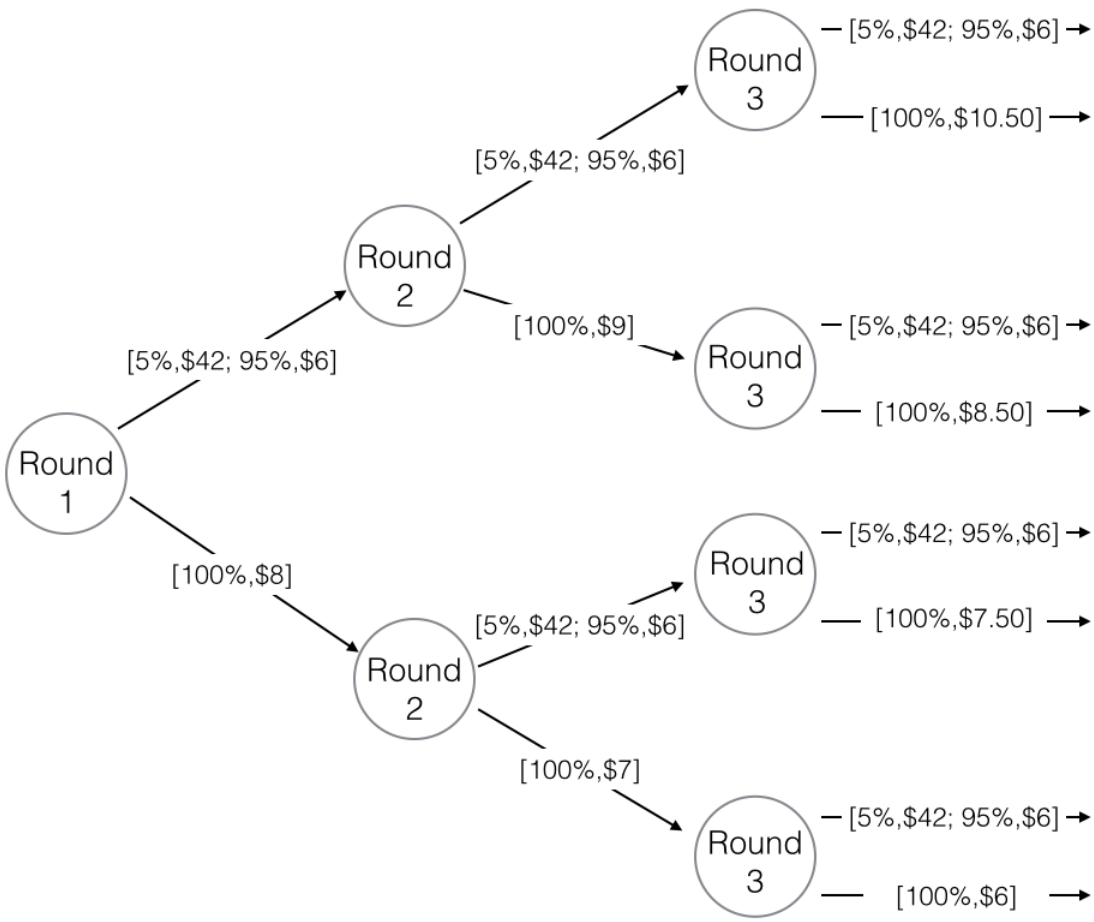

Table A1: Variable Definitions

Variable Name	Definition
Fraction of Equity in Individual Stocks	Individual stock holdings as a % of total assets invested in equity
Relative Sharpe Ratio Loss	1 minus the Sharpe ratio of the individual's stock portfolio divided by the Sharpe ratio of the market index
Total Skewness	Average skewness of daily returns of the individual stocks
Idiosyncratic Skewness	Average skewness of the residuals of a two factor model ($RMRF$ and $RMRF^2$) of the individual stocks
Max. One-Day Return	Average maximum one-day return of the individual stocks
Idiosyncratic σ	Average annualized standard deviation of the residuals from the FF 5-factor model of the individual stocks
Stock β	Average market beta of the individual stocks
Mutual Funds Only	Indicator that respondent holds only stock mutual funds
Individual Stocks Only	Indicator that respondent holds only individual stocks
Both Mutual Funds and Individual Stocks	Indicator that respondent holds both stock mutual funds and individual stocks
Age	Age in years
Female	Indicator for female
Married	Indicator if respondent is married or has a partner
White	Indicator if respondent considers himself primarily White
Hispanic	Indicator if respondent considers himself primarily Hispanic
Number of Household Members	Number of additional members in the household
Employed	Indicator if respondent is employed
Family Income	Total income for all household members older than 15, including from jobs, business, farm, rental, pension benefits, dividends, interest, social security, and other income
Financial Wealth	The sum of checking and savings account, CDs, government and corporate bonds, T-bills, and stocks
No College Degree	Indicator if respondent had less than a bachelor or associate's degree
Bachelor or Associate's Degree	Indicator if respondent completed a bachelor or associate's degree
Master or Higher Degree	Indicator if respondent has a master or higher degree
Utility curvature	Average risk premium required for utility curvature lottery questions
Optimism	Subjective life expectancy minus objective life expectancy (see Online Appendix)
Financial Literacy	Number of financial literacy questions answered correctly (out of 3 total; see Online Appendix)
Numeracy	Number of numeracy questions answered correctly (out of 3 total; see Online Appendix)
Trust	Ranges from 0 to 5; 0 corresponds to "you can't be too careful" and 5 corresponds to "most people can be trusted"