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Household Portfolio Underdiversification and Probability Weighting: Evidence from the Field

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This paper is part of the NBER's Research Program on the Economics of Aging and the Working Group on Household Portfolios.

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Keywords

household finance, behavioral economics, probability weighting, rank dependent utility, cumulative prospect theory, salience theory, portfolio underdiversification, household portfolio puzzles.

Disciplines

Economics

Comments

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We test whether probability weighting affects household portfolio choice in a representative survey. On average, people display inverse-S shaped probability weighting, overweighting low probability tail events. As theory predicts, probability weighting is positively associated with portfolio underdiversification and significant Sharpe ratio losses. Analyzing respondents' individual stock holdings, we find higher probability weighting is associated with owning lottery-type stocks and positively-skewed equity portfolios. People with higher probability weighting are less likely to own mutual funds and more likely to either avoid equities or hold individual stocks. We are the first to empirically link individuals' elicited probability weighting and real-world investment behavior.

JEL Codes: G11, D81, D14, C83, D90

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People frequently violate the tenets of expected utility theory for low probability events: for example, they simultaneously buy insurance and lottery tickets, over-insure 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 decision making under risk, such as the demand for "extended warranty" type insurance against small losses and a preference for low deductibles when insuring large losses (Bernard, He, Yan, and Zhou, 2015). In finance, probability weighting can explain underdiversified household portfolios (Polkovnichenko, 2005) and the popularity of lottery-type stocks (Barberis and Huang, 2008; Bordalo, Gennaioli, and Shleifer, 2013). Overweighting low probability tail events makes the negative skewness of well-diversified portfolios (e.g., the market index) less attractive, while making the positive skewness of an underdiversified portfolio containing a few individual stocks more attractive.[2]

Directly measuring the empirical 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

[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), Chapman and Polkovnichenko (2011), De Giorgi and Legg (2012), Carlson and Lazrak (2016), and He, Kouwenberg, and Zhou (2018).

explain actual household portfolio decisions, most notably portfolio underdiversification, skewness seeking, and investments in lottery-type stocks.

To elicit individuals' probability weighting preferences, we design and field a purpose-built internet survey module using 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*. The respondents were eligible to receive real monetary incentives based on their choices (we paid $16,020 to the 2,703 eligible respondents). The survey module also obtains subjects' portfolio allocations and the names of their five largest individual stockholdings.

Our 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 focus on 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 underdiversification. We find that a one standard deviation increase in *Inverse-S* implies a 12.7 percentage point increase in the portfolio allocation to individual stocks. We also construct an alternative measure of underdiversification: the relative Sharpe ratio loss from investing in individual stocks compared to investing in the market portfolio (see Calvet, Campbell, and Sodini, 2007). Results show that high *Inverse-S* is associated with large Sharpe ratio losses due to idiosyncratic risk: a one-standard deviation increase in *Inverse-S* implies an annual cost to the average (median) stockholder of $2,504 ($351), since for the same level of risk, the person could have had a higher expected return. In addition, we find that probability weighting can help explain the *type* of individual stocks people choose. To this end, we asked subjects who own individual stocks to list their five largest holdings. Consistent with theory, subjects with high *Inverse-S* tend to hold lottery-type stocks with high positive (expected) skewness. We find similar results for portfolio characteristics.

We then broaden the sample of survey respondents to include equity non-participants, and here the theoretical predictions on non-participation are less clear. Probability weighting reduces the perceived value of diversification, which can result in either non-participation *or* underdiversification, depending upon the subject's beliefs regarding the expected return, volatility, and skewness of individual stocks. First, we show that probability weighting is not associated with equity market participation, when participation is defined to include both mutual fund and individual stock ownership. Second, using a multinomial logit model, we show that *Inverse-S* is positively associated with non-participation *and* ownership of individual stocks, and thus negatively associated with owning only mutual funds.

It is unlikely that *Inverse-S* inadvertently measures an alternative component of preferences or individual characteristics for several reasons. First, the pattern of responses to our elicitation questions is inconsistent with the possibility that our measure inadvertently captures other preference parameters such as risk aversion or loss aversion. More generally, any alternative interpretation of our *Inverse-S* measure would need to generate risk seeking choices for low probability events *and* risk aversion for high probability events. Second, our measure of probability weighting exhibits little correlation with empirical measures of risk aversion, loss aversion, overconfidence, ambiguity aversion, optimism, trust, numeracy, education, and financial literacy. Third, we demonstrate that alternative interpretations do not predict the pattern of results found in the data.

As a robustness test, we estimate parametric measures of probability weighting using the functions proposed by Tversky and Kahneman (1992), Prelec (1998), and Bordalo, Gennaioli, and Shleifer (2012). We find similar results as with the non-parametric measure. We also create a measure of utility function curvature (risk aversion) using questions included in our module, and we show that the results are robust to including this control.

Our work contributes to the empirical literature on probability weighting outside of laboratory settings. Prior studies recover preferences from choices in betting markets (Jullien and Salanié, 2000; Snowberg and Wolfers, 2010; Chiappori, Salanié, Salanié, and Gandhi, 2019) and insurance markets (Sydnor, 2010; Barseghyan, Molinari, O'Donoghue, and Teitelbaum, 2013). These studies, however, require strong assumptions to overcome the fundamental identification problem of separating probability weighting from biased beliefs. In contrast, our survey experiment states objective probabilities enabling us to estimate preferences separated from beliefs, and we link these preferences to individuals' real-world choices under risk.

Our paper also adds to the household portfolio choice literature by testing theoretical models that incorporate probability weighting.[3] Specifically, it is the first to show a relation between

[3] See Shefrin and Statman (2000), Polkovnichenko (2005), Barberis and Huang (2008), Chapman and Polkovnichenko (2011), De Giorgi and Legg (2012), Carlson and Lazrak (2016), and He, Kouwenberg, and Zhou (2018).

directly-elicited probability weighting preferences and actual household portfolio decisions. Relatedly, Polkovnichenko (2005) uses stock return data to calibrate a model and shows that household portfolio underdiversification is consistent with probability weighting. Rieger (2012) and Erner, Klos, and Langer (2013) link elicited probability weighting metrics to hypothetical financial decisions 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.

Moreover, our paper contributes to the empirical literature showing many households hold underdiversified portfolios.[4] For example, Kumar (2009) finds that household portfolio underdiversification is related to the demand for stocks with lottery-like features. We provide evidence of the underlying preferences driving these findings, and we also analyze stock market participation choices.

Finally, this 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.[5] Though we do not directly address asset pricing implications, our findings do support the preference-based explanation offered in the studies cited. That is, we find a direct link between investors' probability weighting preferences and skewness-seeking behavior.

[4] For example, Blume and Friend (1975), Kelly (1995), Calvet, Campbell, and Sodini (2007), Mitton and Vorkink (2007), Goetzmann and Kumar (2008), and von Gaudecker (2015).

[5] For equities see, Boyer, Mitton, and Vorkink (2010), Bali, Cakici, and Whitelaw (2011), Conrad, Dittmar, and Ghysels (2013), Conrad, Kapadia, and Xing (2014). For options see, Boyer and Vorkink (2014) and Li, Subrahmanyam, and Yang (2018).

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:

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

Yet Allais (1953) demonstrates that linearity in probabilities is often violated.[6] The Allais paradox shows 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 is large. Further, 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 (Fehr-Duda and Epper, 2012).

A large literature shows that Allais' findings can be explained by non-expected utility models that incorporate probability weighting (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). Probability weighting is similar in CPT and RDU: the differences between the theories are in their treatment

[6] For example, consider the choice between a 100% certainty of receiving \$1 million versus a 98% chance of winning \$5 million. Most people prefer \$1 million with certainty. Next, consider a modification 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 implies $0.01 \times U(1{,}000{,}000) < 0.0098 \times U(5{,}000{,}000)$.

of utility curvature (risk aversion). In these models, individuals rank the possible outcomes from worst to best ($c_1 < c_2 < \cdots < c_N$) and assign each outcome a decision weight, π_i, based on the cumulative probability of the outcome. For example:

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

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

where π_i is determined by an increasing weighting function $w(P_i)$, with $w(0) = 0$ 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 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 overweighting can generate risk seeking towards good outcomes with low probabilities and extreme risk aversion towards bad outcomes with low probabilities.

Bordalo, Gennaioli, and Shleifer (2012) propose a model in which probability weighting is determined by the salience of the payoffs, with salience determined by the contrast between payoffs. 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) find that, relative to expected utility theory, salience theory implies a strong preference for positively skewed securities and reduced demand for a diversified portfolio. Accordingly, in what follows, we do not seek to distinguish between RDU, CPT, and salience theory.

1.2 Hypotheses

The extant theoretical literature shows that probability weighting increases sensitivity to skewness, because investors overweight 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) and well-diversified portfolios less attractive (Polkovnichenko, 2005; Chapman and Polkovnichenko, 2011; De Giorgi and Legg, 2012). Thus, theory predicts that higher probability weighting results in greater underdiversification.

We illustrate this prediction using a simple calibrated portfolio choice model. 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 generally follows Polkovnichenko (2005); see Online Appendix A for details.) Figure 3 shows the optimal fraction of equity allocated to the individual stock for different levels of the probability weighting parameter – denoted *Inverse-S* – and for the CRRA parameter – denoted γ. 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 also show that the relative allocation between risky assets is quite 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.

1.3 The Elicitation Procedure

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 this paper, we 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, utility curvature does not fully explain risk preferences: instead, risk preferences are determined by a combination of utility curvature and probability weighting.

Accordingly, the challenge is to separate the effects of probability weighting from utility 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. Hence deviations from risk-neutrality are due to probability weighting. With narrow framing, however, separating the effects of probability weighting from utility curvature is not trivial because the subject evaluates decisions in isolation and utility curvature can affect even small stake gambles. Prior studies address this issue using two methods. First, parametric methods, which assume a 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 assume a specific functional form and the resulting estimation error in individual level parameter estimates. Second, non-parametric methods 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 method can produce `noisy' probability weighting functions" (e.g., a response error in the first question affects all subsequent questions).

Our solution 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 to reduce error propagation and the length (due to the time constraints of a general population survey rather than a classroom experiment).[7] 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: 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. 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 in the next round Option B is made more attractive by increasing the

[7] 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 in the next round 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 approximated. For each question, the subject is then presented with a fourth choice used only to evaluate consistency with prior choices.

The questions are phrased in terms of lotteries instead of the stock market to mitigate reverse causality problems and to ensure that subjects know the probabilities of outcomes. Indeed an advantage of our experimental survey approach is that we can explicitly state the exact probability for each outcome. This allows us to measure *preferences* towards probabilities, rather than *beliefs* about probabilities; in contrast, for natural events, it is difficult to disentangle preferences and beliefs (for further discussion see Barberis 2013b, p. 614).

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 Options A and B. Thus the effect of probability weighting largely cancels out in the comparison between Options A and B, as the probabilities are 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 more accurately measure 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 and estimate the percentage risk premium.[8] In the remaining five sets of probability weighting 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 for subjects' choices, as elicited preferences likely contain measurement error (Harless and Camerer, 1994; Hey and Orme, 1994). After each subject completes three rounds of the question, we ask a question where only one response is consistent with previous choices, as the sure amount falls outside the subject's indifference bounds. (See Online Appendix B for details.)

In addition to a fixed participation fee, the subjects in our survey 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. The American Life Panel (ALP) was responsible for determining and making the incentive payments, and subjects in the ALP regularly receive payments from the ALP. The involvement of the ALP should minimize subjects' potential concerns about the credibility of the incentives.

[8] For the 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 elicited indifference value and the lottery's expected value.

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 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, but it is inconsistent with any model of expected utility including models that incorporate skewness preferences (Quiggin, 1993). This pattern is also inconsistent with many of the features commonly incorporated in non-expected utility models, such as loss-aversion and narrow framing (see Online Appendix E). 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, the switch from over- to underweighting probabilities occurs, on average, in the range between 25% and 50%. Note that, however, a positive risk premium for the 25% question does not necessarily imply underweighting of the 25% probability. 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 underweighting range less the premiums in the overweighting range. Higher values indicate a more pronounced *Inverse-S* shape for the probability weighting function. (Online Appendix Table F.1 shows that results are robust to two alternative *Inverse-S* measures based on $[(PW_{88\%} + PW_{75\%}) - (PW_{25\%} + PW_{12\%})]$ and $(PW_{88\%} - PW_{12\%})$.)

The *Inverse-S* measure is parsimonious and allows us to avoid assuming a specific functional form for probability weighting. If individuals frame narrowly and utility curvature affects the responses, taking the difference between the percentage premiums largely differences out the influence of curvature, because curvature affects all premiums similarly. The cost of the tradeoff we made in our survey design – limiting chaining to avoid measurement error – is that it is theoretically possible for utility curvature to influence our *Inverse-S* measure. Section 2.5 shows that, in practice, this does not appear to be the case, as the correlation between utility curvature and Inverse-S is close to zero (r = 0.092). Nevertheless, to ensure that *Inverse-S* does not inadvertently measure utility curvature, in robustness tests we jointly estimate utility curvature and probability weighting 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 its features are consistent with experimental findings. We also estimate the salience function proposed by Bordalo, Gennaioli, and Shleifer (2012, Eq. 5), which uses the salience of payoffs to provide an intuitive psychological foundation for why probability weighting occurs. Further, we estimate the probability weighting function proposed by Tversky and

Kahneman (1992, Eq. 6), which is often used in the finance literature.[9] Online Appendix C provides details about the estimation of the three parametric functions.

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[10] 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 obtained from earlier survey modules. The ALP invited 3,397 panel members and closed the survey when 2,703 of them completed the survey, a completion rate of 79.5%.[11] Our data are cross-sectional and the ALP does not contain a time-series of investments or wealth.

Respondents who indicate that they hold individual stocks are asked to list the names (or tickers) of their five largest holdings. We match the holdings to the CRSP database[12] and construct various measures of stock characteristics using daily returns from July 1, 2016 to June 30, 2017. We select this period because our survey was fielded from June 20 to July 19, 2017.

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[9] Although widely used in the finance literature, the Tversky and Kahneman (1992) function generates an artificial negative correlation between the utility curvature and the probability weighting parameters (Fehr-Duda and Epper, 2012). Thus, for this function we do not jointly estimate the utility curvature and probability weighting parameters.
[10] Online Appendix D and https://www.rand.org/labor/alp.html provide further information on the ALP.
[11] Of the 2,703 subjects, 2,671 completed all six probability weighting questions.
[12] We include only U.S. based common stocks. We are unable to match 12.1% of the holdings because the holding was a foreign or private company, or because the reported name was unmatchable.

Table 2 provides summary statistics of the key variables (Appendix Table A1 defines the variables), both for the full sample and for the 741 respondents who directly own equity outside of their retirement accounts. Our main analyses focus on the sample of 741 equity holders. We focus on equity investments outside retirement accounts, because retirement investments may not reflect active choices due to limited investment options and the Department of Labor's acceptance of target date funds as investment defaults.[13] Few 401(k) plans allow investment in brokerage accounts, and if they do, only a small fraction of pension assets is invested via these accounts (Keim and Mitchell, 2018; Vanguard, 2018). For a limited number of respondents we have data on home ownership and pension assets invested in equity. In Online Appendix Table F.3, we show that our results are robust to controlling for these assets.

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 that this variable is a good proxy for portfolio underdiversification. Indeed, in our sample we find that half of individual stock owners hold shares in only one or two companies, which is consistent with the *Fraction of Equity in 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:

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[13] For more on target date funds and 401(k) plans, see Mitchell and Utkus (2012). Further, this largely avoids underdiversification due to employee stock ownership, which occurs primarily through tax deferred plans such as 401(k) and employee stock ownership plans (Curcuru, Heaton, Lucas, and Moore, 2010).

$$RSRL_i = 1 - \frac{\mu_i / \sigma_i}{\mu_M / \sigma_M} = 1 - \frac{\beta_i \cdot \sigma_M}{\sigma_i}, \quad (5)$$

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 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, which DeMiguel, Garlappi, and Uppal (2009) show generates out-of-sample diversification benefits similar to that of optimal strategies. The investor's *RSRL* will equal zero if he holds a fully diversified portfolio, while larger values indicate underdiversification.

Using daily stock returns, we generate several stock level measures of (expected) skewness at the individual stock level and also at the portfolio level (by combining the investors' mutual fund holdings and individual stockholdings). *Total Skewness* is the skewness of daily 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}. *Idiosyncratic* σ is the annualized standard deviation of the residuals from the Fama and French (2015) five-factor model. *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. *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 each 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% of the respondents whose equity ownership consists exclusively of mutual funds. *Individual Stocks Only* is an indicator variable equal to one for the 7% of the sample whose equity ownership consists exclusively of individual company stocks. *Both Mutual Funds and Individual Stocks* is an indicator variable equal to one for the 9% of the sample who own both equity mutual funds and individual stocks.

2.3 Control Variables

The empirical tests control for respondents' demographic and economic characteristics including age, sex, race, ethnicity, marital status, number of household members, education, employment status, family income, and financial wealth.[14] Our 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 from factors that are conceptually similar to probability weighting. For example, utility curvature could be correlated with probability weighting. Thus, our regressions control for utility curvature to ensure that our probability weighting variable captures a distinct component of preferences. 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.

Optimism could influence the overweighting of small probabilities (i.e., optimists may overestimate the probabilities of positive outcomes). Accordingly, following Puri and Robinson (2007), we include a question assessing individuals' subjective life expectancies and measure optimism by comparing subjective and objective life expectancies (where the latter are derived

[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 6% of the observations are missing. In all regressions using these controls, we include dummies for observations with imputed missing data.
[15] Online Appendix D provides the exact wording of these questions.

from age/sex population mortality tables). Prior studies also show that financial literacy 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, we include 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 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 are risk seeking for low probability questions with $p = 0.05$ and $p = 0.12$; indeed, the average risk premiums are negative (-7.1% and -2.3%, respectively). For these questions, any required risk premium from utility curvature is more than offset by the risk seeking from 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. The overall pattern is consistent with inverse-S-shaped probability weighting: overweighting of small probabilities and underweighting of high probabilities.

Panel A of Table 3 summarizes the probability weighting measure, *Inverse-S*. Consistent with probability weighting in the general population, the sum of the risk premiums for the three high probability questions is 71 percentage points higher than the sum of the risk premiums for the three low probability questions, on average. *Inverse-S* is positive for 81% of the respondents, indicating an inverse-S shaped probability weighting function[16] 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, a result that may help explain the observed large heterogeneity in portfolio allocations. 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).

2.5 Alternative Interpretations of Inverse-S

Next, we examine the possibility that our *Inverse-S* measure might inadvertently capture some other component of our subjects' preferences or characteristics. Specifically, we examine utility curvature, loss-aversion, and narrow framing; optimism and overconfidence; ambiguity aversion; trust; and probability unsophistication.[17] We argue that these alternatives cannot capture our *Inverse-S* measure for several reasons. First, we show that the observed pattern of negative risk premiums for low probabilities and positive risk premiums for high probabilities is inconsistent with these alternative interpretations. Second, we create direct measures of alternative preferences and characteristics, and show that these measures have low correlations with *Inverse-S*. We further show, in the results section, that our main results are robust to controlling for these direct measures. Third, in the later sections we demonstrate that our results are inconsistent with the implications of these alternative interpretations.

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[16] Similarly, when we fit the Prelec (1998) weighting function jointly with a CRRA utility function using all 10 questions, 73% of the subjects have an inverse-S shaped function (see Online Appendix C).

[17] Some of the variables we examine are available for only a limited subset of our observations as the other modules' samples only partially overlap with our own. See Table A2 for a description and summary statistics of the Barsky, Juster, Kimball, and Shapiro (1997) measure of risk aversion, loss aversion, overconfidence, and ambiguity aversion.

We first consider the possibility that *Inverse-S* inadvertently measures some component of the utility function, rather than of the (weighted) probabilities applied to utility. Online Appendix E shows that utility curvature and loss aversion (with or without narrow framing) cannot explain the pattern of risk premiums found in our survey. First, neither utility curvature nor loss aversion can explain our finding of negative risk premiums for low probabilities and positive risk premiums for high probabilities *for the same individual*. Second, the within-person monotonic increase in risk premiums as the probabilities increase cannot be explained by utility curvature or loss aversion. In the absence of narrow framing, utility curvature predicts small positive risk premiums with little variation across probabilities (Online Appendix Figure E.1). With narrow framing, both utility curvature and loss aversion predict a hump-shaped pattern with low risk premiums for the tail probabilities and relatively large risk premiums for intermediate probabilities (Online Appendix Figures E.2 to E.4). This is because the variance of a binary lottery is $p(1-p)$, which is small as p approaches 0 or 1 and largest for intermediate probabilities.

Thus, as Online Appendix E shows, the effects of utility curvature or loss aversion are largely differenced out from the *Inverse-S* measure. Further, Panel B of Table 3 shows that the correlation between utility curvature and *Inverse-S* is low ($r = 0.09$), with utility curvature explaining less than 1% of the variation in *Inverse-S*; in contrast, the average correlation among the risk premiums of the four utility curvature questions is $r = 0.70$. Similarly, Appendix Table A2 shows the correlation between *Inverse-S* and loss aversion is low ($r = 0.03$). Accordingly, *Inverse-S* appears to be separate from parameters governing the shape of the utility function.

The tendency to frame payoffs narrowly could influence the risk premiums for the probability weighting questions. In our module, we also elicit utility curvature for small stakes with separate elicitations. Thus if narrow framing affects *Inverse-S,* it should also affect our measure of utility curvature, however, in our data the correlation between utility curvature and *Inverse-S* is close to zero (r = 0.09), implying that variation in narrow framing does not drive *Inverse-S*. Probability weighting, on the other hand, has almost no impact on the utility curvature questions (as the probability of winning is equal for Option A and B), and can therefore explain why the correlation between the two measures is low. As an additional robustness test, we also create the Barsky, Juster, Kimball, and Shapiro (1997) risk aversion measure based on large stake gambles (for the subset of our sample that overlaps with earlier ALP modules that included the Barsky et al. questions). The correlation between *Inverse-S* and the Barsky et al. measure is small (r = -0.07).

Optimism (or overconfidence) 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. Our results confirm that the correlation between *Inverse-S* and optimism is not significant (Table 3). Similarly, Appendix Table A2 shows that the correlation between *Inverse-S* and a measure of overconfidence is insignificant. Further, Appendix Table A2 also shows the correlation between Inverse-S and ambiguity aversion is small.

Finally, we consider trust and probability sophistication (proxied by education, numeracy, and financial literacy). It is not obvious that these concepts would create a systematic pattern in the risk premiums for different probabilities. As Panel B of Table 3 shows, the correlations between these variables and *Inverse-S* are small. More generally, any alternative interpretation of our measure would need to explain: (1) the same individual requiring negative risk premiums for small probabilities and positive risk premiums for larger probabilities, (2) a within-person monotonic increase in risk premiums as the probabilities increase (despite the variance of the lotteries having a hump-shape with the largest variance at 50%), and (3) the relatively low correlations between *Inverse-S* and reasonable empirical proxies for the alternative concepts.

3. Probability Weighting and Household Portfolio Underdiversification

Figure 7 provides a simple visual summary of the relation between *Inverse-S* and portfolio underdiversification. For ease of interpretation, we standardize the *Inverse-S* variable to have a mean of zero and a standard deviation of one. The y-axis shows the fraction of equity allocated to individual stocks, and the x-axis shows the standardized *Inverse-S* measure. The curve is fitted using kernel weighted polynomial smoothing, and the grey shading shows the 95% confidence interval. Consistent with theoretical predictions, the curve has a positive slope indicating greater probability weighting is associated with portfolio underdiversification.

Next we test the relation between probability weighting and household portfolio underdiversification. Following Dimmock, Kouwenberg, Mitchell, and Peijnenburg (2016), all specifications control 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 controls for utility curvature, numeracy, financial literacy, optimism, and trust. 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 makes underdiversified portfolios more attractive due to their positive skewness (Shefrin and Statman, 2000; Polkovnichenko, 2005; Barberis and Huang, 2008). The results in Panel A are consistent with this prediction, showing a significant positive relation between *Inverse-S* and the fraction of equity allocated to individual stocks. The coefficient 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.

The coefficient on *Inverse-S* is stable across the four columns as more controls are added, and the adjusted-R^2 increases. This pattern suggests that, although other investor characteristics are important for portfolio underdiversification, the effect of probability weighting is largely independent of these other characteristics.

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.[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*.

Several robustness tests are provided in Online Appendix Tables F.1 to F.3. First, we show using transformations of our *Inverse-S measure* that the results are not driven by outliers and that the results are similar if we use OLS instead of Tobit regressions. Second, we confirm that the results are robust to excluding subjects who performed poorly on the consistency check questions or who answered the elicitation questions unusually quickly. Third, for the subset of subjects for whom we have data on home ownership or the value of pension assets (these variables are taken from other ALP modules whose samples do not fully overlap with our own), we include these variables as controls. In all cases, the coefficient on *Inverse-S* remains significant with these controls included.

3.2 Probability Unsophistication and Financial Knowledge

A possible concern with our analysis might be that the relation between probability weighting and underdiversification might reflect omitted variables. To alleviate this concern, our previous analyses use a battery of controls. In this section, we devote particular attention to probability

[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 subjects did not report the name or ticker of their holdings and 56 subjects gave names or tickers that were not domestic common stocks or could not be matched to a single security.

unsophistication – the possibility that some individuals have difficulty with probabilistic reasoning – which could affect both their elicited *Inverse-S* values and their portfolio choices.

This alternative interpretation of our probability weighting measure appears unlikely, given the results 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 four restricted samples. In columns (1), (2), and (3) of Table 5, we include only subjects with a college degree, who correctly answer all three of the numeracy questions, or who correctly answer all three financial literacy questions, respectively. In all three columns, *Inverse-S* is significantly positively related to portfolio underdiversification, suggesting that *Inverse-S* does not reflect poor quantitative reasoning.

In column (4), we include 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.'" The results show that *Inverse-S* is positively associated with underdiversification, even for investors who understand the benefits of diversification. Subjects with high *Inverse-S* hold individual stocks despite knowing they are riskier than mutual funds.

Our finding that the relation between *Inverse-S* and underdiversification is due to preferences rather than probabilistic unsophistication has implications for whether probability weighting is a preference or a "mistake," in the sense that people would choose differently if they understood decision theory (Fehr-Duda and Epper, 2012; Barberis, 2013a,b). Specifically, our results are consistent with experimental studies finding that people are unwilling to change choices violating the independence axiom even after the axiom is explained to them (MacCrimmon, 1968; Slovic and Tversky, 1974). Of course, probability weighting can still be considered a mistake in the sense that it violates the independence axiom. Nevertheless, this is a fundamentally different type of mistake and one that is more difficult to change.

3.3 Additional Robustness Tests Related to Preferences

We also obtain additional control variables from other ALP modules for a subset of our sample. In this section, we use these additional controls to address possible omitted variable concerns related to preferences. Specifically, Table 6 reports results for regressions that include additional controls for the Barsky, Juster, Kimball, and Shapiro (1997) broadly framed measure of utility curvature, loss aversion, overconfidence, and ambiguity aversion. Appendix Table A2 provides more details on these variables. In Table 6, the odd-numbered columns provide estimations without the control variable in the subsample for which the control variable is available, while the even-numbered columns include the additional control. In all cases, the coefficient on *Inverse-S* remains statistically significant and its magnitude is largely unchanged by the inclusion of the control variable. Accordingly, Table 6 provides evidence that these alternative preferences do not affect the relation between *Inverse-S* and portfolio choice.

3.4 Parametric Measures of Probability Weighting Preferences

Our main analyses use a parsimonious non-parametric measure for the *Inverse-S* parameter. 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 from Prelec (1998, Eq. 3.1), Bordalo, Gennaioli, and Shleifer (2012, Eq. 5), and Tversky and Kahneman (1992, Eq. 6). The three parametric measures are defined so that higher values indicate a more pronounced inverse-*S* shape, and are standardized to have a mean of zero and standard deviation of one.

For all three measures, the results reported in Table 7 are similar to those in the main specification. Importantly, the Prelec (1998) probability weighting parameter is jointly estimated along with utility function curvature, so our conclusions are robust to using this alternative method of separating probability weighting from utility curvature.

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 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 measures of skewness: *Total Skewness, Idiosyncratic Skewness, Idiosyncratic σ,* and *Max. One-Day Return*. Although people may not understand the statistical concept of "skewness," they likely do understand which stocks have more lottery-like features – those with higher skewness. We include *Idiosyncratic σ* because it is a proxy for expected positive skewness (Boyer, Mitton, and Vorkink, 2010), not because probability weighting implies a preference for idiosyncratic risk itself. We also include the market beta, *Stock β*, as a measure of systematic risk.

Table 8 shows regression estimates for the five dependent variables described above. The key independent variable is *Inverse-S.* Here our 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. In this panel, the focus is on the characteristics of the investor's overall equity portfolio.

Columns (1) and (2) show that *Inverse-S* is significantly and positively related to *Total Skewness* and *Idiosyncratic Skewness.* That is, investors with higher probability weighting choose lottery-type stocks that have high expected positive skewness. Column (3) 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 in Panel B. Column (4) shows that the results are similar using *Max. One-Day Return* as an alternative proxy of expected skewness. This alternative proxy captures the point that high returns receive more news coverage and are more salient to investors.

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 8 indicates that investors with high *Inverse-S* prefer high expected positive skewness but not higher systematic risk. Importantly, this pattern is exactly what is implied by probability weighting, but it is not an obvious implication of alternative explanations. For example, if *Inverse-S* inadvertently measured risk seeking preferences (utility 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, 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. Barberis and Huang (2008) argue that probability weighting can cause positively skewed securities to have low returns. Our results support these studies' conclusions 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 structured products that exploit investors' probability weighting preferences and have large negative abnormal returns.

5. Equity Market Nonparticipation, 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 than in the tests discussed above. If the choice set includes only the risk-free asset and a diversified portfolio, probability weighting can cause non-participation as it makes a diversified negatively skewed portfolio less attractive. When an individual stock is added to the choice set, however, the predictions are less clear. Probability weighting can result in non-participation or 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.

We begin by testing the participation decision and ignoring the *type* of equity held in the portfolio. Panel A of Table 9 reports the results of a logit model in which the dependent variable is *Equity Participation*. We find that *Inverse-S* is not significantly related to participation.

A key implication of probability weighting, however, is that a diversified portfolio of equities, such as a mutual fund, can be less attractive than an undiversified but positively skewed security, such as an individual stock. Accordingly, in Panel B of Table 9, we disaggregate equity ownership into multiple categories and estimate a multinomial logit model. In this model, the dependent variable takes one of four values: *Non-Participation*, *Mutual Funds Only*, *Individual Stocks Only*, and *Both Mutual Funds and Individual Stocks*. *Mutual Funds Only* serves as the excluded category because this is theoretically the least attractive choice for an investor with probability weighting preferences.

Our results show that subjects with higher *Inverse-S* are more likely to choose either non-participation or individual stock ownership, and thus are less likely to own only mutual funds. The economic magnitudes implied by the coefficient estimates are large. For instance, the coefficient 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 is subject to a caveat, however, as theoretically determining whether high *Inverse-S* results in non-participation *or* underdiversification depends on the subject's beliefs about expected 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 do not participate in the stock market, while others buy positively-skewed individual stocks.

We emphasize that the pattern of results in Table 9 is broadly consistent with the theoretical predictions of probability weighting, but it is inconsistent with most alternative interpretations. For example, if *Inverse-S* inadvertently measured utility curvature or loss aversion, it would be positively related to non-participation but negatively related to underdiversification. Alternatively, if *Inverse-S* inadvertently measured optimism or overconfidence, it would be negatively related to non-participation. Instead, however, *Inverse-S* is empirically positively related to *both* non-participation and underdiversification.

6. Conclusion

Our paper is the first study to empirically link individuals' elicited probability weighting preferences to actual household portfolio allocations. We measure probability weighting in an incentivized survey module fielded in a large, 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 show that investors with higher *Inverse-S* tend to hold lottery-type stocks and invest in positively-skewed equity portfolios. Furthermore, people who overweight small probabilities are less likely to invest in mutual funds and instead, either do not participate in the equity market, or else invest in individual stocks.

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 results in large heterogeneity in realized returns which could potentially exacerbate wealth inequality.[20]

[20] See for instance, Bach, Calvet, and Sodini (2017), Lusardi, Michaud, and Mitchell (2017), Campbell, Ramadorai, and Ranish (2019), and Fagereng, Guiso, Malacrino, and Pistaferri (2019).

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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 $N = 2,671$ and the number of equity owners is $N = 741$.

	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. Variable definitions appear in Appendix Table A1. 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. Variable definitions appear in Appendix Table A1. 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: Probability Unsophistication

This table reports Tobit regression results in which the dependent variable is *Fraction of Equity in Individual Stocks*. We run the analysis on different subsets of respondents. 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. Variable definitions appear in Appendix Table A1. 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 6: Additional Control Variables

This table reports Tobit regression results in which the dependent variable is *Fraction of Equity in Individual Stocks*. In columns (1) and (2), the sample is restricted to include only those observations for which we have a measure of the subject's Barsky, Juster, Kimball, and Shapiro (1997) broadly framed measure of utility curvature. The alternative utility curvature variable is included as a control variable in column (2). In columns (3) and (4), the sample is restricted to include only those observations for which we have a measure of the subject's loss aversion. The loss aversion variable is included as a control variable in column (4). In columns (5) and (6), the sample is restricted to include only those observations for which we have a measure of the subject's overconfidence. The overconfidence variable is included as a control variable in column (6). In columns (7) and (8), the sample is restricted to include only those observations for which we have a measure of the subject's ambiguity aversion (see Dimmock, Kouwenberg, Mitchell, and Peijnenburg, 2016). The ambiguity aversion variable is included as a control variable in column (8). 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. Variable definitions appear in Appendix Table A1. All results use ALP survey weights. The symbols *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

	Barsky et al. Utility Curvature		Loss Aversion		Overconfidence		Ambiguity Aversion	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Inverse-S	0.139**	0.146**	0.133*	0.136*	0.188***	0.164**	0.179***	0.191***
	(2.206)	(2.374)	(1.653)	(1.695)	(2.609)	(2.416)	(2.929)	(3.095)
Additional Control	no	yes	no	yes	no	yes	no	yes
Full Controls	yes	yes	yes	yes	yes	yes	yes	yes
Observations	472	472	286	286	222	222	376	376
Adj. R^2	0.065	0.069	0.125	0.125	0.098	0.124	0.089	0.092

Table 7: Alternative *Inverse-S* Measures

This table reports Tobit regression results in which the dependent variable is *Fraction of Equity in Individual Stocks*. 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. 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. Variable definitions appear in Appendix Table A1. All results use ALP survey weights. The symbols *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

	Prelec	*Salience Theory*	*Tversky and Kahneman*
	(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

Table 8: 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. 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 *Idiosyncratic* σ is the annualized standard deviation of the residuals from the Fama-French five-factor model. In column (4), the dependent variable *Max. One-Day Return* is the maximum one-day return. 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. Variable definitions appear in Appendix Table A1. 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	Idiosyncratic σ	Max. One-Day Return	Stock β
	(1)	(2)	(3)	(4)	(5)
Inverse-S	0.111**	0.144***	0.012*	0.006**	0.015
	(2.524)	(2.742)	(1.767)	(2.297)	(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	0.037	0.049	0.077

Panel B: Analysis at the portfolio level

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

Table 9: Non-participation, Participation in Mutual Funds, Individual Stocks, and Both

This table reports the coefficients of a logit and a multinomial logit regression. The key independent variable is *Inverse-S*. In Panel A, we report the coefficients of a logit regression in which the dependent variable is *Non-participation*. *Non-participation* equals one if the respondent does not participate in the stock market and zero otherwise. In Panel B, we report the coefficients of a multinomial logit regression with categories *Non-Participation*, *Individual Stocks Only*, *Mutual Funds Only*, and *Both Mutual Funds and Individual Stocks*. The baseline excluded category is *Mutual Funds Only*. 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. Variable definitions appear in Appendix Table A1. All results use ALP survey weights. The symbols *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

	Panel A: logit	***Panel B: multinomial logit***		
	Non-participation	Non-Participation	Individual Stocks Only	Both Mutual Funds and Individual Stocks
	(1)	(2)	(3)	(4)
Inverse-S	-0.105	0.290***	0.335**	0.271*
	(-1.336)	(2.693)	(2.395)	(1.930)
Full Controls	yes		yes	
Observations	2671		2,671	
Adj. R^2	0.177		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.

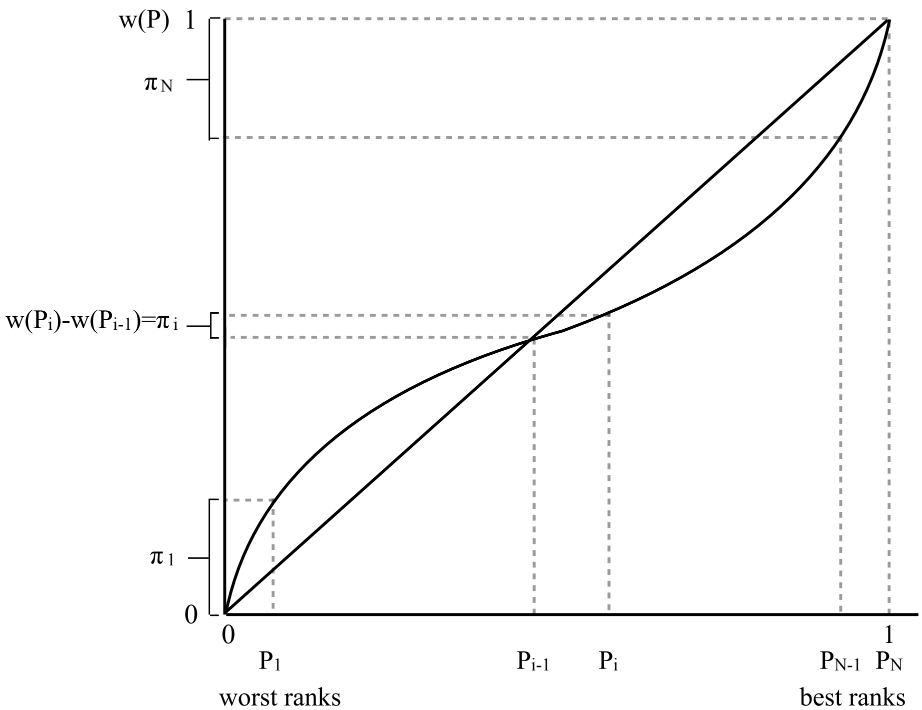

Figure 2: Standard Deviation and Skewness Against Number of Stocks

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.

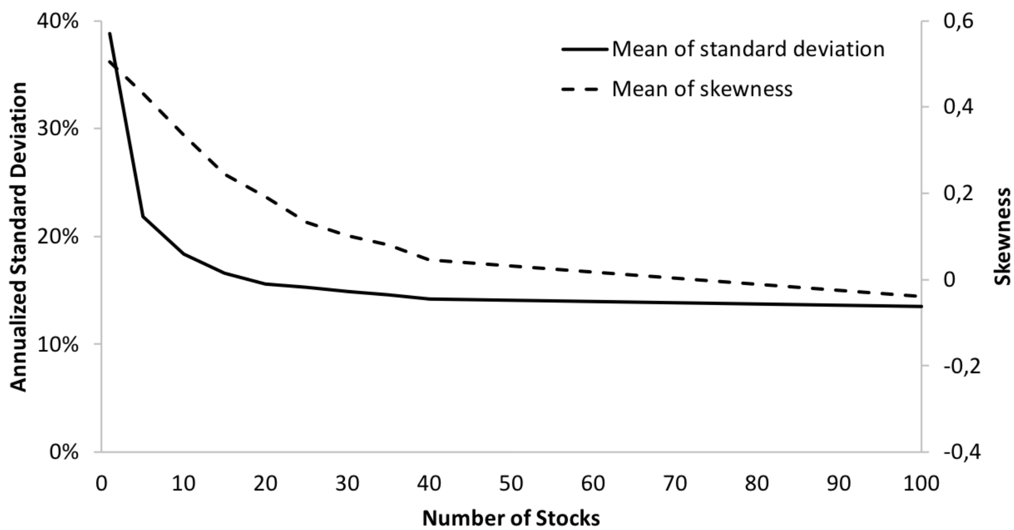

Figure 3: Optimal Fraction of Equity in Individual Stocks

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.

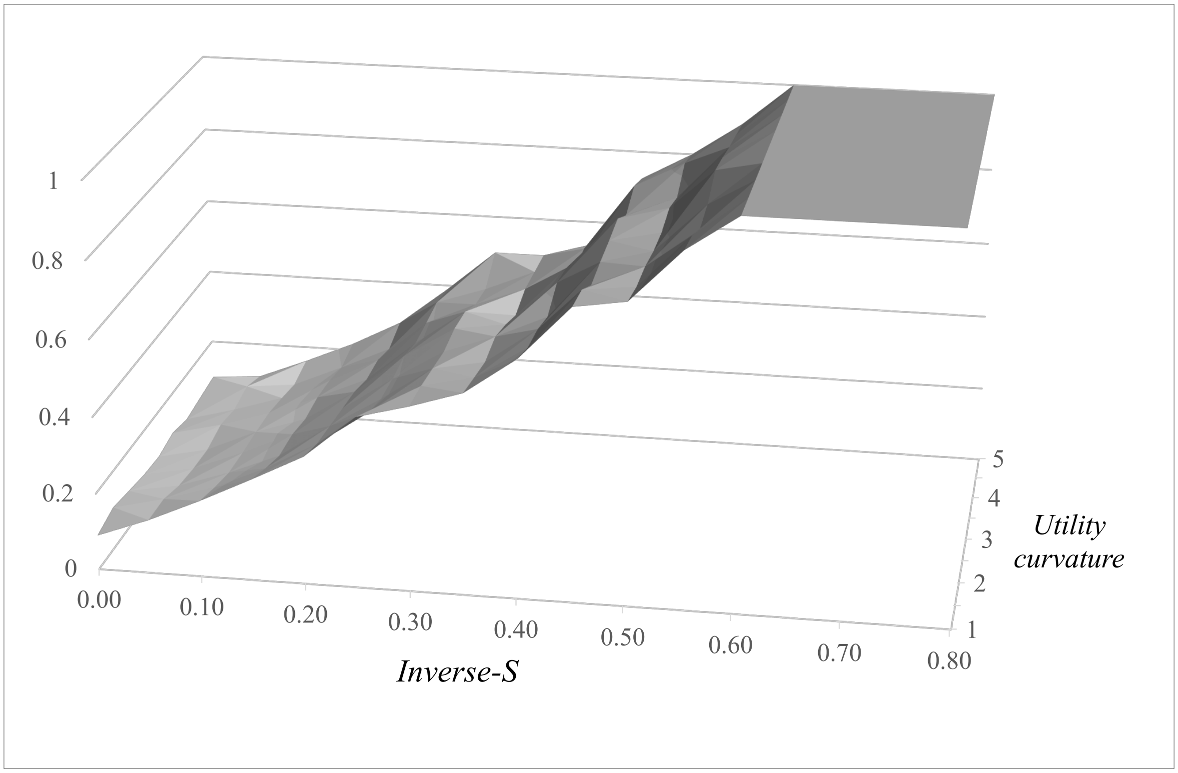

Figure 4: Example of a Question to Elicit Utility Curvature

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.

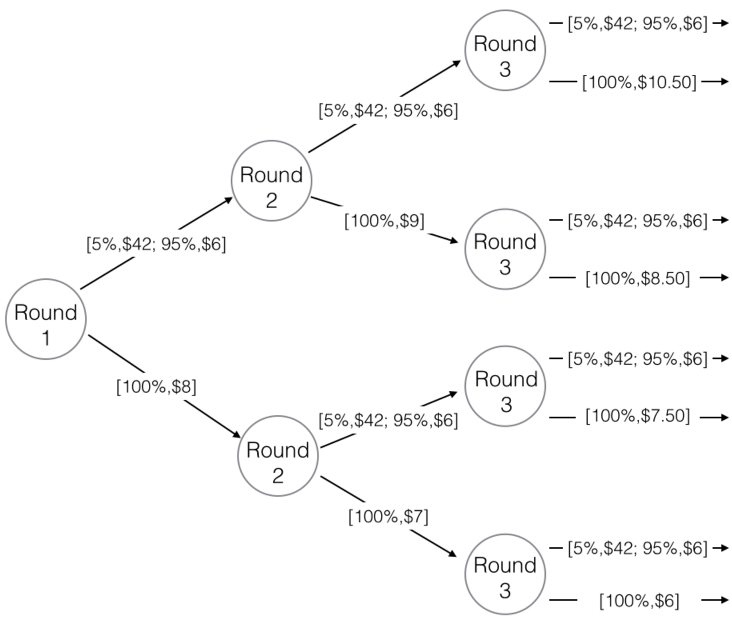

Figure 7: Probability Weighting and Underdiversification

This figure displays the fitted curve from a local polynomial regression. The dependent variable is *Fraction of Equity in Individual Stocks* and the independent variable is *Inverse-S*. *Inverse-S* is restricted from -2 standard deviations to +2 standard deviations around the mean. The shaded area shows the 95% confidence interval. This result uses ALP survey weights.

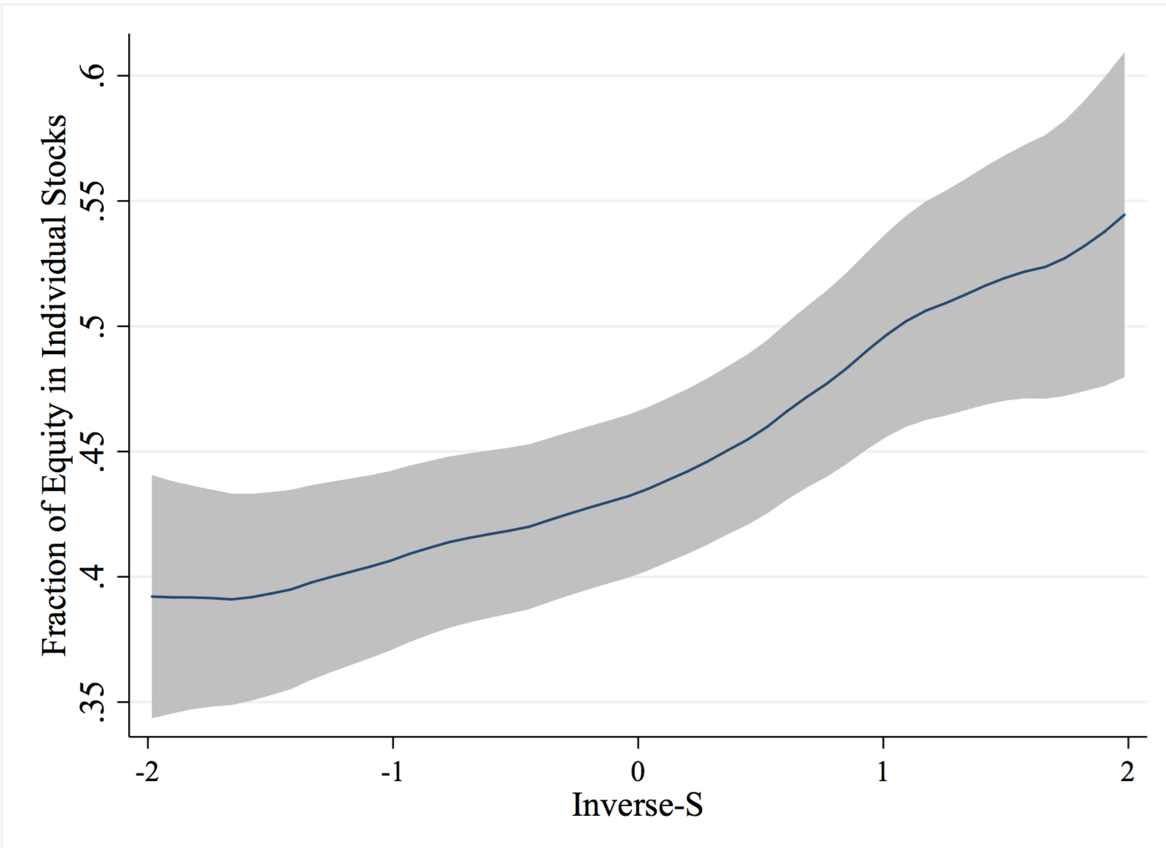

Table A1: Variable Definitions

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"

Table A2: Summary Statistics for Additional Control Variables

This table reports summary statistics for additional control variables. For a subset of our data, we are able to create additional controls using variables from other ALP modules. However, we can create these variables for only a limited subset of our sample due to incomplete overlap with the other modules' samples. For, 62% of our sample, we can create the risk aversion measure developed by Barsky, Juster, Kimball, and Shapiro (1997), based on choices between a sure lifetime income and a risky lifetime income. This variable ranges from one to six with higher values indicating greater risk aversion. For 39% of our sample we have a proxy for loss aversion taken from an ALP module conducted by Choi and Robertson (2019), based on the question: "The possibility of even small losses on my stock investments makes me worry." This is an ordinal variable ranging from one to five, with higher values indicating greater loss aversion. For 30% of our sample, we have an indicator for overconfidence based on a person's overestimation of their actual performance on financial literacy questions (Moore and Healy, 2008). For 51% of our sample we can create the ambiguity aversion measure from Dimmock, Kouwenberg, Mitchell, and Peijnenburg (2016) based on choices between ambiguous and risky urns; higher values indicate greater aversion to ambiguity. Panel A reports summary statistics for the additional control variables. Panel B shows the pairwise correlations between *Inverse-S* and variables measuring Barsky et al. utility curvature, loss aversion, overconfidence, and ambiguity aversion. All results use ALP survey weights. The symbols *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Panel A: Summary statistics

	Equity Owners			All Respondents		
Variable	Mean	Median	Std	Mean	Median	Std
Barsky et al. utility curvature	4.44	5.00	1.28	4.48	5.00	1.35
Loss aversion	2.31	2.00	1.16	2.50	2.00	1.34
Overconfidence	0.08	0.00	0.26	0.19	0.00	0.39
Ambiguity aversion	-0.00	0.00	0.20	0.02	0.03	0.21

Panel B: Bivariate correlations with Inverse-S measure

Variable	Correlation
Barsky et al. utility curvature	-0.068***
Loss aversion	-0.032
Overconfidence	-0.031
Ambiguity aversion	0.057**