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Probability Weighting and Household Portfolio Choice: Empirical Evidence

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Abstract

This paper tests the relationship between probability weighting and household portfolio choice. In a representative household survey, we measure probability weighting preferences using custom-designed incentivized lotteries. We find that, on average, people display "*Inverse-S*" shaped probability weighting, overweighting small probabilities but underweighting large probabilities. As theory predicts, our *Inverse-S* measure is positively associated with both non-participation and individual stock ownership, but negatively associated with mutual fund ownership. Conditional on equity ownership, *Inverse-S* is positively associated with portfolio under-diversification. We match respondents' individual stock holdings to CRSP data and show that *Inverse-S* is positively related to skewness and idiosyncratic risk. We show that these choices reflect preferences, not limited financial knowledge or probability unsophistication.

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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, overinsure against small losses, and hold undiversified positions in individual stocks with high positive skewness.[1] Such anomalous behaviors involving low probability events is 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) and rank-dependent utility (Quiggin, 1982; Yaari, 1987), people tend to overweight small probabilities and underweight large probabilities.[2]

Several theoretical papers show that probability weighting can explain anomalies in household portfolio decisions, such as nonparticipation (Chapman and Polkovnichenko, 2011) and under-diversification (e.g., Barberis and Huang, 2008). The empirical literature is less developed, offering mostly indirect evidence using calibrated portfolio choice models (e.g., Polkovnichenko, 2005). Obtaining direct empirical evidence on the role of probability weighting is challenging, because individual preferences such as probability weighting are not directly observable. The present paper provides direct evidence that probability weighting can explain actual household portfolio decisions, most notably nonparticipation in equity markets, and portfolio under-diversification and skewness seeking among those who do participate.

To elicit individuals' probability weighting preferences, we designed and fielded a purpose-built internet survey module and fielded the module in a nationally-representative sample of several thousand respondents in the American Life Panel (ALP). Our module elicits certainty equivalents for a series of binary lotteries adapted from Wakker and Deneffe (1996) and Abdellaoui (2000). The probabilities of winning the lotteries vary from small to large, allowing us to obtain a measure of each respondent's probability weighting behavior, which we term *Inverse-S*. In addition to a fixed participation fee, all respondents had the opportunity to receive real monetary incentives based on their choices (we paid a total of $16,020 to 2,072 out of 2,702 respondents).

Our general population estimates of probability weighting are consistent with those found in laboratory studies. Specifically, we find that most people have inverse-S shaped probability weighting functions, although there is substantial heterogeneity across subjects. On average, when the probability of winning a lottery is only 5%, our subjects demand a certainty equivalent that is larger than the expected value of the lottery. By contrast, when the probability of winning a lottery is higher (e.g., 50%), our subjects accept a certainty equivalent that is smaller than the expected value of the lottery.

Previous theoretical work provides us with hypotheses on the relationship between probability weighting and portfolio choice. Conventional portfolio choice models, based on expected utility, counterfactually predict that essentially all households will participate in the equity market (Merton, 1969; Heaton and Lucas, 2000). By contrast, numerous models based on probability weighting predict nonparticipation for two reasons. First, probability weighting increases sensitivity to skewness. Given the negative skewness of the aggregate stock market (Albuquerque, 2012), probability weighting makes owning a well-diversified equity portfolio less attractive, and will induce households to either hold individual stocks or not participate at all (e.g., Polkovnichenko, 2005; Chapman and Polkovnichenko, 2011; De Giorgi and Legg, 2012; and He, Kouwenberg, and Zhou, 2017). More generally, even if the stock market returns would exhibit zero skewness, overweighting of the good and the bad tail, and hence underweighting of the more likely outcomes (such as a moderate positive equity premium), makes stocks less attractive to risk averse investors (see He, Kouwenberg, and Zhou, 2017). Second, probability

1 For further discussion, see the review articles of Fehr-Duda and Epper (2012) and Barberis (2013a).

2 This study does not differentiate between rank dependent utility and cumulative prospect theory, as their treatments of probability weighting are similar. The two theories differ in their treatment of utility curvature and not probability weighting.

weighting falls in the class of first-order risk aversion (FORA) utility models. These models exhibit kinked indifference curves around zero stock-holding, resulting in nonparticipation even with a positive equity premium.[3]

Conventional portfolio choice models also counterfactually predict that households will hold well-diversified portfolios, although numerous empirical studies show that many own undiversified portfolios with large positions in one or a few individual stocks (e.g., Blume and Friend, 1975; Kelly, 1995; Calvet, Campbell, and Sodini, 2007; Goetzmann and Kumar, 2008; Kumar, 2009). These undiversified portfolios have high idiosyncratic risk and high positive skewness.[4] These empirical findings are consistent, however, with models that incorporate probability weighting, because overweighting small probabilities makes undiversified, positively skewed portfolios more attractive (e.g., Shefrin and Statman, 2000; Polkovnichenko, 2005; Barberis and Huang, 2008; Jin and Zhou, 2008). Moreover, probability weighting makes holding a diversified equity portfolio such as a mutual fund relatively unattractive, due to its negative skewness. Thus, theory predicts that people with high *Inverse-S* will prefer to either avoid equities completely or hold undiversified portfolios containing a small number of individual stocks.

We test this prediction using a multinomial logit model with four categories: non-participation, mutual funds only, individual stocks only, and both mutual funds and individual stocks. We show that *Inverse-S* is positively associated with nonparticipation *and* ownership of individual stocks, and thus negatively associated with owning only mutual funds. A one-standard deviation increase in *Inverse-S* is associated with a 3.1 percentage point decrease in the probability of owning equity mutual funds only, with corresponding increases in non-participation and individual stock ownership (including individual stock ownership alongside mutual funds). Our results also provide evidence that probability weighting is not simply a proxy for risk aversion, as the subjects choose either the least risky choice (nonparticipation) or the riskiest choice (an undiversified portfolio), which is inconsistent with predictions following from risk aversion.

For equity market participants, we look within their portfolios and measure the fraction of equity holdings allocated to individual stocks, which Calvet, Campbell, and Sodini (2007) show is a good proxy for portfolio under-diversification. We find that a one standard deviation increase in *Inverse-S* implies a 12.8 percentage point increase in the fraction of the portfolio allocated to individual stocks (28.4% relative to the baseline allocation of 45.0 percentage points).

Our results are robust to controlling for variables commonly used in the literature such as age, income, financial assets, education, marital status, number of household members, and employment, as well as additional controls for risk aversion, financial literacy, trust, optimism, and numeracy. Furthermore, the module recorded the time the subjects spent on the elicitation questions and included check questions to assess whether subjects' choices were internally consistent. The results are robust to excluding subjects who answered the elicitation questions unusually quickly or who made multiple errors on the check questions.

In addition to explaining the choice between mutual funds and individual stocks, probability weighting can help explain the *type* of individual stocks people choose. The survey module asked the respondents who own individual stocks to provide the names (or tickers) of their five largest holdings. We match these names to the CRSP daily stock return database, and construct various measures of the stocks' characteristics. Consistent with the predictions of theory, we find that respondents with high *Inverse-S* tend to hold individual stocks with high positive skewness and high idiosyncratic risk (i.e., "lottery stocks").

[3] For examples, see Epstein and Zin (1990), Segal and Spivak (1990), and Chapman and Polkovnichenko (2011). Probability weighting is typically modelled with rank-dependent utility or cumulative prospect theory, and in both models probability weighting generates first-order risk aversion.

[4] See Albuquerque (2012) for a discussion of the positive skewness of individual stocks.

Next, we evaluate whether probability weighting is an attribute of preferences versus probability unsophistication or the result of financial illiteracy. That is, we test whether an underlying concept such as poor quantitative reasoning ability could cause both probability weighting and observed portfolio choices. Based on our summary statistics this seems unlikely, as probability weighting is weakly *positively* correlated with education, financial literacy, and numerical reasoning ability. Additional tests show our results are similar when we restrict the sample to subjects who made no errors on questions measuring numerical reasoning or financial literacy. The results are also similar when we restrict the sample to 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.'" Overall, our results are consistent with the conclusion that probability weighting reflects preferences and not probability unsophistication or limited financial knowledge.

This paper contributes to the household portfolio choice literature by testing theoretical models of probability weighting and household investment behavior.[5] It is the first to show a direct relation between elicited probability weighting preferences and actual household portfolio decisions. Relatedly, Polkovnichenko (2005) uses stock return data to obtain the numerical results for his calibrated model that links probability weighting and under-diversification. Rieger (2012) and Erner, Klos, and Langer (2013) associate elicited probability weighting metrics to hypothetical financial decisions about structured products in laboratory experiments using university students. In contrast, we relate elicited preferences to real financial decisions in the field. Consistent with the predictions of theory, we show that probability weighting can explain both nonparticipation and portfolio under-diversification. This paper also contributes to the literature on household portfolio under-diversification (e.g., Blume and Friend, 1975; Kelly, 1995; Calvet, Campbell, and Sodini, 2007; Goetzmann and Kumar, 2008). For instance, Kumar (2009) finds that households hold under-diversified portfolios and this behavior is related to the demand for stocks with lottery-like features. Our results explore the underlying preferences that drive this demand, and we further show that these preferences are related to nonparticipation in the equity markets.

Additionally, this paper relates to a branch of the asset pricing literature which posits that probability weighting can explain the historically low returns of many securities with positive skewness. Several authors have found that stocks with positive expected skewness have unusually low returns (e.g., Boyer, Mitton, and Vorkink, 2010; Bali, Cakici, and Whitelaw, 2011; Conrad, Dittmar, and Ghysels, 2013; Conrad, Kapadia, and Xing, 2014), and Boyer and Vorkink (2014) provide similar results for equity option returns. Although our paper does not directly address asset pricing, the findings support the preference-based explanation offered in the cited studies. That is, we find a direct link between households' probability weighting preferences and skewness-seeking behavior.

Our survey data contains detailed information about household portfolios, allowing us to test a rich set of hypotheses. Our paper is the first non-laboratory analysis to provide direct evidence relating probability weighting to households' portfolio choices, in particular, non-participation, under-diversification, and positively skewed individual stock holdings. These results are consistent with a large number of theoretical models predicting that probability weighting can help explain puzzling features of households' portfolio choices.

The rest of this paper is organized as follows. Section 1 summarizes the key features of *Inverse-S* preferences, describes the procedure by which we elicit peoples' weighting of small versus large probability lotteries, and defines our probability weighting measure. Section 2 summarizes the data and key variables. Section 3 tests the relation between *Inverse-S* and household portfolio choice. Section 4 tests the relationship between

5 For example, see Shefrin and Statman (2000), Polkovnichenko (2005), Barberis and Huang (2008), Jin and Zhou (2008), Chapman and Polkovnichenko (2011), De Giorgi and Legg (2012), and He, Kouwenberg, and Zhou (2017), among others.

Inverse-S and the characteristics of individual stocks held by the subjects in our sample. Section 5 explores whether the effects of probability weighting are due to preferences versus cognitive errors or financial illiteracy. A final section concludes.

1. Eliciting individuals' probability weighting and risk aversion

1.1 Rank-dependent utility and probability weighting

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

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

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

This phenomenon, known as the Allais paradox, demonstrates that risk preferences can depend non-linearly on the probability of outcomes. It has been replicated many times including in experiments with large real monetary rewards (e.g., Starmer 2000). The general point is that many people are risk-seeking when the probability of winning is small, but strongly risk averse when the probability of winning is large (for a review see Fehr-Duda and Epper, 2012). Similarly, many people are risk-seeking for small probabilities of winning, but simultaneously risk averse for small probabilities of losing. For example, the same person may buy both lottery tickets and insurance.

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

$$V_{RDU} = \sum_{i=1}^{N} \pi_i \cdot U(c_i) \qquad (2)$$

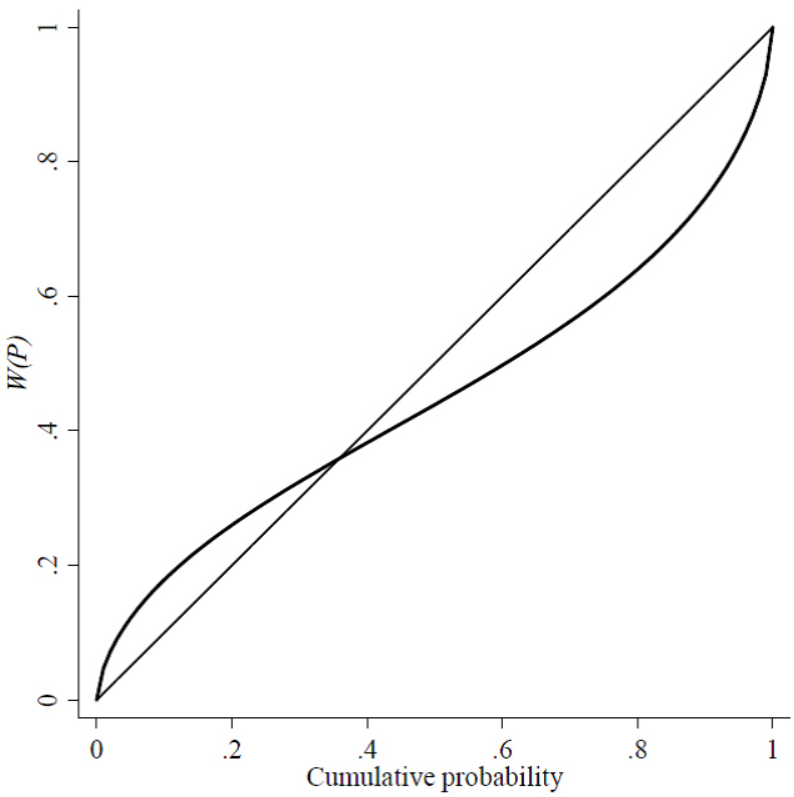
$$\pi_i = w(P_i) - w(P_{i-1}) = w(p_1 + p_2 + \cdots + p_i) - w(p_1 + p_2 + \cdots + p_{i-1}) \qquad (3)$$

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

Figure 1 displays the inverse-S shaped pattern of $w(P_i)$ typically found in experimental studies, in which low probability tail outcomes are substantially overweighted relative to objective probabilities

($w(p_1)>p_1$). The fact that the weighting function is steep on both the left and the right sides of the figure implies that low probability tail outcomes are substantially overweighted for both extreme good outcomes and extreme bad outcomes.

Figure 1



In cumulative prospect theory, probability weighting is similar—the differences between the two theories come from their treatment of utility curvature and not probability weighting—except that the probabilities for loss outcomes ($c_1<c_2<\cdots<c_k<0$) and gain outcomes ($0<c_{k+1}<c_{k+2}<\cdots<c_N$) are transformed by two separate weighting functions, $w^-(P_i)$ and $w^+(P_i)$. Empirically, the two weighting functions for losses and gains tend to have the same inverse-S shaped pattern as in Figure 1 (Tversky and Kahneman, 1992). Therefore, low probability outcomes in both tails are overweighted, similar to rank-dependent utility. Thus, for the purposes of this paper, we do not seek to distinguish between RDU and CPT.

1.2 The elicitation procedure

Estimating empirical individual-level measures of probability weighting appears complicated at first sight, because rank dependent utility is based on the product of two (usually non-linear) functions: probability weighting and utility. Nevertheless, we can disentangle the two functions by using two different types of choice problems: one specifically designed to measure utility curvature (risk aversion),[6] and the other designed to measure probability weighting.

To this end, we designed and fielded a customized module in the American Life Panel (ALP) survey that presents subjects with 10 multi-round questions. The first four questions measure risk aversion, and the remaining six measure probability weighting. Each question asks the subject to choose between two options, Option A and Option B. There are three rounds per question, and based on the subject's choice in a round, one option is changed to become either more or less attractive in the subsequent round. For example, Figure 2 shows the first round of the first question: Option A offers a 33% chance of winning $12 and a 67% chance of winning $3, while Option B initially offers a 33% chance of winning $18 and a 67% chance of winning $0. Accordingly, both options have an expected value of $12, and offer the same chance of winning the larger payoff (33%), but Option B is riskier. If the subject selects the safer Option A, then Option B is made more attractive by increasing the winning amount to $21. If, instead, the subject chooses Option B, then Option B is made less attractive by decreasing the winning amount to $16. This process continues for three rounds, until the subject's indifference point is closely approximated. For each question, the subject is then presented with a fourth choice but this choice is used only to evaluate consistency with prior choices.

Figure 2

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 $6 if the ball drawn is purple (33% chance) and $3 if the ball drawn is orange (67% chance). For option B, you win $12 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 $6 67% chance of winning $3	33% chance of winning $12 67% chance of winning $0

6 Throughout the paper we frequently use the term "risk aversion" to refer to the curvature of the utility function. Technically, with probability weighting the curvature of the utility function alone does not fully describe risk aversion, but we continue to use "risk aversion" as it is the conventional term.

Panel A of Table 1 shows the structure of the four risk aversion elicitation questions. In all four questions, the probability of winning the large prize is fixed at 33% for both Options A and B, but the potential winning amounts increased with each question. Therefore, this set of questions is suited to measure utility curvature ($U(c_i)$), as the probability of winning (p_i=0.33) is constant in all pairwise choices. We thus minimize the effect of probability weighting, as it largely cancels out in the comparison between Option A and Option B.

Table 1. Questions to elicit risk aversion and probability weighting

Panel A: Risk Aversion Questions

	Option A		Option B		Estimates of $X in Data	
	Probability	Amount	Probability	Amount	Mean	Risk Premium %
Questions $RA_{\$12}$	33%	$12	33%	$X	22.1	22.2%
	67%	$3	67%	$0		
Questions $RA_{\$18}$	33%	$18	33%	$X	27.5	14.1%
	67%	$3	67%	$0		
Questions $RA_{\$24}$	33%	$24	33%	$X	34.9	16.1%
	67%	$3	67%	$0		
Questions $RA_{\$30}$	33%	$30	33%	$X	41.9	16.2%
	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	8.3	-7.0%
	95%	$6				
Questions $PW_{12\%}$	12%	$42	100%	$X	10.5	-2.1%
	88%	$6				
Questions $PW_{25\%}$	25%	$42	100%	$X	14.3	4.7%
	75%	$6				
Questions $PW_{50\%}$	50%	$42	100%	$X	20.3	15.4%
	50%	$6				
Questions $PW_{75\%}$	75%	$42	100%	$X	25.6	22.4%
	25%	$6				
Questions $PW_{88\%}$	88%	$42	100%	$X	27.3	27.6%
	12%	$6				

This table shows the lottery questions used to elicit probability weighting and risk aversion. Panel A shows the four questions used to elicit risk aversion and Panel B shows the six questions used to elicit probability weighting.

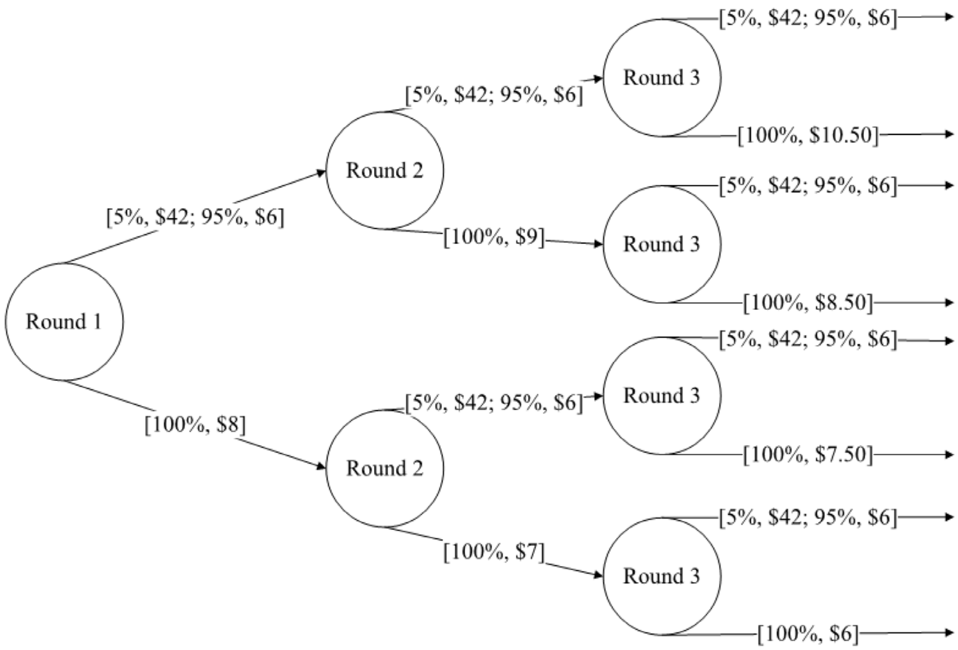
We next present each subject with six questions specifically designed to measure the subject's probability weighting preference. They elicit the certainty equivalent of Option A, which is a risky choice with two possible outcomes. Figure 3 depicts the first round of one of the questions: Option A offers 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 in the first round. 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 4.

Figure 3

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 4



In the other five probability weighting questions, the probabilities, p, of winning the large prize in Option A are 12%, 25%, 50%, 75%, and 88%, and in each case, we again elicit the certainty equivalent. Panel B of Table 1 summarizes the parameters for the six probability weighting questions. Responses to these six questions are especially sensitive to how a person weighs probabilities, because a subject maximizing expected utility required similar risk premiums for low and high probability questions (e.g., for both p = 5% and p = 88%), when expressed as a percentage of the expected value of the lottery. Nevertheless, a decision maker with an inverse-S shaped weighting function will demand risk premiums that increase steeply as a function of p (e.g., switching from risk seeking for p = 5% to risk averse for p = 88%).

The subjects in our survey module could win real rewards based on their choices. This is important, as prior studies have shown that real rewards produce more reliable estimates of preferences (Smith, 1976). At the beginning of the survey, the subjects were told that one of their choices would be randomly selected and played for real money. We paid a total of $16,020 in real incentives to 2,072 of the 2,702 subjects who completed the survey. The American Life Panel (ALP) was responsible for determining and making the incentive payments; subjects in the ALP regularly participate in and receive payment from the ALP surveys, which should minimize potential concerns about the credibility of the incentives.

An advantage of our experimental survey approach is that we can set the probabilities thereby ensuring that beliefs about the likelihood of outcomes are known. This allows us to disentangle the effects of preferences from beliefs, which limits previous papers based on observing phenomena consistent with probability weighting. For instance, the popularity of cell phone insurance can be due to people having probability weighting preferences, or because they overestimate the likelihood of losing or damaging their phone.

Our survey questions for measuring probability weighting and risk aversion are adapted from Wakker and Deneffe (1996) and Abdellaoui (2000) where the indifference point elicited in one question was used as a payoff (or a probability of winning) offered in a subsequent question. Through this "chaining" of questions, the respondent's utility function and probability weighting function can be estimated independently and non-parametrically. A difficulty with applying this approach is that, as Abdellaoui (2000, pg. 1511) noted "...error propagation in the trade-off method can produce `noisy' probability weighting functions." For example, a response error in the first question will affect all subsequent questions. Because our survey was administered in the general population and time for repeated measurements to minimize errors was limited, we broke the link between subsequent questions to minimize the risk of error propagation. Instead, as a starting point for each question, we used the answer of a risk-neutral expected utility maximizer. That is, the choices offered to our subjects were determined only by their prior answers within the three rounds of a single question, rather than across different questions. Furthermore, each question included a fourth consistency check round allowing us to identify respondents who made errors that contradicted their previous three choices.

1.3 The probability weighting measure

Using the six indifference values elicited with the probability weighting questions described, 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 (Choice A). For example, suppose a subject is indifferent between the options [5%, $42; 95%, $6] and [100%, $8.50]. The expected value of the first option is $7.80, implying a percentage risk premium of: $PW_{5\%}=(7.80-8.50)/7.80=-8.97\%$. 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 presented in Table 1. For small probabilities (5% and 12%), on average, people are willing to pay more than the expected value to own the lottery, but at high probabilities they demand large positive risk premiums: a pattern consistent with overweighting of small probabilities. For low probabilities, *Inverse-S* weighting counters and even reverses the effect of utility function curvature, but at higher probabilities, *Inverse-S* weighting reinforces the effect of utility function curvature.

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

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

In the experimental literature, individuals have switched from overweighting to underweighting probabilities in the range between 25% and 50%.[7] Thus this measure is simply the premiums in the overweighting range less the premiums in the underweighting range. Higher values indicate a more pronounced *Inverse-S* shape for the probability weighting function.

This measure is simple and avoids assuming a specific functional form for the probability weighting function. Taking the difference between percentage premiums also reduces the influence of utility function curvature, as greater curvature increases all premiums and this increase is partially differenced out. As the summary statistics in the next section will show, the *Inverse-S* variable is not significantly correlated with our measure of risk aversion and the empirical results are theoretically inconsistent with the *Inverse-S* measuring risk aversion, rather than probability weighting.

2. Data and variables

2.1 American Life Panel Survey Data

We fielded our survey module in the RAND American Life Panel[8] from June 20 to July 19, 2017. The ALP includes several thousand households that regularly answer internet surveys, and households lacking internet access at the recruiting stage are provided with a laptop and wireless service to limit selection biases. 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 measured the key outcome variables and some control variables. Other controls such as demographic and economic characteristics of the subjects are gathered from earlier survey modules conducted by the ALP. Appendix Table A1 defines the variables, and Table 2 provides summary statistics.

7 Note that underweighting probabilities is not the same as having a negative premium for the probability weighting questions, as for mid-range probabilities, the effects of risk aversion can fully offset the effects of probability weighting.

8 For a comparison of the ALP and alternative data sources see https://mmicdata.rand.org/alp/index.php?page=comparison.

Table 2. Summary statistics for outcome and control variables

Variable	Mean	Std	p25	p50	p75
Outcome variables					
Non-Participation	0.767	0.423	1	1	1
Mutual Funds Only	0.082	0.274	0	0	0
Individual Stocks Only	0.068	0.251	0	0	0
Both Mutual Funds and Individual Stocks	0.084	0.277	0	0	0
Fraction Allocated to Individual Stocks Conditional	0.448	0.413	0	0.5	1
Total Skewness	-0.002	0.792	-0.429	-0.016	0.447
Idiosyncratic Skewness	-0.022	0.996	-0.552	0.003	0.529
Max. One-Day Return	0.066	0.052	0.037	0.055	0.072
Lottery Stock	0.289	0.454	0	0	1
Idiosyncratic σ	0.184	0.12	0.123	0.151	0.208
Stock β	0.989	0.254	0.826	0.969	1.118
Control variables					
Age	47.653	16.575	32	47	61
Female	0.518	0.500	0	1	1
Married	0.587	0.492	0	1	1
White	0.756	0.430	1	1	1
Hispanic	0.190	0.393	0	0	0
Number of Household members	2.369	1.511	0	1	2
Employed	0.531	0.499	0	1	1
Bachelor or Associate Degree	0.267	0.443	0	0	1
Master or Higher Degree	0.129	0.336	0	0	0
Family Income ($ thousands)	67.0	55.9	17.5	45.0	112.5
Financial Wealth ($ thousands)	87.7	1325.4	0	0.5	15.0
Numeracy	2.353	0.865	2	3	3
Financial Literacy	2.134	0.968	1	2	3
Trust	3.301	1.365	2	3	5
Risk Aversion	0.173	0.250	-0.044	0.125	0.401
Optimism	0.360	9.827	-5.59	0.36	6.47

This table reports summary statistics for the variables used in our study. Variable definitions appear in Table A1. The summary statistics for *Fraction Allocated to Individual Stocks Conditional* are shown only for respondents with a nonzero allocation to equity. The individual stock characteristics (*Total Skewness, Idiosyncratic Skewness, Max. One-Day Return, Lottery Stock, Idiosyncratic σ, and Stock β*) are shown only for respondents who own individual stocks. All results use ALP survey weights.

2.2 Dependent variables

The dependent variable for the multinomial logit regression, *Portfolio Choice*, is a categorical variable with four categories; nonparticipation, mutual funds only, individual stocks only, and both mutual funds and individual stocks. Table 2 summarizes these categories separately for ease of interpretation. *Nonparticipation* is an indicator equal to one for the 76.7% of the respondents who do not own any equity.[9] *Mutual Funds Only* is an indicator variable equal to one for the 8.2% of the sample who own equity mutual funds only and no individual stocks. *Individual Stocks Only* is an indicator variable equal to one for the 6.8% of the sample whose equity ownership consisted exclusively of individual company stocks and no equity mutual funds. *Both Mutual Funds and Individual Stocks* is an indicator variable equal to one for the 8.4% of the sample who own both equity mutual funds and individual stocks. The fraction of the total equity portfolio invested in individual stocks is denoted by the variable *Fraction of Equity in Individual Stocks*. Conditional on nonzero equity ownership, the average fraction allocated to individual stocks is 45%. Calvet, Campbell, and Sodini (2007, 2009) present evidence that this measure is a good proxy for portfolio under-diversification. In addition, for a subsample of individual stock owners, we can observe the number of individual shares that they own. We find that, conditional on owning individual stocks, half of the respondents hold shares in only one or two individual companies, which confirms that the fraction of the equity portfolio allocated to individual stocks is a reasonable proxy for under-diversification.

Respondents who indicated that they hold individual stocks were asked to list the names (or tickers) of their five largest holdings. We match these names or tickers by hand to the CRSP daily stock return database.[10] Using this matched database, we construct various measures of stock characteristics with daily return data from the period July 1, 2016 to June 30, 2017. We use this specific period as our survey was fielded from June 20 to July 19, 2017. For investors who report multiple holdings, we use an equally weighted average of their stocks' characteristics. *Total Skewness* is the skewness of daily returns. *Idiosyncratic Skewness* is the skewness of the residuals from a two-factor model (the market risk premium, RMRF, and its square, $RMRF^2$). *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. *Lottery Stock* defined following Kumar (2009) is set equal to one if the investor owns a stock with below-median price, above-median idiosyncratic skewness, and above-median idiosyncratic standard deviation. *Idiosyncratic* σ is the annualized standard deviation of the residuals from the Fama and French (2015) five-factor model. *Stock* β is the market beta of the investor's holding.

2.3 Control variables

In all empirical tests, we control for demographic and economic characteristics including age, sex, race, ethnicity, marital status, number of household members, education, employment status, family income, and financial wealth. Controlling for these variables partials out the potential confounding effects that they might have on household portfolio choice, thus providing cleaner estimates of the effect of probability weighting.

Our ALP survey module also included additional questions to measure optimism, financial literacy, numeracy, trust, and risk aversion. These variables are incorporated in the multivariate models to mitigate omitted variable bias if these affect portfolio choice due to something conceptually similar to probability weighting. For example, overweighting of small probabilities could be influenced by individual optimism (i.e., optimists may assume that small probability lotteries always resolve in their favor). For this reason, we follow Puri and Robinson

9 Our sample has a lower equity participation rate than that reported in some other studies because we exclude equity ownership in 401(k) plans. Such equity holdings may not reflect active choices by the respondent, as a result of the U.S. Department of Labor's introduction of target-date funds as an investment default. This permits employees to hold equities by default, instead of due to active choice. For more on target date funds and 401(k) plan investment options, see Mitchell and Utkus (2012).

10 In our tests, we use only U.S. based common stocks.

(2007) and include a question assessing individuals' subjective life expectancies; this permits us to measure optimism by comparing subjective and objective life expectancies (where the latter are derived from age/sex population mortality tables).

We also control for financial literacy which prior studies show has a strong association with financial decisions (e.g., Lusardi and Mitchell, 2007, 2014; van Rooij, Lusardi, and Alessie, 2011). To ensure that overweighting of small probabilities is not simply a proxy for low financial literacy, our survey module included the "Big Three" questions implemented by Lusardi and Mitchell (2007) in the Health and Retirement Study (HRS). Our index of financial literacy is the number of correct responses to these questions, and on average, respondents answered slightly more than two of the questions correctly. The module also included three questions to assess numeracy based on the HRS and the English Longitudinal Study of Ageing. We also included the trust question from the World Values Survey, as Guiso, Sapienza, and Zingales (2008) reported a relation between trust and portfolio choice.

We included a control measuring risk aversion for two reasons. First, to ensure that our probability weighting variable captures a component of preferences that is distinct from risk aversion. Second, if probability weighting and risk aversion are correlated, then overweighting of small probabilities might provide little incremental information about preferences. Our risk aversion measure was derived using four sets of choice problems (shown in Panel A of Table 1 and Figure 3): we take the average of each respondent's risk premiums for the four risk aversion questions described earlier. The average risk premium is positive for all four risk aversion questions in Table 1, and Table 3 shows that the average respondent is risk averse though there is substantial variation.

2.4 Probability weighting

Panel B of Table 1 and Table 3 describe the average responses to the six probability weighting questions from the ALP survey module. Panel B of Table 1 shows that, 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 (7.0% and 2.1%, respectively). This is consistent with overweighting of small probabilities. For the p = 0.25 question, the average risk premium is 4.7%, indicating slight risk aversion. At larger probabilities, p = 0.5, 0.75 and 0.88, the average risk premiums increase steadily to 15.4%, 22.4%, and 27.6%, respectively. Overall, the pattern in the average risk premiums is consistent with *Inverse-S*-shaped probability weighting: overweighting of small probabilities and underweighting of high probabilities.

Table 3. Probability weighting in the U.S. population

Panel A: Summary statistics *Inverse-S* measure

Measure	Mean	Standard Deviation	Minimum	Median	Maximum
Inverse-S	0.679	0.774	-1.809	0.694	2.955

Panel B: Bivariate correlations with *Inverse-S* measure

Variable	Correlation
Risk Aversion	0.094***
Financial Literacy	0.121***
Numeracy	0.106***
Education	0.088*
Optimism	0.012

Panel C: Summary statistics consistency checks

Question	Consistent	Inconsistent
5% question	71.6%	28.4%
12% question	73.2%	26.8%
25% question	75.6%	24.4%
50% question	73.0%	27.0%
75% question	75.8%	24.2%
88% question	77.5%	22.5%

This table shows summary statistics on probability weighting in the US 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 risk aversion, financial literacy, numeracy, education, and optimism. Education is a categorical variable ranging from 1 to 14. The sample size is N = 2,674. The symbols *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Our probability weighting variable *Inverse-S* is positive for 83% of the respondents, indicating an inverse-S shaped probability weighting function.[11] In other words, more than four-fifths of the nationally representative sample overweight small probabilities, a result corroborating laboratory experiments using students (Abdellaoui, 2000; Bruhin, Fehr-Duda, and Epper, 2010). Panel A of Table 3 summarizes our non-parametric probability weighting measure, *Inverse-S*. On average, the sum of the risk premiums for the three high-probability questions exceed the sum of the risk premiums for the three low-probability questions by 68 percentage points. Again this provides clear evidence of inverse-S probability weighting, though there is important heterogeneity. This finding has important implications for the finance literature, as it may help explain the observed large heterogeneity in portfolio allocations.

Panel B of Table 3 depicts the pairwise correlations between *Inverse-S* and risk aversion, financial literacy, numeracy, education, and optimism; although not the main focus of our paper, we include these correlations to explore the underlying distribution of our *Inverse-S* measure. The correlation between risk aversion and *Inverse-S* is low and positive ($p = 0.094$), with risk aversion explaining less than 1% (R^2) of the variation in *Inverse-S*. To place this small correlation in perspective, the average correlation among the risk premiums of the four risk aversion questions in Panel A of Table 1 is $p = 0.70$ (demonstrating strong internal consistency across the risk aversion questions). Accordingly, *Inverse-S* and risk aversion appear to be separate components of preferences.

Some might be concerned that overweighting of small probabilities could be a cognitive error caused by poor probabilistic reasoning. Although the magnitudes of the correlations are not large, Panel B of Table 3 shows that overweighting of small probabilities is *positively* rather than negatively correlated with proxies for intelligence. The correlations are directionally inconsistent with the cognitive error view, providing indirect support for the preference view. Indeed, the *Inverse-S* variable is significantly larger for individuals who correctly answered the three numeracy questions than for those who made errors. Moreover, in a subsequent section, we show that the relation between probability weighting and under-diversification also holds for respondents who understand that individual stocks are riskier than equity mutual funds.

3. Probability weighting and household portfolio choice

This section tests the relation between probability weighting and household portfolio choice decisions. For ease of interpretation, we standardize the *Inverse-S* variable so it has a mean of zero and a standard deviation of one. Following Dimmock, Kouwenberg, Mitchell, and Peijnenburg (2016), all specifications include controls for age, age squared, education, log(family income), log(financial wealth), sex, white, Hispanic, log(number of household members), employment status, and dummies for individuals for whom we imputed missing values. Our baseline specifications also include controls for numeracy, financial literacy, risk aversion, and optimism. For all specifications, we report *z*-scores calculated using robust standard errors.

3.1 Probability weighting and household investment in individual stocks and mutual funds

Table 4 shows the results of multinomial logit models in which the dependent variable *Portfolio Choice* takes one of four values: *Nonparticipation*, *Mutual Funds Only*, *Individual Stocks Only*, and *Both Mutual Funds and Individual Stocks*. Theory predicts a negative relation between *Inverse-S* and *Mutual Funds Only*, but a positive relation between *Inverse-S* and the other three categories. Thus, because *Mutual Funds Only* is the odd category out, it serves as a natural basis of comparison and we use it as the excluded category (the base category). In Panel A, the specification includes the demographic and economic controls listed above. In Panel B, the specification also controls for numeracy, financial literacy, trust, risk aversion, and optimism.[12]

[11] Similarly, when we fit a parametric probability weighting function for each respondent individually, approximately 85% of the respondents exhibit an *Inverse-S* shaped function (results available on request).

[12] Dimmock, Kouwenberg, Mitchell, and Peijnenburg (2016) find that ambiguity aversion relates to portfolio choices of households. For some of our respondents, we have their measure of ambiguity aversion. Our results do not change when adding this variable as control (results are available upon request).

Table 4. Participation in mutual funds, individual stocks, and both

Panel A: Demographic controls only

	Non-Participation (1)	Individual Stocks Only (2)	Both Mutual Funds and Individual Stocks (3)
Inverse-S	0.281**	0.335**	0.267*
	(2.41)	(2.28)	(1.83)
Demographic controls	yes	yes	yes
Observations	2,671	2,671	2,671
Adj. R^2	0.140	0.140	0.140

Panel B: Full specification

	Non-Participation (1)	Individual Stocks Only (2)	Both Mutual Funds and Individual Stocks (3)
Inverse-S	0.289***	0.337**	0.273*
	(2.69)	(2.42)	(1.95)
Numeracy	-0.217	-0.088	-0.43
	(0.85)	(0.28)	(1.62)
Financial Literacy	-0.443**	-0.268	-0.195
	(2.19)	(1.06)	(0.83)
Trust	0.019	0.032	0.004
	(0.16)	(0.25)	(0.03)
Risk Aversion	0.188	-0.373	-0.519
	(0.46)	(0.70)	(1.09)
Optimism	-0.035*	-0.022	-0.027
	(1.81)	(0.90)	(1.27)
Demographic controls	yes	yes	yes
Observations	2,671	2,671	2,671
Adj. R^2	0.158	0.158	0.158

This table reports the coefficients of multinomial logit regressions for *Non-Participation, Individual Stocks Only, and Both Mutual Funds and Individual Stocks*. The excluded category is Mutual Funds Only. In column (1), the dependent variable equals one if the respondent does not participates in the stock market. In column (2), the dependent variable equals one if the respondent invests only in individual stocks. In column (3), the dependent variable equals one if the respondent invests both in mutual funds and individual stocks. In all columns, the key independent variable is Inverse-S. Panel A includes a constant and controls for age, age-squared divided by a thousand, female, married, white, Hispanic, number of household members, employment status, education, (ln) family income, and (ln) wealth. Panel B further includes controls for numeracy, financial literacy, trust, risk aversion, and optimism. The sample size is N = 2,674. All results use ALP survey weights. The symbols *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Consistent with the predictions of theory, individuals with higher *Inverse-S* (greater probability weighting) are more likely to choose either nonparticipation or individual stock ownership, and less likely to own only equity mutual funds.[13] Theoretically, higher *Inverse-S* has two effects. First, probability weighting causes increased sensitivity to skewness. As Albuquerque (2012) shows, the overall stock market is negatively skewed, while individual stocks are positively skewed. High *Inverse-S* implies a strong aversion to negative skewness, which makes holding a diversified equity portfolio unattractive (e.g., see Polkovnichenko, 2005; Chapman and Polkovnichenko, 2011; De Giorgi and Legg, 2012; He, Kouwenberg, and Zhou, 2017). People with high *Inverse-S* either choose not to participate in the stock market or hold a few positively skewed individual stocks (e.g., see Polkovnichenko, 2005; Barberis and Huang, 2008). Second, probability weighting in a rank-dependent model (e.g., RDU or prospect theory) causes first-order risk aversion due to kinked indifference curves around zero stock-holding, resulting in optimal nonparticipation even with a positive equity premium.

The estimated economic magnitudes implied by our coefficients are large. For instance, the coefficient in column (1) of Panel B implies that a one-standard deviation increase in *Inverse-S* raises the probability of choosing *Nonparticipation* instead of *Mutual Funds Only* by one-third ($e^{0.289} = 1.34$). Likewise, a one-standard deviation increase in *Inverse-S* raises the probability of choosing *Individual Stocks Only* instead of *Mutual Funds Only* by 40.1% and choosing *Both Mutual Funds and Individual Stocks* instead of *Mutual Fund Only* by 31.4%.

We emphasize that the pattern of results in Table 4 is consistent with the theoretical predictions of probability weighting, but inconsistent with most alternative interpretations of our measure. For example, if *Inverse-S* were inadvertently measuring risk aversion, it would be positively related to nonparticipation, but negatively related to individual stock ownership. Instead, however, *Inverse-S* is positively related to both nonparticipation and individual stock ownership.

3.2 Probability weighting and the allocation of equity holdings to individual stocks

Table 5 reports Tobit regressions in which the dependent variable is the fraction of the subject's equity holdings invested in individual stocks (which is bounded by zero and one). This measure is a good proxy for under-diversification (e.g., see Polkovnichenko, 2005; Calvet, Campbell, and Sodini, 2007). For these regressions, the sample includes only those subjects with nonzero equity holdings. Column (1) includes the economic and demographic control variables. Column (2) also controls for numeracy, financial literacy, trust, risk aversion, and optimism.

[13] The coefficients on *Inverse-S* are not significantly different from each other across the three equations of each multinomial logit regression.

Table 5. The fraction of equity invested in individual stocks

	(1)	(2)
Inverse-S	0.123**	0.129**
	(2.50)	(2.48)
Numeracy		0.126
		(1.32)
Financial Literacy		-0.220**
		(2.40)
Trust		-0.014
		(0.33)
Risk Aversion		-0.000
		(0.00)
Optimism		-0.012
		(1.59)
Demographic controls	yes	yes
Observations	741	741
Adj. R^2	0.0384	0.0504

This table reports Tobit regression results in which the dependent variable is the *Fraction of Equity in Individual Stocks*. In both columns, the key independent variable is *Inverse-S*. Column (1) includes a constant and controls for age, agesquared divided by a thousand, female, married, white, Hispanic, number of household members, employment status, education, (ln) family income, and (ln) wealth. Column (2) further includes controls for numeracy, financial literacy, trust, risk aversion, and optimism. The sample size is N = 741. All results use ALP survey weights. The symbols *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

As predicted by theory, there is a significant and positive relation between *Inverse-S* and the fraction of equity holdings allocated to individual stocks. Probability weighting makes under-diversified portfolios more attractive due to their positive skewness. The economic magnitude implied by the coefficient reported in column (2) is that a one-standard deviation increase in *Inverse-S* results in a 12.9 percentage point increase in the fraction of the portfolio allocated to individual stocks (28.7% relative to the baseline rate of 45.0 percentage points).[14]

3.3 Measurement error in preference elicitation

A large literature, beginning with Harless and Camerer (1994) and Hay and Orme (1994), shows that subjects often give inconsistent responses to questions designed to elicit preferences. If such errors are pure noise, this will reduce the power of tests but does not introduce bias. If, however, errors in elicited preference are correlated with errors in actual decisions (e.g., holding an undiversified portfolio), this could potentially affect inferences. In our context, the ALP module includes two features that allow us to address this issue empirically. First, we included the check questions described earlier to test the internal consistency of subjects' choices. Second, the ALP module recorded the amount of time subjects spent on each question, which allows us to identify subjects who answered the elicitation questions unusually quickly. Accordingly, this section reports additional tests that use restricted subsamples (aside from these sample restrictions, the specifications are identical to the baseline specifications). For both restricted samples, the first three columns of the panel show the results for the multinomial logit and the last column shows the result for the Tobit. In Panel A of Table 6, the sample excludes all subjects who made more than three errors on the check questions for the probability weighting questions. In Panel B, the sample excludes all subjects who spent less than 90 seconds answering the probability weighting questions. Results are similar to those in the full sample for both cases, suggesting that our main results are not driven by measurement error in elicited preferences or by individuals who failed to understand the elicitation questions.

[14] In Appendix Table A2, we estimate alternative versions of Tables 4 and 5 using the rank transformation of the *Inverse-S* variable (with zero indicating the lowest level of probability weighting and one the highest). We use this rank transformation to show the results are not driven by outliers, and find similar results.

Table 6. Robustness to measurement error in preference elicitation

Panel A: Results excluding respondents who made more than 3 errors on the consistency check questions

	Multinomial logit			Tobit
	Non-Participation (1)	Individual Stocks Only (2)	Both Mutual Funds and Individual Stocks (3)	Fraction of Equity in Individual Stocks (4)
Inverse-S	0.262**	0.295**	0.344**	0.156**
	(2.35)	(2.03)	(2.39)	(2.56)
Controls and constant	yes	yes	yes	yes
Observations	2,418	2,418	2,418	674
Adj. R^2	0.156	0.156	0.156	0.053

Panel B: Results excluding respondents who took less than 1.5 minutes for probability weighting questions

	Multinomial logit			Tobit
	Non-Participation (1)	Individual Stocks Only (2)	Both Mutual Funds and Individual Stocks (3)	Fraction of Equity in Individual Stocks (4)
Inverse-S	0.297***	0.342**	0.287**	0.122**
	(2.68)	(2.43)	(2.03)	(2.27)
Controls and constant	yes	yes	yes	yes
Observations	2,547	2,547	2,547	724
Adj. R^2	0.157	0.157	0.157	0.054

Columns (1) to (3) report the coefficients of multinomial logit regressions for *Non-Participation, Individual Stocks Only*, and *Both Mutual Funds and Individual Stocks*. The excluded category is *Mutual Funds Only*. In column (1), the dependent variable equals one if the respondent does not participates in the stock market. In column (2), the dependent variable equals one if the respondent investts only in individual stocks. In column (3), the dependent variable equals one if the respondent invests both in mutual funds and individual stocks. Column (4) shows Tobit regression results in which the dependent variable is the *Fraction of Equity in Individual Stocks*. In all columns, the key independent variable is *Inverse-S*. Panel A excludes respondents who made more than 3 errors on the consistency check questionsand Panel B excludes respondents who gave send less than 1.5 minutes on the probability weighting questions. Allmodels include a constant and controls fo age, age-squared divided by a thousand, female, married, white, Hispanic, number of household members, employment status, education, (ln) family income, (ln) wealth, numeracy, financial literacy, trust, risk aversion, and optimism All results use ALP survey weights. The symbols *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

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 the investor chooses. Investors who overweight small probabilities should choose individual stocks with high positive skewness and high idiosyncratic risk, but will not exhibit a preference for high systematic risk (e.g., see Barberis and Huang, 2008; Boyer, Mitton, and Vorkink, 2010). The appeal of investing in a positively skewed stock is that the person has a chance, albeit a small chance, of becoming rich if the stock turns out to be the "next Apple."

To allow us to test these predictions, our survey module asked the subjects who owned individual stocks to list the names (or tickers) of their five largest individual stock holdings. These five largest holdings encompass most of the person's stock portfolio as about half of our respondents hold only one or two stocks. As described in Section 2.2., we match these stocks to the CRSP daily stock return database and construct various stock characteristics measuring idiosyncratic risk and skewness: *Total Skewness, Idiosyncratic Skewness, Max. One-Day Return, Lottery Stock,* and *Idiosyncratic* σ. We also calculate *Stock* β, which is the market beta of the investor's holding and is included as a measure of systematic risk.

Table 7 shows regression results for the six dependent variables described above. The sample includes only those individuals who report usable individual stockholding information. The key independent variable is *Inverse-S*, and the models include the same control variables used in the main specification. Columns (1-4) show that *Inverse-S* has a significant and positive relation with all four proxies of expected skewness: *Total Skewness*, *Idiosyncratic Skewness*, *Max. One-Day Return*, and *Lottery Stock*. Investors with higher probability weighting choose individual stocks with higher expected positive skewness.

Column (5) shows a positive and significant (at the 10% level) relation between *Inverse-S* and *Idiosyncratic* σ. Interestingly, column (6) shows that the relation between *Inverse-S* and systematic risk, measured by *Stock* β, is not significant. This pattern of results is consistent with the implications of probability weighting. High *Inverse-S* investors accept higher idiosyncratic risk, because it is closely related to positive skewness and increases the probability of an extreme positive return. The high *Inverse-S* investors, however, do not take on higher systematic risk as it does not provide lottery-like return potential.

Although our data do not allow tests directly related to the pricing of positively skewed securities, the results in this section are related to studies of positive skewness in the asset pricing literature. Boyer, Mitton, and Vorkink (2010), Bali, Cakici, and Whitelaw (2011), Conrad, Dittmar, and Ghysels (2013), Conrad, Kapadia, and Xing (2014) show that stocks with positive expected skewness have very low returns. Barberis and Huang (2008) argue that probability weighting can cause positively skewed securities to have low returns. The results in this section support the arguments of these asset pricing studies, by providing direct evidence linking individuals' probability weighting preferences to their selection of specific stock characteristics.

Table 7. Probability weighting and ths sStock characteristics of individual stock holdings

	Total Skewness (1)	Idiosyncratic Skewness (2)	Max. One-Day Return (3)
Inverse-S	0.112**	0.145***	0.006**
	(2.48)	(2.69)	(2.27)
Controls	yes	yes	yes
Observations	439	439	439
R^2	0.17	0.165	0.095

	Lottery Stock (4)	Idiosyncratic σ (5)	Stock β (6)
Inverse-S	0.053*	0.012*	0.015
	(1.77)	(1.79)	(0.95)
Controls	yes	yes	yes
Observations	439	439	439
R^2	0.099	0.074	0.138

All columns report the coefficients of OLS regressions. The key independent variable is *Inverse-S*. The dependent variables are the characteristics of the stocks held by the subject, and are calculated using daily returns from the period July 1, 2016 to June 30, 2017. In column (1), the dependent variable *Total Skewness* is skewness of daily returns. In column (2), the dependent variable *Idiosyncratic Skewness* is the skewness of the residuals from a two factor model (RMRF and $RMRF^2$). In column (3), the dependent variable *Max. One-Day Return* is the maximum one-day return. In column (4), the dependent variable *Lottery Stock* equals one if the subject owns a lottery stock as defined in Kumar (2009). In column (5), the dependent variable *Idiosyncratic* σ is the annualized standard deviation of the residuals from the Fama-French five-factor model. In column (6), the dependent variable *Stock* β is the market beta of the investor's stock holdings. All models include a constant and controls for age, age-squared divided by a thousand, female, married, white, Hispanic, number of household members, employment status, education, (ln) family income, (ln) wealth, numeracy, financial literacy, trust, risk aversion, and optimism. All results use ALP survey weights. The sample size is N = 439. The symbols *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

5. Preference, probability unsophistication, or financial knowledge?

Thus far, we have interpreted probability weighting as a component of *preferences:* that is, we posit the relationship between *Inverse-S* and portfolio choice arises because subjects maximize their preference function, but their preference function uses weighted rather than objective probabilities. In this section, we consider two closely related alternative explanations. (1) Probability unsophistication—that some individuals have difficulty with probabilistic reasoning, and this difficulty affects both their elicited *Inverse-S* values and their portfolio choices. (2) Limited financial knowledge —the idea that, for some reason, *Inverse-S* is correlated with a lack of financial knowledge.

For both of these alternative explanations, probability weighting (and nonparticipation and under-diversification) represent clear mistakes. That is, if a high *Inverse-S* respondent was educated about probabilities or financial markets, he would likely make different choices. With preferences, on the other hand, such interventions would not result in different choices. Do note that even if probability weighting reflects preferences, it may still be considered a mistake, as it constitutes a violation of the independence axiom, but it is a fundamentally different type of mistake and one that is more difficult to change.

5.1 Preference or probability unsophistication

The first alternative explanation is based on probability unsophistication. For example, due to limited quantitative reasoning skills, some subjects may have difficulty evaluating questions involving probabilities and such cognitive limitations could also cause subjects to make investment errors. This explanation appears unlikely based on the summary statistics presented in Panel B of Table 3, which show that *Inverse-S* has a small but significantly *positive* correlation with education, numeracy, and financial literacy. Hence, the alternative explanation of probability weighting reflecting probability unsophistication appears unlikely. Furthermore, we perform additional tests using a restricted sample. Aside from the sample restriction, the specifications are identical to the baseline. In Panel A of Table 8, the subsample includes only those subjects who correctly answered all three of the numeracy questions. The results within this subsample are generally similar to those in the full sample. Even for individuals who correctly answered the numerical reasoning questions, *Inverse-S* has a significant positive relationship with both nonparticipation and individual stock ownership (relative to mutual fund ownership). Combined with the simple correlations discussed above, these results suggest that *Inverse-S* does not reflect poor quantitative reasoning.

Table 8. Preference, probability unsophistication, or financial knowledge

Panel A: Results including only respondents who answer all three numeracy questions correctly

	Multinomial logit			Tobit
	Non-Participation (1)	Individual Stocks Only (2)	Both Mutual Funds and Individual Stocks (3)	Fraction of Equity in Individual Stocks (4)
Inverse-S	0.369***	0.288*	0.384**	0.094*
	(2.80)	(1.85)	(2.17)	(1.72)
Controls	yes	yes	yes	yes
Observations	1,717	1,717	1,717	567
Adj. R^2	0.160	0.160	0.160	0.078

Panel B: Results including only respondents who answer all three financial literacy questions correctly

	Multinomial logit			Tobit
	Non-Participation (1)	Individual Stocks Only (2)	Both Mutual Funds and Individual Stocks (3)	Fraction of Equity in Individual Stocks (4)
Inverse-S	0.371***	0.453***	0.352**	0.149**
	(2.82)	(2.78)	(2.08)	(2.41)
Controls	yes	yes	yes	yes
Observations	1,558	1,558	1,558	577
Adj. R^2	0.133	0.133	0.133	0.075

Panel C: Results including only respondents who know individual stocks are riskier than stock mutual funds

	Multinomial logit			Tobit
	Non-Participation (1)	Individual Stocks Only (2)	Both Mutual Funds and Individual Stocks (3)	Fraction of Equity in Individual Stocks (4)
Inverse-S	0.267**	0.361**	0.278*	0.115**
	(2.13)	(2.36)	(1.90)	(2.08)
Controls	yes	yes	yes	yes
Observations	1,786	1,786	1,786	634
Adj. R^2	0.141	0.141	0.141	0.062

Columns (1) to (3) report the coefficients of multinomial logit regressions for *Non-Participation, Individual Stocks Only*, and *Both Mutual Funds and Individual Stocks*. The excluded category is *Mutual Funds Only*. In column (1), the dependent variable equals one if the respondent does not participates in the stock market. In column (2), the dependent variable equals one if the respondent invests only in individual stocks. In column (3), the dependent variable equals one if the respondent invests both in mutual funds and individual stocks. Column (4) shows Tobit regression results in which the dependent variable is the *Fraction of Equity in Individual Stocks*. In all columns, the key independent variable is *Inverse-S*. Panel A only includes respondents that answer all three numeracy questions correctly, Panel B only includes respondents that answer all three financial literacy questions correctly, and Panel C only includes respondents who answered correctly the question "Buying a stock mutual fund usually provides a safer return than a single company stock." All models include a constant term and controls for age, age-squared divided by a thousand, female, married, white, Hispanic, number of household members, employment status, education, (ln) family income, (ln) wealth, numeracy, financial literacy, trust, risk aversion, and optimism. All results use ALP survey weights. The symbols *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

5.2 Preference or limited financial knowledge

The second alternative explanation is that, for some reason, *Inverse-S* is correlated with a lack of financial knowledge. For example, some subjects may simply be unaware of the benefits of diversification or fail to understand financial risks, resulting in investment errors,[15] and it is possible that this investment behavior is correlated with *Inverse-S*. However, it is not obvious why a lack of financial knowledge would be correlated with *Inverse-S*. Indeed, a key advantage of eliciting probability weighting preferences using lotteries, instead of natural events, is that it allows us to clearly define the relevant probabilities in an unambiguous manner, limiting the scope for beliefs to affect the subjects' responses (for further discussion of this point see Barberis, 2013b pg. 614).

We test this alternative using two restricted samples. In Panel B of Table 8, the sample includes only those subjects who correctly answered all three financial literacy questions. In Panel C, the sample includes only those subjects who correctly answered the question "Please tell us whether this statement is true or false. 'Buying a stock mutual fund usually provides a safer return than a single company stock.'" In this sample, all subjects correctly stated that a mutual fund is usually safer than an individual stock.[16] The results in these restricted samples are generally similar to those in the full sample: that is; *Inverse-S* is positively associated with nonparticipation and with portfolio under-diversification even for investors who were aware of the risks associated with under-diversification. These subjects did not choose individual stocks because they misunderstand the risks; rather, they were aware that holding individual stocks was riskier than holding mutual funds. This suggests that the relationship between *Inverse-S* and portfolio choice is due to preferences towards return distributions, rather than a lack of knowledge about the risks associated with holding an under-diversified portfolio.

Conclusion

We measure probability weighting using real incentives in a survey module fielded in a large and nationally representative sample of the U.S. population. We show that most individuals exhibit probability weighting—overweighting small probabilities and underweighting large probabilities—and there is also heterogeneity in probability weighting. We then test how probability weighting relates to two puzzling anomalies in household portfolio choice, and we find that probability weighting is associated with nonparticipation in equity markets and portfolio under-diversification among those who do participate. We also show that, among investors who own individual stocks, probability weighting is associated with higher positive skewness and idiosyncratic risk. Finally, we find evidence consistent with probability weighting being a component of preferences, rather than the result of probability unsophistication or lack of financial knowledge.

This paper 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.[17] Although we do not directly address asset pricing, our results offer support for a direct link between household probability weighting preferences and skewness-seeking behavior.

Our results also have implications for how financial advisors should frame investment decisions, as well as for the design of financial products. For example, people have a tendency to focus on salient extreme events such as a particular individual stock doubling in price within a matter of months. Providing better information about the distribution of long-term expected outcomes

15 For instance, von Gaudecker (2015) finds that under-diversification is related to low financial literacy.

16 Interestingly, in simple cross-tabulations we find that subjects who correctly answered this question are *more likely* to own individual stocks relative to those who answered incorrectly.

17 See Boyer, Mitton, and Vorkink (2010), Bali, Cakici, and Whitelaw (2011), Conrad, Dittmar, and Ghysels (2013), and Conrad, Kapadia, and Xing (2014). Boyer and Vorkink (2014) show a similar result for equity option returns.

may help people frame these financial decisions in a way that encourages better decisions. Our results also provide an explanation for the popularity of structured products combining safe (capital-guaranteed) and risky components (e.g., a call option on an individual stock or an index), despite the large negative abnormal returns that are guaranteed by these products (Bergstresser, 2008; Henderson and Pearson, 2011).

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Appendix

Table A1. Variable definitions

Variable name	Definition
Portfolio Choice	Categorical variable equal to 1 if respondent does not own any equity, 2 if respondent holds only stock mutual funds, 3 if respondent holds only individual stocks, and 4 if respondent holds both stock mutual funds and 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
Fraction of Equity in Individual Stocks	Individual stock holdings as a % of total assets invested in equity
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
Lottery Stock	Indicator that respondent owns a lottery stock, defined as a stock with below median price, above median idiosyncratic skewness, and above median idiosyncratic standard deviation
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
Age	Age in years
Female	Indicator for female
Married	Indicator if respondent is married or has a partner
Number of household members	Number of additional members in the household
White	Indicator if respondent considers himself primarily White
Hispanic	Indicator if respondent considers himself primarily Hispanic
No College Degree	Indicator if respondent had less than a bachelor or associate degree
Associate or Bachelor Degree	Indicator if respondent completed a bachelor or associate degree
Master or Higher Degree	Indicator if respondent has a master or higher degree
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
Trust	Ranges from 0 to 5; 0 corresponds to "you can't be too careful" and 5 corresponds to most people can be trusted
Risk Aversion	Average risk premium required for risk aversion lottery questions
Numeracy	Number of numeracy questions answered correctly (out of 3 total; see Online Appendix)
Financial Literacy	Number of financial literacy questions answered correctly (out of 3 total; see Online Appendix)
Optimism	Subjective life expectancy minus objective life expectancy (see Online Appendix)

Table A2. *Inverse-S* rank robustness tests

	Multinomial logit			Tobit
	Non-Participation (1)	Individual Stocks Only (2)	Both Mutual Funds and Individual Stocks (3)	Fraction of Equity in Individual Stocks (4)
Inverse-S	0.327***	0.350**	0.233	0.130**
	(2.92)	(2.33)	(1.63)	(2.50)
Controls	yes	yes	yes	yes
Observations	2,671	2,671	2,671	741
Adj. R^2	0.151	0.151	0.151	0.0508

Columns (1) to (3) report the coefficients of multinomial logit regressions for *Non-Participation, Individual Stocks Only*, and *Both Mutual Funds and Individual Stocks*. The excluded category is *Mutual Funds Only*. In column (1), the dependent variable equals one if the respondent does not participates in the stock market. In column (2), the dependent variable equals one if the respondent invests only in individual stocks. In column (3), the dependent variable equals one if the respondent invests both in mutual funds and individual stocks. Column (4) shows Tobit regression results in which the dependent variable is the *Fraction of Equity in Individual Stocks*. In all columns, the independent variable of interest is *Inverse-S* Rank. All models include a constant and controls for age, age-squared divided by a thousand, female, married, white, Hispanic, number of household members, employment status, education, (ln) family income, (ln) wealth, numeracy, financial literacy, trust, risk aversion, and optimism. All results use ALP survey weights. The symbols *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Online appendix: The impact of probability weighting on insurance and savings

In the main text we test the relation between probability weighting and household portfolio choice. However, probability weighting may also influence consumers' decisions to annuitize retirement wealth and buy insurance protection. For instance, Hu and Scott (2007) suggest that the puzzlingly low demand for annuities observed in practice may results from people overweighting the small probability of an early death (e.g., within a year of purchasing the annuity). Gottlieb and Mitchell (2015) follow a similar line of reason to explain the low up-take of long-term care insurance. Furthermore, the demand for life insurance could also be influenced by probability weighting, though in the opposite direction. That is, if an individual may be more likely to purchase life insurance if he over-weights the low probability of dying soon after buying the policy.

In fact, there are multiple – sometimes conflicting – ways that probability weighting can influence the demand for insurance and annuities. For example, if a decision maker focuses on the small probability of living to a very old age (e.g., 90 years), overweighting of small probabilities could reduce the demand for life insurance, but increase the demand for annuities and long-term care insurance. Further, rank-dependent utility models with probability weighting imply first-order risk aversion, which makes people willing to pay a premium to avoid small losses. Through this effect, probability weighting can increase the demand for insurance. Further, as first-order risk aversion stimulates higher precautionary savings, probability weighting may also increase the demand for annuities.

Through its effect on portfolio choice, probability weighting can also impact household wealth. On the one hand, investors who overweight extreme events may accumulate lower financial wealth, because they prefer to hold lottery stocks with low expected returns instead of the diversified market portfolio that has historically outperformed other investments. On the other hand, the precautionary savings effect of first-order risk aversion, induced by probability weighting, could lead to higher wealth accumulation.

Thus, due to these opposing effects, there are no unambiguous predictions for the effect of probability weighting on savings and the demand for annuities, life insurance, and long-term care insurance. The overall effect, therefore, is an empirical question. In Table A3, we show regression results that explore the relation between *Inverse-S* and these four important variables. In columns (1), (2), and (3), the dependent variables are dummies set equal to one to indicate ownership of annuities, life insurance, and long-term care insurance, respectively. In column (4) the dependent variable is logarithm of financial wealth, used as a proxy for savings. The four regression models include the same control variables as Table 4 of the main text. In addition, we include the respondent's subjective 10-year survival probability, as life expectancy may influence ownership of annuities and insurance. To show the effect of age more clearly, we include three age group dummies (35-49, 50-64, 65 years and up), while younger than 35 years is the base category.

The results in Table A3 show that probability weighting has a significant positive effect on annuity ownership. The estimated logit coefficient in column (1) implies that a one standard deviation increase in *Inverse-S* is associated with 3.0 percentage point higher rate of annuity ownership. Compared to the baseline annuity ownership rate of 11.8% in the ALP, this represents a sizeable increase of 26%. The positive effect of *Inverse-S*on annuity ownership suggests that either pre-cautionary savings motives (first-order risk aversion) are important, or overweighting of the small probability of outliving one's savings.

The impact of *Inverse-S* on ownership of life insurance, long-term care insurance, and financial wealth is not significant. Thus, although our main results show that probability weighting has a strong effect on household portfolio composition, we do not find that *Inverse-S* influences insurance demand and total financial wealth. Whereas the theoretical finance literature provides clear hypotheses about the effect of probability weighting on portfolio diversification, portfolio skewness, and stock market participation, the potential effect on insurance demand and savings is less clear-cut, with multiple possibly opposing effects. Accordingly, tentatively, the insignificant impact on financial wealth in Table A3 suggests that the negative effects of *Inverse-S* on household portfolios are offset by increased precautionary savings due to increased first-order risk aversion.

Table A3. Probability weighting and annuities, insurance and savings

	(1) Annuity ownership	(2) Life insurance ownership	(3) Long-term care insurance ownership	(4) Log of financial wealth
Inverse-S	0.443***	0.009	-0.250	0.177
	(2.60)	(0.09)	(-1.41)	(0.89)
Numeracy	-0.052	0.324**	0.058	0.384
	(-0.18)	(2.16)	(0.21)	(1.18)
Financial literacy	0.183	-0.173	-0.349	0.915***
	(0.66)	(-1.09)	(-1.34)	(3.12)
Trust	-0.021	-0.072	0.053	0.071
	(-0.17)	(-0.82)	(0.41)	(0.44)
Risk aversion	0.583	-0.452	-0.219	0.883
	(0.93)	(-1.14)	(-0.36)	(1.14)
Optimism	-0.012	0.040***	0.016	-0.017
	(-0.45)	(2.90)	(0.60)	(-0.62)
Subjective 10-year	-0.009	-0.002	-0.004	-0.007
survival probability	(-1.08)	(-0.45)	(-0.49)	(-0.68)
Age 35-49	1.973**	0.689**	-0.103	2.421***
	(2.44)	(1.99)	(-0.14)	(3.36)
Age 50-64	1.377*	0.808**	-0.303	2.152***
	(1.68)	(2.33)	(-0.41)	(2.96)
Age 65 and older	2.374***	0.769**	0.352	5.018***
	(2.74)	(1.97)	(0.42)	(6.06)
Household income	0.668**	0.298**	0.599*	2.329***
	(2.35)	(1.98)	(1.79)	(8.14)
Demographic controls	Yes	Yes	Yes	Yes
Observations	647	969	641	1,924
Pseudo R-squared	0.147	0.122	0.114	0.119

This table reports regression coefficients. In column (1), the dependent variable equals one if the respondent own annuities. In column (2), the dependent variable equals one if the respondent has a life insurance policy. In column (3), the dependent variable equals one if the respondent has long-term care insurance. For the dependent variables in columns (1), (2) and (3), logit model coefficients are reported. In column (4), the dependent variable is the logarithm of (1 + Financial Wealth), which consists of the sum of checking and savings accounts, CDs, government and corporate bonds, T-bills, and stocks. Column (4) shows coefficients from a Tobit regression, with zero as the lower bound. Every regression model includes a constant and controls for numeracy, financial literacy, trust, risk aversion, optimism, age groups (the excluded category is less than 35 years old), female, married, white, Hispanic, number of household members, employment status, education, (ln) family income, and a dummy for ownership of stocks in a retirement account. The sample size varies in columns (1), (2) and (3), as the source of the insurance and annuity ownership data is another ALP module. All results use ALP survey weights. Robust t-statistics in parentheses. The symbols *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.