Online Appendix

Household Portfolio Underdiversification and Probability Weighting: Evidence from the Field

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Online Appendix A: Optimal Portfolio Choice with Probability Weighting Preferences

In this Online Appendix we solve a calibrated portfolio choice model with probability weighting preferences to illustrate the effect of *Inverse-S* on the fraction invested in a well-diversified equity mutual fund and an individual stock. The setup and calibration of the model follow Polkovnichenko (2005) who develops a similar calibrated model to investigate the effect of probability weighting on portfolio underdiversification.

A.1. Preferences, Constraints, and the Financial Market

We consider an investor who maximizes utility over consumption. Her preferences are described by a CRRA utility function, U, and probability weights, π, as in Prelec (1998):

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

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

where

$$U(c_i) = \begin{cases} \dfrac{c_i^{1-\gamma}}{1-\gamma} & \gamma \neq 1 \\ \ln(c_i) & \gamma = 1 \end{cases},$$

and

$$w(p) = e^{(-(-\ln(p))^{\alpha})}, \text{ with } \alpha > 0 \ ,$$

where $c_1 < c_2 < \cdots < c_N$ and $P_i = p_1 + p_2 + \cdots + p_i$ is the cumulative probability of outcome *i*. Consumption is denoted by c_i, risk aversion by γ, and the probability weighting parameter by α.

Households invest in a risk-free asset, a well-diversified equity mutual fund, and a single individual stock. Initial wealth is normalized to 1. The consumption is:

$$c_i = 1 + \omega_m r_{m,i} + \omega_s r_{s,i} + (1 - \omega_m - \omega_s) r_f,$$

where ω_m, ω_s, and $(1 - \omega_m - \omega_s)$ are the fractions invested in the equity mutual fund, individual stock, and risk-free asset, respectively. The mutual fund return, individual stock return, and risk-free interest rate are denoted by $R_m = [r_{m,1}, \dots, r_{m,N}]'$, $R_s = [r_{s,1}, \dots, r_{s,N}]'$,, and r_f, respectively. The mutual fund return R_m is distributed with a mean of μ_m, standard deviation σ_m, and skewness g_m. The individual stock return R_s is distributed with a mean of μ_s, standard deviation σ_s, and skewness g_s. Investors face short sale and borrowing constraints:

$$\omega_m \geq 0 \quad and \quad \omega_s \geq 0 \quad and \quad \omega_m + \omega_s \leq 1.$$

A.2. Benchmark Parameters for the Portfolio Choice Problem

The risk aversion coefficient γ ranges from 1 to 5, and the probability weighting parameter α ranges from 0.2 to 1. The *Inverse-S* parameter is $1-\alpha$. Following Polkovnichenko (2005), mutual fund returns are distributed with a mean return $\mu_m = 12.9\%$ and standard deviation $\sigma_m = 24.0\%$, and individual stock returns are distributed with a mean return $\mu_s = 12.7\%$ and standard deviation $\sigma_s = 36.0\%$. The skewness of mutual fund returns and individual stock returns are $g_m = -0.3$ and $g_s = +0.3$, respectively. The correlation between the mutual fund returns and the stock returns is 0.6. The risk-free rate is 3%. The marginal distributions of the mutual fund returns and the individual stock returns are skewed normal, with the parameters set to match the first three moments (μ_m, σ_m, g_m, and μ_s, σ_s, g_s, respectively). The return correlation of 0.6 is matched in the simulations by using a Gaussian copula.

A.3. The Investor's Optimization Problem

To solve this problem, we define a two-dimensional grid for the fraction allocated to the individual stock ranging from 0% to 100% with steps of 1%, and the fraction allocated to the equity mutual fund ranging from 0% to 100% with steps of 1%. We simulate 10,000 individual stock returns and 10,000 mutual fund returns from the joint distribution, allowing us to calculate portfolio returns for each combination of permissible grid points. The portfolio returns are ranked from worst to best, each having an objective probability of 1/10,000. The cumulative objective probabilities are then transformed into decision weights using the probability weighting function described above. For each combination of permissible portfolio grid points, we determine the rank dependent utility value RDU, above. The point on the grid with the highest value of RDU determines the optimal fractions allocated to the individual stock and the equity mutual fund.

Figure 3 in the main paper shows the optimal fraction allocated to the individual stock as a percentage of the total assets invested in equity (equity mutual fund and individual stock combined), as a function of the *Inverse-S* parameter and the utility curvature coefficient. Figure 3 demonstrates that portfolio underdiversification rapidly increases with the *Inverse-S* parameter, as the optimal individual stock fraction rises and eventually reaches 100%.

Online Appendix B: Procedure for Eliciting Probability Weighting and Utility Curvature

In this Online Appendix we describe the elicitation method for measuring probability weighting and utility curvature in the ALP survey.

B.1. Pilot Study

Before fielding our main survey module, we ran a pilot study with several question formats in a small-scale module in the ALP with 207 respondents.[1] In this pilot module, we implemented two types of questions to elicit probability weighting and utility curvature: one set of questions based on Abdellaoui (2000), and another set based on the midweight method of van de Kuilen and Wakker (2011). As a starting point for each new question, we used the answer of a risk-neutral expected utility maximizer rather than a previous indifference point of the respondent, to limit the problem of error propagation from one question to the next. We also implemented two different types of question presentation formats: bi-section and choice lists. Half of the respondents were randomly assigned to the bi-section format and the other half were assigned to the choice list format. Both question formats included consistency check questions. Our purpose was to find an elicitation method that takes less than 15 minutes to complete and has a relatively low error rate, suitable for a survey of the general population.

Based on a thorough analysis of the pilot survey results, we found that the midweight method of van de Kuilen and Wakker (2011) led to relatively high rates of mistakes among the ALP respondents, and it also took considerably longer to complete than the questions adapted from Abdellaoui (2000). Therefore the Abdellaoui (2000) questions were implemented in the main survey. The format of the elicitation method in the pilot study, bi-section versus choice lists, did not lead to large differences in elicited indifference values or respondent mistakes. We selected the bi-section format for the main ALP survey, as respondents indicated that the bi-section questions were clearer and more interesting than the choice lists, and the average time taken to complete the bi-section questions was substantially shorter.

B.2. Elicitation Module Introduction and Practice Screen

The module starts with an introduction screen explaining that the remaining questions ask about choices involving unknown outcomes: see Figure B.1. The introduction screen also explains that, after completing the survey, one of the respondent's choices will be played for a real reward. Respondents are then presented one practice question to become familiar with the choice format: see Figure B.1.

B.3. Description of the Bi-Section Elicitation Procedure

After the practice question, the module presents the first utility curvature question as shown in Figure 4 and described in the main text (Section 1.3, The Elicitation Procedure). Each question consists of three bi-section rounds and one consistency check round, where the amount shown for Option B depends on the subject's responses in the previous rounds. In 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. 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. Two similar bi-section rounds then follow.

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[1] Results of this pilot survey are available on request.

B.4. Indifference Amounts

The different prize amounts for Option B shown in the bi-section rounds were chosen so respondents could select both risk averse and risk seeking choices ranging from very mild, to moderate, to large and extreme (four different levels). A subject's choices in the three bi-section rounds (Option A or Option B) give rise to eight possible sequences of responses, or "paths": BBB, BBA, BAB, BAA, ABB, ABA, AAB, and AAA, as shown in Table B.1 below.

Six of these paths, all but the two most extreme, give both a lower bound and an upper bound for the amount where the respondent is indifferent between Option A and Option B. For example, the sequence of choices BBA implies that the indifference amount for the first utility curvature question is between \$14 and \$16. We then take the average of the lower and upper bound as an estimate of the respondent's indifference point: (\$14 + \$16)/2 = \$15.

For the extreme choice path BBB, the indifference value is below the upper bound of \$14 (risk premium ≤ -22%), but the bi-section rounds provide no lower bound. However, if the large payoff X of Option B is \$12 or lower, Option B would be dominated by Option A. Therefore, a natural lower bound for the first question is \$12, and we can estimate the indifference amount similarly as the average of the lower and upper bound: (\$12 + \$14)/2 = \$13.

For the extreme choice path AAA, the indifference value is above the last lower bound of \$25 (risk premium ≥ 39%), but there is no upper bound from the bi-section. In this case we set the indifference amount \$3 above the last lower bound of \$25: \$25 + \$3 = \$28 (risk premium = 56%). In general, we follow these three rules for calculating the indifference amounts for the bi-section paths of the four utility curvature questions and the six probability weighting questions:

1. For paths BBB, BBA, BAB, BAA, ABB, ABA, AAB:

   Indifference amount = (*Lower bound* + *Upper bound*) / 2,

   where the lower bound and upper bound follow from the three bisection rounds, except for path BBB where the lower bound is the payoff for Option B where Option A starts to dominate Option B.

2. For the extreme path AAA on the utility curvature questions:

   Indifference amount = *Lower bound* + Z,

   where Z = \$5 if the *Lower bound* > \$40, Z = \$4 if the *Lower bound* > \$30, Z = \$3 if the *Lower bound* > \$20, Z = \$2 if the *Lower bound* > \$10, and Z = \$1 otherwise.

3. For the extreme path AAA on the probability weighting questions:

   Indifference amount = min(*Lower bound* + Z, (*Lower bound* + 42)/2),

   where \$42 is the sure amount for Option B where Option B starts to dominate Option A, and Z is similar to Rule 2.

For the four utility curvature questions, Tables B.1 through B.4 display the large payoff X for Option B shown in the three bi-section rounds, and in the fourth consistency check round. The tables also show the indifference amounts for the eight possible answer paths, determined according to the rules above. Similarly, for the six probability weighting questions, Tables B.5 through B.10 display the bi-section prize amounts X for Option B and the indifference amounts on the eight answer paths. As mentioned before, the different payoffs for Option B in the bi-section were chosen such that respondents could express both risk averse and risk seeking preferences, ranging from very mild, to moderate, to large and extreme. However, in some cases the range of risk premiums that can be attained by the bi-section algorithm is bounded from above or below, because otherwise Option A would dominate Option B, or vice versa.

B.5. Check Questions

After the three bi-section rounds, a fourth consistency check round follows. Respondents who chose Option A in the first bi-section round were then presented a prize for Option B below their lower bound from the previous three rounds, such that the only consistent response would be Option A. Similarly, respondents who chose Option B in the first bi-section round, were presented a prize for Option B above their upper bound from the previous three rounds, such that the only consistent response would be Option B. The last two columns of Table B.1 to Table B.10 show the prize amount for Option B in the check round, and the corresponding consistent response.

Figure B.1: Introduction to the Probability Weighting Questions

The remaining questions ask about choices involving unknown outcomes. At the end of the survey one of these questions will be played for real money, with your potential winnings determined by your choices. You will now be given a practice question to become familiar with the choices.

Practice Question 1
In the following questions, you will be asked to make a series of choices between two options: Option A and Option B. 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 example, the box below contains 100 balls: 50 purple and 50 orange.

Below is an example of the choice you will be asked to make between Option A and B.

Option A pays off:

- $30 if the ball drawn is purple (50% chance)
- $ 0 if the ball drawn is orange (50% chance)

Option B pays off

- $18 if the ball drawn is purple (50% chance)
- $10 if the ball drawn is orange (50% chance)

Option A	Option B
☐ **50%** chance of winning **$30** **50%** chance of winning **$0**	☐ **50%** chance of winning **$18** **50%** chance of winning **$10**

Table B.1: Bi-Section Paths for Utility Curvature Question 1 (*$RA_{\$12}$*)

Option A: win $12 with 33% chance, or else $3 with 67% chance.

Option B: win $X with 33% chance, or else $0 with 67% chance.

	Round 1		*Round 2*		*Round 3*		*Indifference value*		*Check Round*	
Path	X	Choice	X	Choice	X	Choice	Amount	%	X	Correct
1	18	B	16	B	14	B	13	-28.1%	15	B
2	18	B	16	B	14	A	15	-17.1%	17	B
3	18	B	16	A	17	B	16.5	-8.8%	18	B
4	18	B	16	A	17	A	17.5	-3.3%	19	B
5	18	A	21	B	19	B	18.5	2.3%	17	A
6	18	A	21	B	19	A	20	10.6%	18	A
7	18	A	21	A	25	B	23	27.1%	19	A
8	18	A	21	A	25	A	28	54.8%	23	A

Note: the table shows the payoff for Option B shown in the three bi-section rounds, starting from $18 in round one, on the eight possible answer paths (BBB, BBA, BAA, BAA, ABB, ABA, AAB, AAA).

Table B.2: Bi-Section Paths for Utility Curvature Question 2 (*$RA_{\$18}$*)

Option A: win $18 with 33% chance, or else $3 with 67% chance.

Option B: win $X with 33% chance, or else $0 with 67% chance.

	Round 1		*Round 2*		*Round 3*		*Indifference value*		*Check Round*	
Path	X	Choice	X	Choice	X	Choice	Amount	%	X	Correct
1	24	B	22	B	20	B	19	-21.1%	21	B
2	24	B	22	B	20	A	21	-12.8%	23	B
3	24	B	22	A	23	B	22.5	-6.6%	24	B
4	24	B	22	A	23	A	23.5	-2.5%	25	B
5	24	A	27	B	25	B	24.5	1.7%	23	A
6	24	A	27	B	25	A	26	7.9%	24	A
7	24	A	27	A	31	B	29	20.4%	25	A
8	24	A	27	A	31	A	35	45.3%	29	A

Table B.3: Bi-Section Paths for Utility Curvature Question 3 (*$RA_{\$24}$*)

Option A: win $24 with 33% chance, or else $3 with 67% chance.

Option B: win $X with 33% chance, or else $0 with 67% chance.

	Round 1		*Round 2*		*Round 3*		*Indifference value*		*Check Round*	
Path	X	Choice	X	Choice	X	Choice	Amount	%	X	Correct
1	30	B	28	B	26	B	25	-16.9%	27	B
2	30	B	28	B	26	A	27	-10.3%	29	B
3	30	B	28	A	29	B	28.5	-5.3%	30	B
4	30	B	28	A	29	A	29.5	-2.0%	31	B
5	30	A	33	B	31	B	30.5	1.4%	29	A
6	30	A	33	B	31	A	32	6.3%	30	A
7	30	A	33	A	40	B	36.5	21.3%	31	A
8	30	A	33	A	40	A	44	46.2%	35	A

Table B.4: Bi-Section Paths for Utility Curvature Question 4 (*$RA_{\$30}$*)

Option A: win $30 with 33% chance, or else $3 with 67% chance.

Option B: win $X with 33% chance, or else $0 with 67% chance.

	Round 1		*Round 2*		*Round 3*		*Indifference value*		*Check Round*	
Path	X	Choice	X	Choice	X	Choice	Amount	%	X	Correct
1	36	B	34	B	32	B	31	-14.1%	33	B
2	36	B	34	B	32	A	33	-8.6%	35	B
3	36	B	34	A	35	B	34.5	-4.4%	36	B
4	36	B	34	A	35	A	35.5	-1.6%	37	B
5	36	A	40	B	37	B	36.5	1.1%	35	A
6	36	A	40	B	37	A	38.5	6.7%	36	A
7	36	A	40	A	50	B	45	24.7%	37	A
8	36	A	40	A	50	A	55	52.4%	45	A

Table B.5: Bi-Section Paths for Probability Weighting Question 1 (*$PW_{50\%}$*)

Option A: win $42 with 50% chance, or else $6 with 50% chance.

Option B: win $X for sure (with 100% chance).

	Round 1		*Round 2*		*Round 3*		*Indifference value*		*Check Round*	
Path	X	Choice	X	Choice	X	Choice	Amount	%	X	Correct
1	24	B	20	B	12	B	9	62.5%	16	B
2	24	B	20	B	12	A	16	33.3%	22	B
3	24	B	20	A	22	B	21	12.5%	24	B
4	24	B	20	A	22	A	23	4.2%	26	B
5	24	A	28	B	26	B	25	-4.2%	22	A
6	24	A	28	B	26	A	27	-12.5%	24	A
7	24	A	28	A	32	B	30	-25.0%	26	A
8	24	A	28	A	32	A	36	-50.0%	30	A

Table B.6: Bi-Section Paths for Probability Weighting Question 2 (*$PW_{25\%}$*)

Option A: win $42 with 25% chance, or else $6 with 75% chance.

Option B: win $X for sure (with 100% chance).

	Round 1		*Round 2*		*Round 3*		*Indifference value*		*Check Round*	
Path	X	Choice	X	Choice	X	Choice	Amount	%	X	Correct
1	15	B	13	B	10	B	8	46.7%	12	B
2	15	B	13	B	10	A	11.5	23.3%	14	B
3	15	B	13	A	14	B	13.5	10.0%	15	B
4	15	B	13	A	14	A	14.5	3.3%	16	B
5	15	A	17	B	16	B	15.5	-3.3%	14	A
6	15	A	17	B	16	A	16.5	-10.0%	15	A
7	15	A	17	A	19	B	18	-20.0%	16	A
8	15	A	17	A	19	A	21	-40.0%	18	A

Table B.7: Bi-Section Paths for Probability Weighting Question 3 (*$PW_{75\%}$*)
Option A: win $42 with 75% chance, or else $6 with 25% chance.
Option B: win $X for sure (with 100% chance).

	Round 1		*Round 2*		*Round 3*		*Indifference value*		*Check Round*	
Path	X	Choice	X	Choice	X	Choice	Amount	%	X	Correct
1	33	B	30	B	20	B	13	60.6%	27	B
2	33	B	30	B	20	A	25	24.2%	32	B
3	33	B	30	A	32	B	31	6.1%	33	B
4	33	B	30	A	32	A	32.5	1.5%	34	B
5	33	A	35	B	34	B	33.5	-1.5%	32	A
6	33	A	35	B	34	A	34.5	-4.5%	33	A
7	33	A	35	A	38	B	36.5	-10.6%	34	A
8	33	A	35	A	38	A	40	-21.2%	36	A

Table B.8: Bi-Section Paths for Probability Weighting Question 4 (*$PW_{12\%}$*)
Option A: win $42 with 12% chance, or else $6 with 88% chance.
Option B: win $X for sure (with 100% chance).

	Round 1		*Round 2*		*Round 3*		*Indifference value*		*Check Round*	
Path	X	Choice	X	Choice	X	Choice	Amount	%	X	Correct
1	10.5	B	9	B	7	B	6.5	37.0%	8	B
2	10.5	B	9	B	7	A	8	22.5%	10	B
3	10.5	B	9	A	10	B	9.5	7.9%	10.5	B
4	10.5	B	9	A	10	A	10.25	0.7%	11	B
5	10.5	A	12	B	11	B	10.75	-4.2%	10	A
6	10.5	A	12	B	11	A	11.5	-11.4%	10.5	A
7	10.5	A	12	A	14	B	13	-26.0%	11	A
8	10.5	A	12	A	14	A	16	-55.0%	13	A

Table B.9: Bi-Section Paths for Probability Weighting Question 5 (*$PW_{88\%}$*)
Option A: win $42 with 88% chance, or else $6 with 12% chance.
Option B: win $X for sure (with 100% chance).

	Round 1		*Round 2*		*Round 3*		*Indifference value*		*Check Round*	
Path	X	Choice	X	Choice	X	Choice	Amount	%	X	Correct
1	37.5	B	34	B	20	B	13	65.5%	30	B
2	37.5	B	34	B	20	A	27	28.3%	36	B
3	37.5	B	34	A	36	B	35	7.1%	37.5	B
4	37.5	B	34	A	36	A	36.75	2.5%	38	B
5	37.5	A	39	B	38	B	37.75	-0.2%	36	A
6	37.5	A	39	B	38	A	38.5	-2.2%	37.5	A
7	37.5	A	39	A	41	B	40	-6.2%	38	A
8	37.5	A	39	A	41	A	41.5	-10.1%	40	A

Table B.10: Bi-Section Paths for Probability Weighting Question 6 (*$PW_{5\%}$*)
Option A: win $42 with 5% chance, or else $6 with 95% chance.
Option B: win $X for sure (with 100% chance).

	Round 1		***Round 2***		***Round 3***		***Indifference value***		***Check Round***	
Path	X	Choice	X	Choice	X	Choice	Amount	%	X	Correct
1	8	B	7	B	6	B	6.25	19.9%	6.5	B
2	8	B	7	B	6	A	6.5	16.7%	7.5	B
3	8	B	7	A	7.5	B	7.25	7.1%	8	B
4	8	B	7	A	7.5	A	7.75	0.6%	8.5	B
5	8	A	9	B	8.5	B	8.25	-5.8%	7.5	A
6	8	A	9	B	8.5	A	8.75	-12.2%	8	A
7	8	A	9	A	10	B	9.5	-21.8%	8.5	A
8	8	A	9	A	10	A	11	-41.0%	9.5	A

Online Appendix C: Probability Weighting Measures Estimated Parametrically

C.1. Prelec Model

As a robustness test, we estimate the *Inverse-S* measure using the one-parameter probability weighting function specified by Prelec (1998). The probability weighting function is:

$$w(p) = e^{(-(-\ln(p))^{\alpha})}, \text{ with } \alpha > 0, \tag{C1}$$

where α is the probability weighting parameter. Expected utility is a special case for $\alpha = 1$, while the values $0 < \alpha < 1$ correspond to an inverse-S shaped weighting function, and for $\alpha > 1$ the function is S-shaped. Hence, we use $1 - \alpha$ as a parametric measure of *Inverse-S*. The curve features a fixed intersection point at $p = 1/e = 0.37$, which is consistent with experimental findings.

We assume the respondent has a CRRA (power) utility function:

$$U(x) = \frac{x^{1-\gamma}}{1-\gamma}, \text{ with } \gamma < 1. \tag{C2}$$

where γ is the coefficient of relative risk aversion. We assume that the respondent narrowly frames the prizes $x \geq 0$ that she can win, rather than integrating the payoffs with her total wealth. Respondents who integrate the prizes with a larger amount of wealth (say \$1,000) accept nearly all small-stake bets with a positive risk premium (Arrow, 1971; Rabin, 2000), and as a result they would require very small positive risk premiums for all our questions. Because in our survey most respondents require relatively large risk premiums (see Table 1), the narrow framing assumption gives the expected utility model a better chance to fit the data. Finally, we note that the relative risk aversion coefficient γ in (C2) has an upper limit of 1 to avoid division by zero, as some of the payoffs are zero ($x = 0$).

We jointly estimate α and γ for each respondent separately using the ten certainty equivalents from the six probability weighting questions and four utility curvature questions. For instance, using the first probability weighting question (see Panel B in Table 1), suppose that the respondent is indifferent between receiving the sure amount X_{indif} and the lottery that pays off \$42 with 5% chance and \$6 with 95% chance. Indifference implies:

$$U(X_{indif}) = \mathrm{w}(0.05)\mathrm{U}(42) + (1 - \mathrm{w}(0.05))\mathrm{U}(6), \tag{C3}$$

which is equivalent to

$$X_{indif} = U^{-1}\Big(w(0.05)\big(U(42) - U(6)\big) + U(6)\Big). \tag{C4}$$

Similarly, using the first utility curvature question (see Panel A in Table 1), suppose that the respondent is indifferent between receiving the amount X_{indif} with a probability of 33% and nothing otherwise, and the lottery that pays off \$12 with 33% chance and \$3 with 67% chance. Using $U(0) = 0$, this indifference implies:

$$\mathrm{w}(0.33)U(X_{indif}) = \mathrm{w}(0.33)\mathrm{U}(12) + (1 - \mathrm{w}(0.33))\mathrm{U}(3), \tag{C5}$$

which is equivalent to

$$X_{indif} = U^{-1}\left(U(12) + \left(\left(1 - w(0.33)\right)/w(0.33)\right)U(3)\right). \tag{C6}$$

In total, we have 10 equations defining the indifference amounts for the ten questions as a function of parameters α and γ: six equations (C4) for the probability weighting questions, and four equations (C6) for the utility curvature questions. We estimate the parameters α and γ for each respondent separately with non-linear least squares. To ensure that all ten questions have similar weights regardless of the payoff sizes, all indifference amounts are first divided by the risk neutral response to the question. This way we fit the respondent's percentage risk premiums (%) for the questions, rather than indifference amounts in dollars.

We note that α and γ are estimated *jointly*, using all 10 questions simultaneously. Therefore, if a respondent's pattern of risk premiums can be best explained with the expected utility model, that is, without probability weighting, the estimate of α equals 1. Table C.1 below shows descriptive statistics of the estimated parameters γ and α. On average, the ALP respondents are slightly risk averse (avg. γ = 0.08, median γ = 0.16), and have an inverse-S shaped probability weighting function (avg. $1 - \alpha$ = 0.13, median $1 - \alpha$ = 0.19). However, there is strong cross-sectional variation in both preference parameters (stdev. γ = 0.36, stdev. $1 - \alpha$ = 0.42). Overall, the majority of respondents have a concave utility function (77% with $\gamma > 0$) and an *inverse-S* shaped probability weighting function (73% with $1 - \alpha > 0$).

Table C.1: Descriptive Statistics of Estimated Prelec and CRRA Model Parameters

	mean	median	stdev	min	max	% > 0	N
γ CRRA	0.08	0.16	0.36	-2.22	0.37	0.77	2641
α Prelec	0.87	0.81	0.42	0.23	4.43	1.00	2641
$(1 - \alpha)$ *Inverse-S*	0.13	0.19	0.42	-3.43	0.77	0.73	2641

Note: The parameters γ and α are estimated jointly using Non-Linear Least Squares, using the respondent's risk premiums for the six probability weighting questions and four utility curvature questions. The preference model, consisting of a Prelec probability weighting function and a power utility function with constant relative risk aversion (CRRA), is estimated separately for each respondent. The descriptive statistics are estimated using ALP survey weights.

C.2. Salience Model

As a further robustness test, we also estimate a parametric *Inverse-S* measure using the salience model of Bordalo, Gennaioli, and Shleifer (2012). In the salience model, people overweight the probability of states that have relatively large – and therefore salient – differences in lottery payoffs. The salience of state *s* is defined by the following function of the lottery payoffs *x* in Bordalo et al. (2012, p. 1250):

$$\sigma(x_s^A, x_s^B) = \frac{|x_s^A - x_s^B|}{|x_s^A| + |x_s^B| + \theta}, \text{ with } \theta > 0 , \quad \text{(C7)}$$

where x_s^A is the payoff of Option A in state s, x_s^B is the payoff of Option B in state s and $\theta > 0$ is a scaling parameter. The salience function has a relatively large value when the difference in the prizes of Option A and Option B is large.

In the salience model, people give higher weights to states with more salient payoff differences. Following Bordalo et al. (2012, p. 1255), we assume the decision maker distorts the probability p_s of state *s* into the decision weight π_s with a smooth increasing function of salience differences, defined by:

$$\pi_s = \frac{1}{c} p_s \delta^{-\sigma(x_s^A, x_s^B)}, \text{ with } 0 < \delta \leq 1, \quad \text{(C8)}$$

$$c = \sum_{s=1}^{S} p_s \delta^{-\sigma(x_s^A, x_s^B)}, \quad \text{(C9)}$$

where δ is the parameter of the probability weighting function, and *c* is a scaling factor that ensures the decision weights π_s sum up to 1. No probability weighting is the special case of $\delta = 1$. The values $0 < \delta < 1$ correspond to overweighting the probability of salient states with large σ, that is, states with large differences in the payoffs of Option A and B. Hence, we use $1 - \delta$ as an alternative parametric measure of *Inverse-S*.

We follow Bordalo et al. (2012, p. 1249) in assuming that the decision maker evaluates the lottery payoffs with a linear value function $V_{Sal}(L)$:

$$V_{Sal}(L^A) = \sum_{s=1}^{S} \pi_s x_s^A, \quad \text{(C10)}$$

$$V_{Sal}(L^B) = \sum_{s=1}^{S} \pi_s x_s^B. \quad \text{(C11)}$$

The decision maker prefers lottery A over B if and only if $V_{Sal}(L^A) > V_{Sal}(L^B)$.

For example, in the first round of the probability weighting question $PW_{5\%}$ (see Panel B in Table 1), the respondent is offered a choice between Option A that pays \$42 with 5% chance and \$6 with 95% chance, and Option B that pays \$8 for sure (more than the expected value of Option A, which is \$7.8). Let us assume that δ is 0.5, so that the decision maker overweights the probability of salient states, and the scaling parameter θ is 1. Table C.2 below summarizes the evaluation of Option A and B by the salience model. In state *s* = 1, occurring with a probability of 5%, Option A pays \$42 and the alternative Option B pays \$8. Due to the large difference in the payoffs (\$42 vs. \$8), in state 1 the salience function has a relatively large value: $\sigma(x_1^A, x_1^B) = 0.667$. By contrast, in state *s* = 2, the payoffs are similar, \$6 for Option A versus \$8 for Option B, and the salience function has a relatively small value, $\sigma(x_2^A, x_2^B) = 0.133$. As a result, the probability of the salient state 1 ($p_1 = 0.05$) is overweighted to a decision weight of $\pi_1 = 0.071$, while the probability of state 2 is underweighted to π_2 = 0.929. Because the decision maker overweights state 1 where Option A pays the large prize \$42, he prefers Option A over Option B: $V_{Sal}(L^A)$ = 8.55 > 8 = $V_{Sal}(L^B)$. Because the expected payoff of Option A (\$7.8) is lower than the payoff of Option B (\$8), the example illustrates that the salience model can give rise to risk-seeking behavior for large payoffs that occur with small probability, similar to *Inverse-S* probability weighting.

Table C.2: Salience Model Evaluation of the First Probability Weighting Question

States	Probability	Payoffs Option A	Payoffs Option B	Salience	Distortion Factor	Decision Weight
s	p_s	x_s^A	x_s^B	$\sigma(x_s^A, x_s^B)$	$\delta^{-\sigma(x_s^A, x_s^B)}$	π_s
State 1	5%	42	8	0.667	1.587	7.1%
State 2	95%	6	8	0.133	1.097	92.9%
Salience function value $V_{Sal}(L)$		8.55	8			

For the salience model, in general it is not possible to derive analytical expressions for certainty equivalents or indifference values (Dertwinkel-Kalt and Köster, 2017). This is due to the complexity of the model, as the probability weights are a non-linear function of the payoffs. As an alternative method for estimating the model parameters, we simulate the choices a decision maker with given values for the salience model parameters δ and θ would have made on our probability weighting questions, calculating the corresponding risk premiums. We consider a grid of 100 possible values for δ ranging from 0.01 to 1, with steps of 0.01, and eight different values of the scaling parameter θ: 0.1, 0.5, 1, 2, 5, 10, 25 and 50. Next we select the pair of values δ and θ on the grid that minimizes the sum of the squared differences between a respondent's six actual risk premiums on the probability weighting questions and the simulated values from the salience model.

Table C.3 below shows descriptive statistics of the fitted salience model parameter δ, the corresponding probability weighting parameter $1 - \delta$, and the scaling parameter θ. On average nearly all ALP respondents overweight the probabilities of salient outcomes (avg. $1 - \delta$ = 0.61, median $1 - \delta$ = 0.72), but with considerable heterogeneity in the estimates (stdev. $1 - \delta$ = 0.35). Only 8.5% of the respondents do not overweight salient outcomes (δ = 1). We note that the salience model of Bordalo et al. (2012) is not defined for $\delta > 1$, that is, underweighting of salient outcomes is not allowed.

Table C.3: Descriptive Statistics of Fitted Salience Model Parameters

	mean	median	stdev	min	max	% > 0	N
δ salience	0.39	0.28	0.35	0.01	1.00	1	2671
θ scaling	10.23	0.10	16.77	0.10	50.00	1	2671
$(1 - \delta)$ *Inverse-S*	0.61	0.72	0.35	0.00	0.99	0.92	2671

Note: The parameters δ and θ are found by minimizing the sum of the squared differences between a respondent's six risk premiums on the probability weighting questions and the simulated values from the salience model, with 100 values for δ ranging from 0.05 to 1, with steps of 0.05, and eight values for the scaling parameter θ: 0.1, 0.5, 1, 2, 5, 10, 25, and 50. The descriptive statistics are estimated using ALP survey weights.

C.3. Tversky-Kahneman Model

As a robustness test, we estimate the *Inverse-S* measure using the one-parameter probability weighting function of Tversky-Kahneman (1992):

$$w(p) = \frac{p^{\kappa}}{(p^{\kappa}+(1-p)^{\kappa})^{1/\kappa}}, \text{ with } \kappa > 0, \tag{C12}$$

where κ is the probability weighting parameter. Expected utility is a special case for $\kappa = 1$, while the values $0 < \kappa < 1$ correspond to an inverse-S shaped weighting function, and for $\kappa > 1$ the function is S-shaped. Hence, we use $1 - \kappa$ as a parametric measure of *Inverse-S*.

Although the function is popular in economics and finance since it was introduced by Tversky and Kahneman to estimate cumulative prospect theory in 1992, it has several drawbacks. First, the function is non-monotonic for $\kappa < 0.279$ (Ingersoll, 2008). Second, the elevation of the probability weighting curve and its intersection point with the diagonal are not independent from one another, which can generate an artificial negative correlation between the probability weighting parameter and the utility curvature parameter (Fehr-Duda and Epper, 2012). For this reason, we do not jointly estimate the utility curvature parameter along with the Tversky-Kahneman probability weighting parameter. Rather, we first independently estimate the coefficient of relative risk aversion γ for a power utility function using only the respondent's risk premiums for the four utility curvature questions. Then, given the fitted power utility function, in the second stage we estimate the Tversky-Kahneman parameter κ using the respondent's risk premiums for the six probability weighting questions.

Table C.4 below shows descriptive statistics of the estimated probability weighting parameter κ. On average, the ALP respondents have an inverse-S shaped Tversky-Kahneman weighting function (avg. $1 - \kappa = 0.15$, median $1 - \kappa = 0.25$), but with strong cross-sectional variation (stdev. $\kappa = 0.45$). The majority of respondents have an inverse-S shaped weighting function (71% with $1 - \kappa > 0$), similar to the results for the other probability weighting models.

Table C.4: Descriptive Statistics of the Estimated Tversky-Kahneman Parameter

	mean	median	stdev	min	max	% > 0	N
κ Tversky-Kahneman	0.85	0.75	0.45	0.23	3.26	1.00	2641
$(1-\kappa)$ *Inverse-S*	0.15	0.25	0.45	-2.26	0.77	0.71	2641

Note: The parameter κ is estimated using Non-Linear Least Squares, using the respondent's risk premiums for the six probability weighting questions, and the estimated parameter γ for a power utility function. The Tversky-Kahneman probability weighting function is estimated separately for each respondent. The descriptive statistics are estimated using ALP survey weights.

C.4. Correlations between Probability Weighting Measures

Table C.5 shows the correlations between the four alternative measures of probability weighting, both non-parametric (*Inverse-S*) and parametric ($1 - \alpha$, $1 - \delta$, $1 - \kappa$). All of the correlations are positive and significant. A factor analysis shows that a single underlying factor can explain about 70% of the variation in the four probability weighting measures.

Table C.5: Correlations of Alternative Probability Weighting Measures

	Non-parametric *Inverse-S*	Prelec model $(1 - \alpha)$	Salience model $(1 - \delta)$	Tversky-Kahneman $(1 - \kappa)$
Inverse-S	1.00			
Prelec $(1 - \alpha)$	0.75^{***}	1.00		
Salience $(1 - \delta)$	0.78^{***}	0.60^{***}	1.00	
TK $(1 - \kappa)$	0.59^{***}	0.41^{***}	0.46^{***}	1.00

Note: The table shows the correlations between the non-parametric *Inverse-S* measure, the estimated Inverse-S parameter $(1 - \alpha)$ for the Prelec model, the fitted probability weighting parameter $(1 - \delta)$ for the salience model, and the estimated Inverse-S parameter $(1 - \kappa)$ for the Tversky-Kahneman function. The correlations are estimated using ALP survey weights. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Online Appendix D: The ALP Survey, Stock Characteristics, and Control Variables

D.1. Description of the American Life Panel

The American Life Panel (ALP) is an online panel of U.S. respondents age 18+; respondents were recruited in one of four ways (https://mmicdata.rand.org/alp/). Most were recruited from respondents to the Monthly Survey (MS) of the University of Michigan's Survey Research Center (SRC). The MS is the leading consumer sentiment survey that incorporates the long-standing Survey of Consumer Attitudes and produces, among others, the widely used Index of Consumer Expectations. Each month, the MS interviews approximately 500 households, of which 300 households are a random-digit-dial (RDD) sample and 200 are re-interviewed from the RDD sample surveyed six months previously. Until August 2008, SRC screened MS respondents by asking them if they would be willing to participate in a long-term research project (with approximate response categories "no, certainly not," "probably not," "maybe," "probably," "yes, definitely"). If the response category is not "no, certainly not," respondents were told that the University of Michigan is undertaking a joint project with RAND. They were asked if they would object to SRC sharing their information about them with RAND so that they could be contacted later and asked if they would be willing to actually participate in an Internet survey. Respondents who do not have Internet were told that RAND will provide them with free Internet. Many MS-respondents are interviewed twice. At the end of the second interview, an attempt was made to convert respondents who refused in the first round. This attempt includes the mention of the fact that participation in follow-up research carries a reward of $20 for each half-hour interview.

Respondents lacking Internet access were provided with so-called WebTVs (http://www.webtv.com/pc/), allowing them to access the Internet using their television and a telephone line. The ALP has also recruited respondents through a snowball sample (respondents suggesting friends or acquaintances who might also want to participate), but we do not use any respondents recruited through the snowball sample in our paper. A new group of respondents (approximately 500) was recruited after participating in the National Survey Project at Stanford University. This sample was recruited in person, and at the end of their one-year participation, they were asked whether they were interested in joining the RAND American Life Panel. Most of these respondents were given a laptop and broadband Internet access.

D.2. Stock holding variables

Q. 1 Not including investments held in your retirement accounts, do you currently own any stocks or stock mutual funds?

1) Yes
2) No →go to Q. 10
3) Don't know →go to Q. 10
4) Refuse→go to Q. 10

Q. 2 Not including investments held in your retirement accounts, do you currently own any stock mutual funds?

1) Yes
2) No →go to Q. 5
3) Don't know →go to Q. 5
4) Refuse→go to Q. 5

Q. 3 What do you think is roughly the total value of those stock mutual funds?

$______________________ →go to Q. 5

1) Don't know

2) Refuse →go to Q. 5

Q. 4 What do you think is roughly the total value of those funds?

1) Between $0 and $500

2) Between $501 and $2,500

3) Between $2,501 and $5,000

4) Between $5,001 and $10,000

5) Between $10,001 and $30,000(

6) Between $30,001 and $100,000

7) Between $100,001 and $200,000

8) More than $200,000

9) Don't know

10) Refuse

Q. 5 Not including investments held in your retirement accounts, do you currently own any stock of individual companies?

1) Yes

2) No →go to Q. 10

3) Don't know →go to Q. 10

4) Refuse→go to Q. 10

Q. 6 What do you think is roughly the total value of those stocks?

$______________________ →go to Q. 8

1) Don't know

2) Refuse →go to Q. 8

Q. 7 What do you think is roughly the total value of those stocks?

1) Between $0 and $500

2) Between $501 and $2,500

3) Between $2,501 and $5,000

4) Between $5,001 and $10,000

5) Between $10,001 and $30,000

6) Between $30,001 and $100,000

7) Between $100,001 and $200,000

8) More than $200,000

9) Don't know

10) Refuse

Q. 8 In about how many different individual companies do you own stocks?

1) 1-2
2) 3-4
3) 5-7
4) 8-10
5) More than 10
6) Don't know
7) Refuse

Q. 9 What are the names of the individual companies whose stocks you own? If you own stocks in more than five companies please list the five most valuable holdings.

____
____
____
____
____

D.3. Control variables

Financial Literacy

The financial literacy questions we posed in the ALP module have been used in two dozen countries and comparable results obtained (Lusardi and Mitchell, 2011):

Suppose you had $100 in a savings account and the interest rate was 2% per year. After 5 years, how much do you think you would have in the account if you left the money to grow?

1) More than $102
2) Exactly $102
3) Less than $102
4) Don't know
5) Refuse

Imagine that the interest rate on your savings account was 1% per year and inflation was 2% per year. After 1 year, would you be able to buy more than, exactly the same as, or less than today with the money in this account?

1) More than today
2) Exactly the same as today
3) Less than today
4) Don't know
5) Refuse

Please tell us whether this statement is true or false. Buying a single company stock usually provides a safer return than a stock mutual fund.

1) True
2) False
3) Don't know
4) Refuse

Trust
The trust question we use was: "Generally speaking, would you say that most people can be trusted, or that you can't be too careful in dealing with people? Please indicate on a score of 0 to 5."). For the answers, we employ a scale ranging from 0 to 5, with 0 indicating "Most people can be trusted" and 5 indicating "You can't be too careful". For the results reported in the main paper we reverse the scale of the trust variable so that higher values indicate stronger trust in others (with 0 indicating "You can't be too careful", and with 5 indicating "Most people can be trusted").

Numeracy
We assess numeracy using three questions based on those in the HRS and the English Longitudinal Study of Ageing:

> If the chance of getting a disease is 10 percent, how many people out of 1,000 would be expected to get the disease?
> 1) About 1 person
> 2) About 10 people
> 3) About 100 people
> 4) About 1000 people
> 5) Don't know
> 6) Refuse
>
> If 5 people all have the winning numbers in the lottery and the prize is two million dollars, how much will each of them get?
> 1) $200,000
> 2) $400,000
> 3) $1,000,000
> 4) $2,000,000
> 5) Don't know
> 6) Refuse
>
> A second hand car dealer is selling a car for $6,000. This is two-thirds of what it cost new. How much did the car cost new?
> 1) $7,000
> 2) $9,000
> 3) $12,000
> 4) $18,000
> 5) Don't know
> 6) Refuse

Optimism
We measure optimism similar to Puri and Robinson (2007) by comparing self-reported life expectancy to that implied by statistical tables. The question we use is "About how long do you think you will live?" The optimism measure equals the self-reported years minus the expected years according to mortality tables (using separate tables for men and women).

Online Appendix E: Utility Curvature, Loss Aversion, and Narrow Framing

This Online Appendix addresses whether utility curvature, loss aversion, or narrow framing can explain the observed pattern of risk premiums for the probability weighting questions.

E.1. Narrow Framing with Expected Utility

We consider a decision maker who maximizes expected utility over consumption. Let $0 \leq x_1 < x_2 < \cdots < x_N$ denote the N outcomes of the prospect under consideration, and p_i is the known probability of outcome i, with $\sum_{i=1}^{N} p_i = 1$. Let $W_0 \geq 0$ denote the initial wealth of the decision maker. As this section aims to explore alternative explanations instead of probability weighting, we assume that the decision maker uses the objective probabilities $(p_1, p_2, \ldots p_N)$ when forming expectations. Preferences are described by a CRRA utility function U:

$$EU = \sum_{i=1}^{N} p_i \cdot U(x_i + W_0),$$

where

$$U(x) = \begin{cases} \dfrac{x^{1-\gamma}}{1-\gamma} & \text{if } \gamma \neq 1 \\ \ln(x) & \text{if } \gamma = 1 \end{cases},$$

We would like to explain the risk premiums for the probability weighting questions PW shown in Panel B of Table I, which have the following parameters: $N = 2$, $x_1 = 6$, $x_2 = 42$, and $p_2 = 1 - p_1$ which is the chance of winning \$42 (varying from 5% to 95% for the six questions).

Our first observation is that respondents who integrate the small lottery payoffs with some positive amount of wealth W_0, for example \$1,000 or more, will be close to risk neutral on all probability weighting question. Figure E.1 illustrates the model risk premiums for the case of W_0 = \$1,000 and three levels of risk aversion (γ = 1, 2, 4), compared to the actual average risk premiums in our ALP data. The model risk premiums are close to zero (risk neutral) as the payoffs are negligible when integrated with the \$1,000 initial wealth.

Next, we consider respondents who narrowly frame the lotteries, meaning that they do not integrate payoffs with their wealth. In the model above, this corresponds to W_0 = 0. We first note that only relative risk aversion levels with $\gamma \leq 1$ are feasible when W_0 = 0, as otherwise utility is not defined for our risk aversion questions where one of the payoffs is 0. However, practically this does not limit the model, as narrow framing greatly magnifies the impact of risk aversion. For example, with W_0 = 0 and relative risk aversion of only γ = 0.5, the average risk premium for the four risk aversion questions (see Table 1, Panel A) is 144.7%, while at γ = 0.2 the average risk premium is 21.5% (average is 16% in the ALP data).

Figure E.2 shows the risk premiums for the probability weighting questions with narrow framing and γ = 0.2, 0.5, 0.8. The risk premiums are all positive and have an inverse U-shaped pattern, driven by the variance of the binary lottery with winning chance p, which is $p(1-p)$. Hence, the risk premium converges to zero as p approaches to 0 or 1 (variance becomes zero), and the maximum occurs for intermediate probabilities between 20% and 40%. The risk premiums only become negative if the decision maker is risk seeking (γ < 0). Therefore, narrow framing in an expected utility framework cannot *simultaneously* generate risk-seeking for small probabilities and large risk aversion for high probabilities. In sum, it cannot explain the actual pattern of risk premiums for the probability weighting question in the ALP data.

Figure E.1: Risk Premiums for Probability Weighting Questions with Broad Framing and Initial Wealth of $1,000

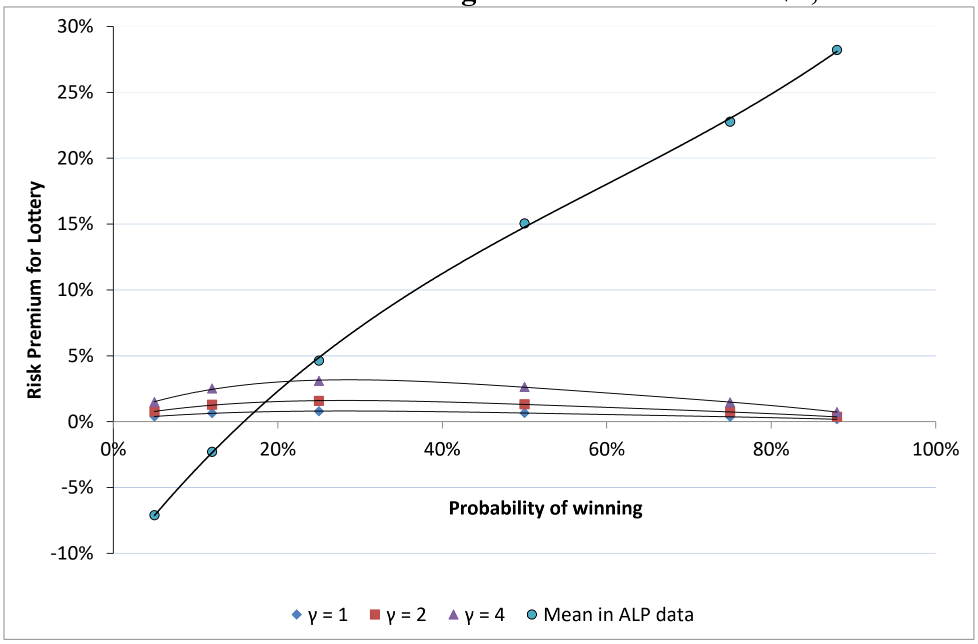
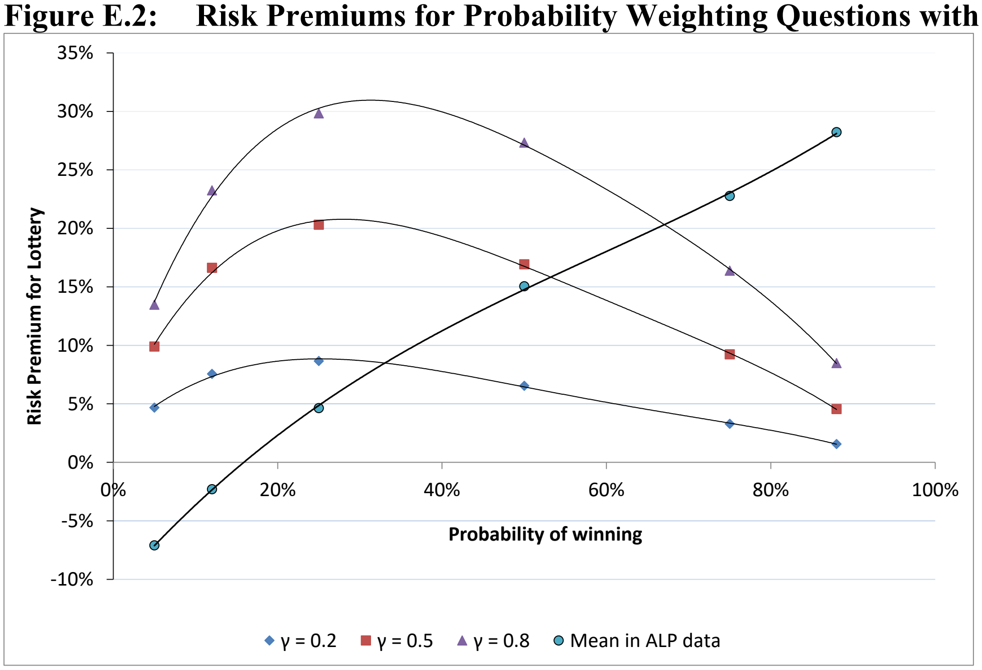


Figure E.2: Risk Premiums for Probability Weighting Questions with Narrow Framing



E.2. Narrow Framing with a Reference Point and Loss Aversion

We now consider a decision maker who frames narrowly and maximizes the value function of prospect theory with reference point θ and loss aversion parameter $\lambda > 1$:

$$EV_{LA} = \sum_{i=1}^{N} p_i \cdot v(x_i),$$

where

$$v(x) = \begin{cases} (x-\theta)^{1-\gamma_1}, & \text{if } x \geq \theta \\ -\lambda(\theta - x)^{1-\gamma_2}, & \text{if } x < \theta \end{cases}$$

with $\gamma_1, \gamma_2 \leq 1$.[2]

Again, our aim is to explain the risk premiums for the probability weighting questions *PW* shown in Panel B of Table I, where $N = 2$, $x_1 = 6$, $x_2 = 42$ and $p_2 = 1 - p_1$ is the chance of winning \$42 (varying from 5% to 95% for the six questions). We first consider the special case where the decision maker's reference point is equal to zero ($\theta = 0$). As the probability weighting questions only have two positive payoffs, which are treated as gains, the value function reduces to a power utility function: $v(x) = x^{1-\gamma_1}$, and we are back to the case of expected utility in Figure E.1 and E.2. Hence, with a reference point of zero, the prospect theory model cannot explain pattern of risk premiums for the probability weighting questions.

Next, we assume the decision maker's reference point is equal to the expected value of the lottery ($\theta = p \cdot 42 + (1-p) \cdot 6$). In our ALP survey questions, the expected value of the lottery is the first sure amount offered to the decision maker (i.e., the sure amount offered in Option B). It is therefore natural to assume that this expected value becomes the reference point. In this case, the small price of \$6 is coded as a loss and loss aversion affects the decision.

For the special case of piece-wise linear curvature ($\gamma_1 = \gamma_2 = 0$) and θ equal to the expected value, we can derive the following analytical expression for the lottery risk premiums:

$$Risk\ premium = p \cdot \left(\frac{42-\theta}{\theta}\right) \cdot \left(\frac{\lambda - 1}{\lambda}\right)$$

where p (=p_2) is the probability of winning \$42, and the reference point $\theta = p \cdot 42 + (1-p) \cdot 6$ is equal to the expected value of the lottery.

The formula shows that a loss averse decision maker ($\lambda > 1$) has positive risk premiums for all probability weighting questions. The largest risk premium occurs at $p = 27.4\%$, irrespective of the level of loss aversion ($\lambda > 1$). (See Figure E.3 for an illustration of the risk premiums for $\lambda = 0.5, 2, 3$.) Similar to expected utility case, with loss aversion ($\lambda > 1$) the pattern of risk premiums is inverse U-shaped, as the variance of the lottery payoff ($p \cdot (1-p)$) is largest for intermediate probabilities. Only if the decision maker is loss seeking ($0 \leq \lambda < 1$) do all the risk premiums become negative, with the most negative risk premium at $p = 27.4\%$. Accordingly, this model

[2] Relative risk aversion is limited to relatively small values ($\gamma_1, \gamma_2 \leq 1$) in the original prospect theory model of Kahneman and Tversky (1979) above, as otherwise the function becomes discontinuous at the reference point ($x = \theta$). In practice this does not limit the model's applications, as the loss aversion parameter (λ) can generate strong first-order risk aversion and high risk premiums for mixed prospects with both gains and losses.

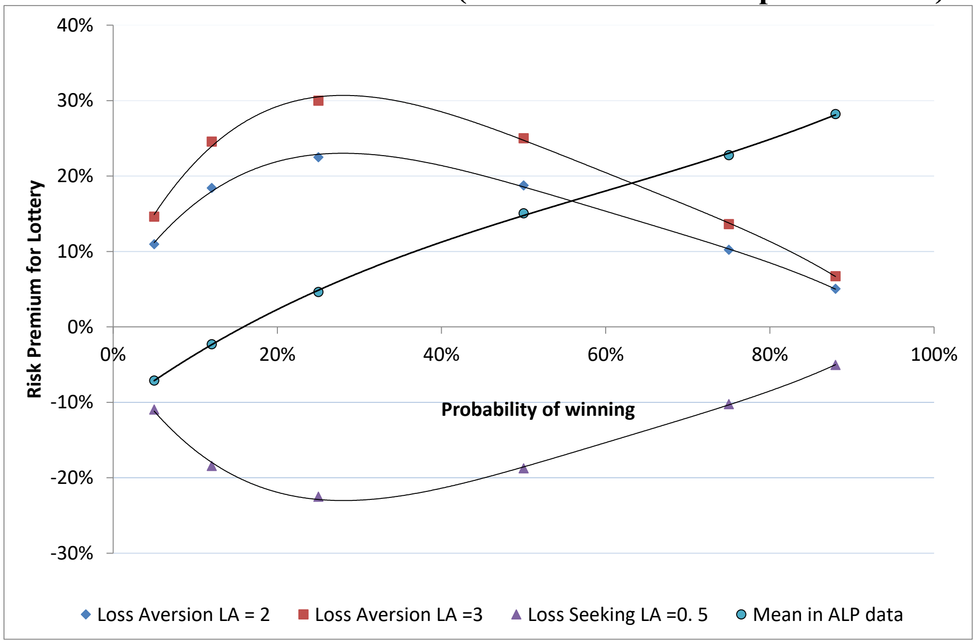
cannot generate simultaneous risk-seeking for small probabilities and relatively large risk aversion for high probabilities, which is the pattern seen in the ALP data.

Based on intuition, some readers may anticipate that narrow framing and loss aversion would give rise to relatively large risk premiums for negatively skewed high probability bets (e.g., at $p = 0.88$). Yet this is not the case, as the expected value and the variance also differ across the six lotteries ($p = 0.05, 0.12, 0.5, 0.75, 0.88$), and these two parameters have a larger impact on the attractiveness of the lotteries than the skewness. For example, the variance ($p \cdot (1 - p)$) and the risk premiums for the lotteries converge to zero when $p \rightarrow 0\%$ and $p \rightarrow 100\%$, regardless of the high skewness in the limit. The risk premium is at its maximum at moderately positive probabilities, where the ratio between risk (variance) and expected payoffs is the highest.

Additional numerical trials show that the model above with a prospect theory value function and a reference point equal to the expected value of the lottery can only generate the observed pattern of risk premiums in the ALP data in two ways. First, it can occur if the decision maker is risk averse over losses ($\gamma_2 > 1$) and *risk seeking* over gains ($\gamma_1 > 1$). In this case, the utility function itself is S-shaped and skewness seeking, which is simply a different way to model probability weighting, but not directly related to narrow framing or loss aversion. Second, it can occur if the decision maker is risk averse over losses ($\gamma_2 > 1$) and *loss seeking* ($\lambda < 1$). Further, the stronger the loss seeking (the further λ below 1), the better the model will fit the data. A model with loss seeking is clearly at odds with the empirical evidence so it does not provide a plausible alternative explanation.

Finally, suppose a decision maker already displays some (small) amount of probability weighting. Can an increase in the loss aversion parameter amplify the probability weighting patterns in the risk premiums? The answer is no. An increase in loss aversion will increase the downside effect of positively skewed low probability bets, reducing their attractiveness and offsetting the effect of probability weighting. For high probability bets, the marginal effect of increased loss aversion is weaker, as decision makers with inverse-S probability weighting already require a relatively high risk premium to take these bets. All in all, an increase in loss aversion leads to a *less* pronounced probability weighting pattern in the risk premiums, rather than amplifying it. In sum, loss aversion cannot explain the actual pattern of risk premiums for the probability weighting question in the ALP data.

Figure E.3: Risk Premiums for Probability Weighting Questions with Narrow Framing and Loss Aversion (Reference Point is Expected Value)



E.3. Different Levels of Narrow Framing with Loss Aversion

In this section we consider the narrow framing model of Barberis and Huang (2009). In this model the decision maker can display different levels of narrow framing, modeled with a separate parameter. Our purpose is to see if variations in narrow framing can give rise to the *inverse-S* pattern in the risk premiums for our probability weighting questions.

In this model the decision maker evaluates the distribution of his overall wealth, including the payoff of the lottery, given by $W = [W_0 + x_1, \dots, W_0 + x_N]'$, with expected utility, $E[U(W)]$. In addition, the investor narrowly frames the gains and losses of the lottery $G = [x_1 - \theta, \dots, x_N - \theta]'$ and evaluates them with the value function: $V(G)$. The prospect theory function V includes both loss aversion and narrow framing. The narrow framing parameter $b_0 \geq 0$ determines the importance of the narrowly framed lottery gains and losses in the overall objective function H.

$$H = U^{-1}(E[U(W)]) + b_0[V(X - \iota\theta)]$$

where

$$EU = \sum_{i=1}^{N} p_i \cdot U(x_i + W_0),$$

$$V(G) = \sum_{j=-M}^{j=-1} v(g_j) + \sum_{j=0}^{K} v(g_j)$$

and

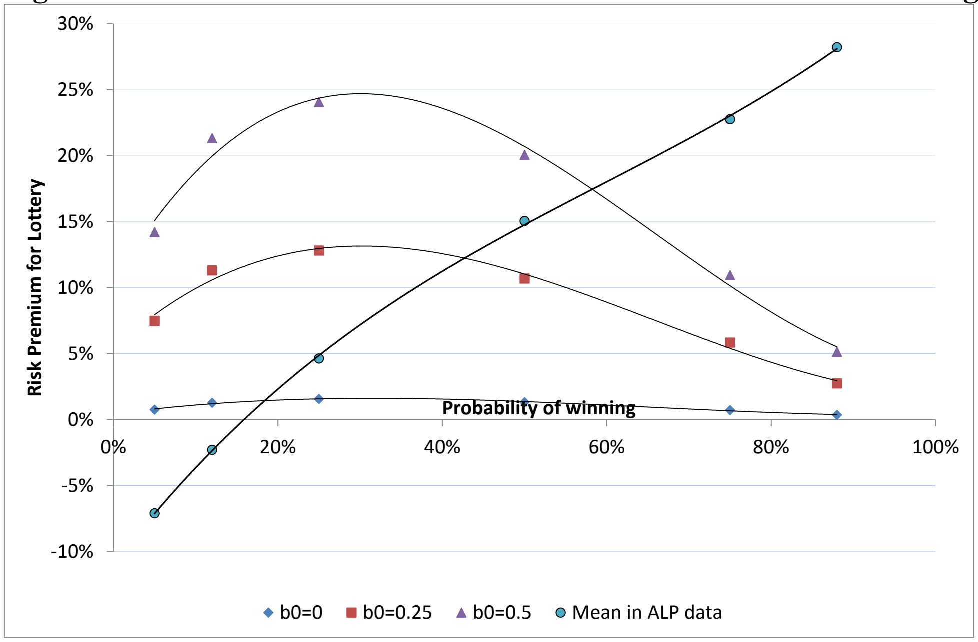
$$v(x) = \begin{cases} x & x \geq 0 \\ \lambda x & x < 0 \end{cases},$$

where $G = X - \iota\theta = [x_1 - \theta, \dots, x_N - \theta]'$ denotes a vector of losses and gains on the prospect (the lottery), relative to the reference point $\theta g_{m,K}$, with corresponding state probabilities p_j, for $j = -M, \dots, 0 \dots, K$. To simplify the model and limit the number of parameters, we make the following assumptions: the value function v is piece-wise linear.

The decision maker frames narrowly and is loss averse. The loss aversion parameter is λ = 2. As before, the reference point equals the expected value of the lottery ($\theta = p \cdot 42 + (1-p) \cdot 6$), which is also the first certainty equivalent shown to the decision maker and therefore a natural anchor. Relative risk aversion for the expected utility part is γ = 2, and initial wealth is W_0 = $1,000.

Figure E.4 shows the shows the risk premiums for the probability weighting questions when the narrow framing parameter is b_0 = 0, 0.25 and 0.5. Without narrow framing (b_0 = 0), all the risk premiums are close to zero, as the lottery payoffs are negligible when integrated with the initial wealth of $1,000. With narrow framing (b_0 = 0.25, 0.5), the risk premiums become large, but they do not resemble the actual pattern in the data, with *Inverse-S* measures of -12.3% and -23.5% (versus 70.8% on average in the ALP data). Narrow framing does not generate simultaneous risk-seeking for small probabilities and high risk aversion for large probabilities, similar to what we found in previous sections for other utility specifications.

Figure E.4: Risk Premiums with Different Levels of Narrow Framing (b_0)



Online Appendix F: Additional Robustness Tests

Table F.1: Alternative Probability Weighting Measures and OLS Regression

This table reports regression results in which the dependent variable is *Fraction of Equity in Individual Stocks*. In column (1), the key independent variable is *Inverse-S Rank*, which is a rank variable of *Inverse-S* ranging from 0 to 1. In column (2), the key independent variable is *Above Median Inverse-S Dummy*, which equals one if *Inverse-S* is above the median. In column (3), the key independent variable is *Inverse-S Dummy* which equals one if *Inverse-S* is above 25%. In column (4), the key independent variable is *Inverse-S* $(PW_{88\%} + PW_{75\%}) - (PW_{25\%} + PW_{12\%})$ standardized to have a mean of zero and a standard deviation of one. In column (5), the key independent variable is *Inverse-S* $PW_{88\%} - PW_{12\%}$ standardized to have a mean of zero and a standard deviation of one. In column (1) to (5), we estimate Tobit models with bounds of 0 and 1 on the equity fraction, while in column (6) we report OLS regression results as a robustness check. All models include a constant, missing data dummies, and controls for age, age-squared divided by one thousand, female, married, white, Hispanic, number of household members, employment status, education, (ln) family income, (ln) financial wealth, numeracy, financial literacy, trust, utility curvature, and optimism. All results use ALP survey weights. The symbols *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Inverse-S Rank	0.444 **					
	(2.477)					
Above Median Inverse-S Dummy		0.235 **				
		(2.278)				
Inverse-S Dummy			0.258 **			
			(2.428)			
Inverse-S$_{(PW88\% + PW75\%) - (PW25\% + PW12\%)}$				0.125 **		
				(2.356)		
Inverse-S$_{(PW88\% - PW12\%)}$					0.125 **	
					(2.449)	
Inverse-S						0.054 **
						(2.312)
Full Controls	Yes	Yes	Yes	Yes	Yes	Yes
Model	Tobit	Tobit	Tobit	Tobit	Tobit	OLS
Observations	741	741	741	741	741	741
Adjusted R^2	0.050	0.048	0.049	0.050	0.050	0.076

Table F.2: Measurement Error

This table reports regression results in which the dependent variable is *Fraction of Equity in Individual Stocks*. Column (1) excludes respondents who made more than 3 errors on the consistency check questions. Column (2) excludes respondents who spend less than 90 seconds on the probability weighting questions. All models include a constant, missing data dummies, and controls for age, age-squared divided by one thousand, female, married, white, Hispanic, number of household members, employment status, education, (ln) family income, (ln) financial wealth, numeracy, financial literacy, trust, utility curvature, and optimism. All results use ALP survey weights. The symbols *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

	Exclude Respondents More Than Three Errors (1)	Exclude Respondents Less than 90 Seconds (2)
Inverse-S	0.155 **	0.120 **
	(2.532)	(2.241)
Control Variables	Yes	Yes
Observations	674	724
Adjusted R^2	0.053	0.054

Table F.3: Additional Controls

This table reports 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 home ownership data. The home ownership dummy is included as a control variable in column (2). The survey module used to generate the home ownership measure was fielded to a subset of the ALP subjects in July 2018 and we can only match these measures to 221 of our subjects. In columns (3) and (4), the sample is restricted to include only those observations for which we have a measure of the amount of pension assets invested in equity. The (ln) pension assets in equity variable is included as a control variable in column (4). All models include a constant, missing data dummies, and controls for age, age-squared divided by one thousand, female, married, white, Hispanic, number of household members, employment status, education, (ln) family income, (ln) financial wealth, numeracy, financial literacy, trust, utility curvature, and optimism. All results use ALP survey weights. The symbols *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

	Home Owner		ln(Pension Assets)	
	(1)	(2)	(3)	(4)
Inverse-S	0.184 **	0.175 **	0.134 ***	0.127 **
	(2.567)	(2.414)	(2.655)	(2.582)
Additional Control	No	Yes	No	Yes
Control Variables	Yes	Yes	Yes	Yes
Observations	221	221	620	620
Adjusted R^2	0.097	0.098	0.059	0.066

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