Web Appendix of
"Ambiguity Attitudes in a Large Representative Sample"; Not for publication

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Web Appendix A. Survey details

WA.1. Representative sampling of LISS

To ensure that its sample is representative of the Dutch population, LISS uses careful procedures to randomly select households from the population register compiled by Statistics Netherlands.[1] Selected households are initially contacted by letter and then by telephone. LISS makes up to 15 attempts to contact a household by phone. If telephone recruitment fails, a LISS representative visits the household. If, after eight in-person visits LISS is unable to establish contact, a new household is selected. To limit the possibility of sample selection bias, recruited households are provided with free computers and internet access if necessary. To encourage participation and retention within the panel, subjects are paid for each survey they complete. Knoef and De Vos (2009) show that the LISS panel is generally representative of the Dutch population. See http://www.lissdata.nl/lissdata/ for more information.

In January 2010 LISS fielded a survey module designed by the authors. From the full LISS panel, CentERdata randomly selected 2,491 individuals to participate in this survey, and 1,935 responded (77.7%). Of the 939 subjects in the real incentives group, we exclude 164 because of missing income or financial asset data, 61 for answering "Indifferent" to *all* ambiguity questions including the two check questions[2], 38 for spending three seconds or less on each set of questions, and 10 for missing other variables. This leaves a sample of 666 subjects. We exclude the subjects who answer indifferent to all of the ambiguity questions or who spend three seconds or less on each of the question sets on the grounds that these subjects likely did not expend effort on their choices.

[1] Participation in the population register is mandatory for all residents of The Netherlands.

[2] Indifferent is not the correct response to the two check questions, suggesting that these subjects are selecting the indifferent option regardless of what is being asked.

WA.2. Control variables from the core LISS modules

Because prior waves of the LISS panel measured only the aggregate value of financial investments (including bonds), our survey module included additional questions to measure stock market participation (summarized in Table 1). Our stock market participation question asked if the subject owned stocks or equity mutual funds as of 31st December 2009.[3] In our sample the stock market participation rate is 20.4%, close to the 23.8% estimate reported by van Rooij, Lusardi and Alessie (2011), using a different survey of Dutch households in 2005.[4]

Following Alessie, Hochguertel, and van Soest (2002), we use a series of indicator variables to control for education. Total financial assets are defined as the aggregate household value of: bank accounts, investments, insurance, loans made to others, and other financial assets. Gross family income refers to aggregate family income per month. The variables Total Financial Assets and Private Business Owner are imported from the 2010 LISS Asset Survey. If the subjects do not respond to the 2010 LISS Asset Survey we use data from the 2008 LISS Asset Survey.

WA.3. Trust

Guiso, Sapienza, and Zingales (2008) show that trust affects stock market participation and argue that although trust is distinct from ambiguity aversion, it may be related. To control for trust, in some of our results we include subjects' responses to the trust measurement question used by Guiso et al. "Generally speaking would you say that most people can be trusted or that you have to be very careful in dealing with people?" Responses are measured on a 10 point scale with low scores indicating low levels of trust.[5] This question was also used, and validated, in the well-known World Values Survey. It is imported from the 2009 LISS Personality survey, or from the 2008 or 2010 survey if the response is missing in 2009.

[3] We also included a question to measure the value of stock market investments. However, approximately half of the stock market participants in the study did not answer this question.

[4] A cross-country comparison in Guiso, Sapienza and Zingales (2008) shows that stock market participation in the Netherlands is relatively low compared to the U.S. (48.9%) and the U.K. (31.5%), but similar to other European countries like France and Germany.

[5] This was our only modification relative to Guiso, Sapienza, and Zingales (2008): they used a dummy variable for trust rather than a 10 point scale. Using their measure does not change our results.

WA.4. Financial literacy

van Rooij, Lusardi, and Alessie (2011) show that financial literacy is related to stock market participation. In our survey module we include three questions from their study: 1) the effect of compounding; 2) the asset class that normally has the highest returns; and 3) diversification. The three financial literacy questions are:

1. Suppose you had €100 in a savings account and the interest rate is 20% per year and you never withdraw money or interest payments. After 5 years, how much would you have in this account in total?
    a. More than €200
    b. Exactly €200
    c. Less than €200
    d. Do not know
    e. Refuse to answer

2. Considering a long time period (for example 10 or 20 years) which asset normally gives the highest return?
    a. Savings accounts
    b. Bonds
    c. Stocks
    d. Do not know
    e. Refuse to answer

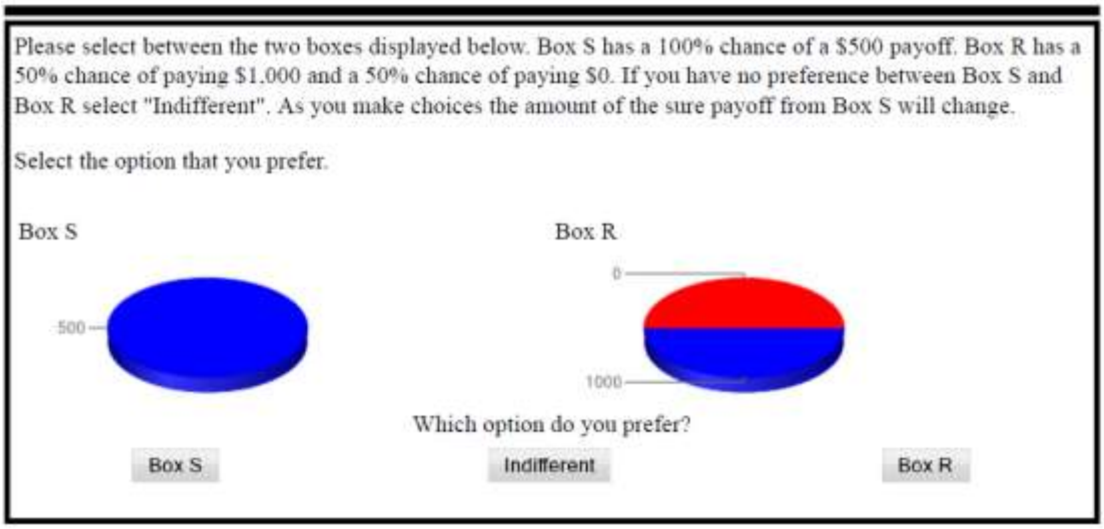
3. When an investor spreads his money among different assets, does the risk of losing money:
    a. Increase
    b. Decrease
    c. Remain the same
    d. Do not know
    e. Refuse to answer

Question 2 asked which asset normally gives the highest return over a long time period. We used the response “do not know” as a proxy for perceived incompetence about investments. As explained in the main text, subjects who answer incorrectly are probably more incompetent, but probably do not perceive themselves this way.

As in van Rooij et al. (2011) to measure financial literacy we extract a factor from the responses to the questions. For each question we create two variables: the first indicates if the response was correct and the second indicates if the subject responded “Do not know”. Our measure of financial literacy is the first principle component extracted from these four variables based on Question 1 and Question 3. We exclude Question 2 because we use it separately as a proxy for perceived incompetence about investments and we want to avoid multicollinearity between this variable and the financial literacy measure.

WA.5. Risk aversion

To elicit risk aversion we include two sets of adaptivve questions asking for hypothetical choices between a sure gain and a risky prospect. We chose large prizes, which cannot be implemented with real incentives, because large prizes are most relevant for the decisions considered here. Further, for small prizes risk preferences are close to risk neutral, with deviations mostly due to noise and biases rather than to genuine risk attitude. For example, the initial choice of the first set is:



If the subject chooses Urn S, then the payoff of this urn is reduced to €250. If the subject then chooses Urn R, then the payoff of Urn S is increased to €750. This process continues for six rounds or until the subject chooses “Indifferent.” The second set of risk aversion questions is similar, but the amounts are substantially larger (€18,000 prize for the risky prospect vs. €10,000 with certainty). Using the responses to these questions, we estimate each subject’s risk aversion parameter by fitting a power (CRRA) utility function.[6]

[6] We calculated CRRA using expected utility, but did so only to obtain an index of risk aversion that is familiar to most readers, and not as a descriptive commitment to expected utility. On our domain of prospects with only one nonzero outcome, risk aversion through utility curvature in expected utility is identical to risk aversion through probability weighting in prospect theory (Wakker 2010 §5.1). Given that we only determine which subjects are risk averse and risk seeking, and which are more so, our assumption entails no restriction. As is most common, we let outcome 0 refer to the status quo, and do not add an extra parameter or estimations of initial wealth. The power coefficient is bounded below by 0 (as payoffs can be 0, and utility would not be defined otherwise). For symmetry reasons, we set the upper bound on the power coefficient equal to 2. Many other studies control for risk aversion using subject’s choices between three statements: “Take substantial financial risks expecting to earn substantial returns;” “Take average financial risks expecting to earn average returns;” “Not willing to take any financial risks.” We do not use this approach because the responses are likely due to subjects’ reflections on their behavior rather than actual risk-aversion (i.e., the cognitive dissonance effect described by Bertrand and Mullainathan 2001).

WA.6. Regression results with all control variables

Table WA.1
Ambiguity attitudes and stock market participation

This table corresponds to Table 5.1 of the main paper, but includes the coefficients for the control variables. This table shows logit regressions with stock market participation as the dependent variable. The ambiguity attitude variables are defined in Table 3: Index *b*: Eq. (11) (ambiguity aversion); index *a*: Eq. (10) (a-insensitivity); $AA_{0.1}$: Eq. (6); $AA_{0.5}$: Eq. (7); $AA_{0.9}$: Eq. (8). The other independent variables are defined in Table 1. The regressions include constants but these are not displayed for brevity's sake. The t-statistics are calculated using standard errors clustered by household.

	(1)	(2)	(3)	(4)
Index *b* (Amb. Aversion)	0.009	0.011		
	[0.55]	[0.65]		
Index *a* (A-insensitivity)	-0.033**	-0.028*		
	[2.16]	[1.82]		
$AA_{0.1}$			0.039**	0.036*
			[2.10]	[1.79]
$AA_{0.5}$			-0.015	-0.012
			[0.80]	[0.59]
$AA_{0.9}$			-0.018	-0.014
			[1.12]	[0.86]
Risk Aversion		-0.002		-0.002
		[0.13]		[0.12]
Trust		0.026*		0.026*
		[1.83]		[1.78]
Financial Literacy		0.077***		0.077***
		[3.62]		[3.62]
Total Financial Assets	0.161***	0.145***	0.162***	0.145***
	[5.68]	[5.09]	[5.73]	[5.10]
Total Fin. Assets Squ.	-0.096***	-0.086***	-0.097***	-0.087***
	[3.26]	[2.97]	[3.32]	[3.01]
Income	0.092*	0.07	0.092*	0.070
	[1.81]	[1.44]	[1.78]	[1.43]
Income Squared	-0.043	-0.031	-0.042	-0.031
	[0.95]	[0.74]	[0.93]	[0.72]
Age	0.098	0.099	0.098	0.098
	[1.23]	[1.21]	[1.23]	[1.19]
Age Squared	-0.071	-0.074	-0.070	-0.072
	[0.90]	[0.91]	[0.89]	[0.88]
Female	-0.113***	-0.083***	-0.11***	-0.081***
	[4.17]	[3.06]	[4.05]	[2.95]
Household Size	-0.014	-0.013	-0.013	-0.013
	[0.84]	[0.78]	[0.81]	[0.77]
Live with Partner	-0.032	-0.031	-0.034	-0.031
	[0.73]	[0.69]	[0.75]	[0.70]
Education (joint p-value)	0.218	0.521	0.222	0.553
Pseudo - R^2	0.194	0.222	0.196	0.223
No. of Observations	666	666	666	666

Web Appendix B. Pilot experiment

To test the validity of our procedure for eliciting ambiguity attitudes, we conducted a pilot experiment prior to the survey.

Stimuli. For details of the stimuli, see §2 of the main paper and Appendix A.

Subjects. The subjects were 85 students taking a fourth year course in computer applications for finance, 69.4% were male. The experiment was conducted on March 23, 2009 at Michigan State University. The students had all taken prerequisite courses in statistics, calculus, finance, and economics. Table WB.1 summarizes the subjects' demographic information.

Procedure. At the beginning of the class, the regular professor introduced the experiment. Subjects were read instructions, advised that participation was voluntary, and asked to sign a consent form. All students agreed to participate. They were randomly assigned to one of two surveys: one in which the initial known probabilities (of Urn K) were fixed, and the other in which the initial known probabilities were random. The two subject groups were demographically similar.

Incentives. Following the experiment, three students were drawn at random to play one of their choices for a chance to win $20 each.

Results. Most students completed the experiment in five to ten minutes. Table WB.2 summarizes the subjects' matching probabilities. Panel A shows summary statistics of all matching probabilities. Panels B and C show responses from the fixed and random initial probability versions, respectively. The difference in responses to m(0.1) and m(0.9) are not significant between the two groups. For m(0.5), the responses of the random initial probability group are higher.

In all panels of Table WB.2, we report t-statistics below the means and z-scores from Wilcoxon signed ranks test below the medians. In all three groups, $m(0.1) > 0.1$. As in the survey, m(0.5) was asked first in the experiment, but is reported here second for the sake of convenient presentation. In all three groups, $m(0.5) < 0.5$ ($p < 0.0001$) and $m(0.9) < 0.9$ ($p < 0.0001$). The degree of ambiguity aversion is very high for m(0.9). All these results agree with the findings of the survey.

Consistency. As in the survey, we tested consistency with two additional questions, where we repeated one iteration for each question. These were chosen uniquely for each subject. Check Question 1 had inconsistencies of 11.8% in the full group, 11.6% in the fixed probability group, and 11.9% in the random probability group. Check Question 2 had inconsistencies of 17.6%, 23.3%, and 11.9% for these three groups. A chi-square test rejects random choice ($p < 0.001$).

Conclusion. The stimuli worked well, were clear, and took the students little time or effort. Inconsistencies of 25% are common in experiments with students for nontrivial choice questions (Harless and Camerer 1994 p. 1263). Hence, the consistency in our data is fine. Whereas one of the observations of fixed versus variable initial probabilities was significantly different, the difference was not large. Hence, we decided to use only fixed initial probabilities for the LISS survey. Our results regarding ambiguity attitudes confirm usual empirical findings in the literature such as a-insensitivity with ambiguity seeking rather than ambiguity aversion for the low likelihood event. These results confirmed that our stimuli are suited for the general public of the LISS sample.

Table WB.1
Subjects' demographic information

	Full Sample	Fixed Initial Probability	Random Initial Probability
Age	21.7	21.6	21.8
Male	69.4%	67.4	71.4
Finance Major	91.7%	90.6	92.9
Accounting Major	5.9%	4.7	7.1
Economics Major	2.4%	4.7	0.0
No. of Observations	85	43	42

Table WB.2
Matching probabilities

Panel A: All Subjects			
	Average	Standard Deviation	Median
m(0.1) (~ 1 of 10 colors)	0.17 ***	0.16	0.10 ***
	[4.34]		[3.24]
m(0.5) (~ 1 of 2 colors)	0.34 ***	0.17	0.39 ***
	[8.24]		[7.01]
m(0.9) (~ 9 of 10 colors)	0.56 ***	0.23	0.51 ***
	[18.70]		[7.98]
Panel B: Fixed Initial Probability			
	Average	Standard Deviation	Median
m(0.1) (~ 1 of 10 colors)	0.14 **	0.12	0.10
	[2.24]		[0.86]
m(0.5) (~ 1 of 2 colors)	0.33 ***	0.16	0.37 ***
	[6.86]		[5.23]
m(0.9) (~ 9 of 10 colors)	0.57 ***	0.24	0.53 ***
	[12.53]		[5.70]
Panel C: Random Initial Probability			
	Average	Standard Deviation	Median
m(0.1) (~ 1 of 10 colors)	0.21 ***	0.18	0.14 ***
	[3.81]		[3.46]
m(0.5) (~ 1 of 2 colors)	0.36 ***	0.18	0.40 ***
	[4.89]		[4.76]
m(0.9) (~ 9 of 10 colors)	0.56 ***	0.21	0.51 ***
	[13.95]		[5.61]

Web Appendix C. Ambiguity Attitudes and Consistency

Table WC.1 (which corresponds to Table 2 in §4) shows the ambiguity attitudes revealed by first round choices for the subsample of subjects who did not make errors on the check questions. The pattern is similar to that in the full sample: the modal responses show ambiguity seeking for low likelihoods ($p = 0.1$) and ambiguity aversion for moderate and high likelihoods ($p = 0.5$; $p = 0.9$).

Table WC.2 (which corresponds to Table 3 in §5) shows the matching probabilities and ambiguity attitude indexes for the subsample of subjects who did not make errors on the check questions. The overall pattern of responses is similar to that in the full sample. The primary difference is that the standard deviations are lower in Table WC.2 than in Table 3, suggesting greater measurement error (although it could also capture more heterogeneity of ambiguity attitudes).

Table WC.1
Ambiguity attitudes revealed by first round choices:
Subjects without errors on the check questions

The table is similar to Table 2, but with the sample limited to 330 respondents who did not make mistakes on the two ambiguity check questions. The table shows the frequency distribution of subjects with ambiguity averse, ambiguity seeking, and ambiguity neutral attitudes at a-neutral probabilities p of 0.10, 0.50, and 0.90.

A-neutral prob. p	0.10	0.50	0.90
Ambiguity Averse	25.5%	69.1	50.0
Ambiguity Seeking	52.1%	20.6	34.2
Ambiguity Neutral	22.4%	10.3	15.8

Table WC.2
Statistics of the ambiguity attitude indexes:
Subjects without errors on the check questions

The table is similar to Table 3, but with the sample limited to 330 respondents who did not make mistakes on the two ambiguity check questions. Rows 1-3 show the matching probabilities for the three ambiguity questions (m(0.1), m(0.5), m(0.9)). Rows 4-6 show the three even-specific indexes of ambiguity attitudes: $AA_{0.1}$, $AA_{0.5}$ and $AA_{0.9}$. The last two rows show the two global indexes: Index *b* (ambiguity aversion) and Index *a* (a-insensitivity).

Variable	Mean	Median	Std. Dev.	Min.	Max.
Matching Probability m(0.1)	0.21	0.11	0.21	0.01	0.99
Matching Probability m(0.5)	0.42	0.44	0.18	0.02	0.98
Matching Probability m(0.9)	0.76	0.89	0.26	0.01	0.99
$AA_{0.1}$	-0.11	-0.01	0.21	-0.89	0.09
$AA_{0.5}$	0.08	0.06	0.18	-0.48	0.48
$AA_{0.9}$	0.14	0.01	0.26	-0.09	0.89
Index *b* (Ambiguity Aversion)	0.07	0.05	0.31	-0.97	0.97
Index *a* (A-insensitivity)	0.32	0.22	0.36	-0.22	2.21

Web Appendix D. Simulations using prospect theory

WD.1. A generalization of the source method to prospect theory for two outcomes

This section presents a generalization of the source method of Abdellaoui et al. (2011) to prospect theory. Given that we model the status quo as 0, *gains* are positive amounts $\alpha > 0$ and *losses* are negative amounts $\beta < 0$. To adapt the source method to prospect theory, we use functions w^+_{So}, w^+, and m^+_{So} for gains and possibly different functions w^-_{So}, w^-, and m^-_{So} for losses, with

$$w^+_{So}(p) = w^+\big(m^+_{So}(p)\big) \text{ and } w^-_{So}(p) = w^-\big(m^-_{So}(p)\big). \qquad \text{(WD.1.1)}$$

Prospects are now evaluated as follows:

$$\text{For } \alpha \geq \beta \geq 0,\ \ \alpha_E\beta \mapsto w^+\big(m^+_{So}(P(E))\big)U(\alpha) + \Big(1-w^+\big(m^+_{So}(P(E))\big)\Big)U(\beta); \qquad \text{(WD.1.2)}$$

$$\text{For } \alpha \geq 0 \geq \beta,\ \ \alpha_E\beta \mapsto w^+\big(m^+_{So}(P(E))\big)U(\alpha) + w^-\big(m^-_{So}(P(E))\big)U(\beta); \qquad \text{(WD.1.3)}$$

$$\text{For } 0 \geq \beta \geq \alpha,\ \ \alpha_E\beta \mapsto w^-\big(m^-_{So}(P(E))\big)U(\alpha) + \Big(1-w^-\big(m^-_{So}(P(E))\big)\Big)U(\beta). \qquad \text{(WD.1.4)}$$

For gains (Eq. WD.1.2), the theory agrees with Eqs. (12) and (13). For losses (Eq. WD.1.4), the theory uses a reflected form. Now the weighting is first applied to the worst, and not to the best, outcome.

One of the strongest empirical findings in the literature is loss aversion. This means that people are especially averse to losses, and weight them more heavily than gains. In other words, U is steeper for losses than for gains. Many empirical studies have demonstrated that U has a kink at 0, with the slope of U often twice as steep below the kink as above. We model loss aversion by defining a *basic utility function* u with $u(0) = 0$, a *loss aversion parameter* $\lambda > 0$, and setting

$$U(\alpha) = u(\alpha) \text{ for } \alpha \geq 0$$
$$U(\alpha) = \lambda u(\alpha) \text{ for } \alpha < 0\,. \qquad \text{(WD.1.5)}$$

Here u captures the intrinsic value of outcomes, and satisfies usual regularity conditions such as smoothness and differentiability at $\alpha = 0$. *Loss aversion* holds if $\lambda > 1$, generating a kink of U at $\alpha = 0$. Tversky and Kahneman (1992) found $\lambda = 2.25$, suggesting that losses are weighted more than twice as much as gains in decisions. U is called *utility* or *overall utility*. The following scaling is common and natural if u is approximately linear on the small interval [–1,1] (Wakker 2010 §8.8):

$$u(1) = 1,\ u(-1) = -1,\ U(1) = 1, \text{ implying } \lambda = -U(-1). \qquad \text{(WD.1.6)}$$

WD.2. Simulations supporting our comparative statics of optimal portfolio allocations to equity under prospect theory, and its dependence on ambiguity attitudes

This section shows that reference dependent prospect theory can explain our findings. Although traditional theories analyze outcomes in terms of final wealth, many studies have demonstrated that people evaluate potential outcomes as gains or losses relative to a reference point, usually the status quo, and that people have a special aversion to losses. Because stock market participation involves the risk of losses, prospect theory and attitudes towards losses are relevant to our study (Benartzi and Thaler 1995).

In our experiment in the LISS panel, we could offer real rewards only for ambiguous gains, and not for ambiguous losses. As such, we measured ambiguity attitudes for gains and not for losses. A crucial issue for interpreting our results, then, is the relation between ambiguity attitudes for gains and for losses. In a prospect theory setting, the hypothesis of reflection means that attitudes towards losses are the mirror of those towards gains. Thus risk and ambiguity aversion for gains turn into risk and ambiguity seeking for losses. As referenced in the main text, few studies have investigated this relation, and no clear results were found.

Table WD.2.1
Relation between ambiguity aversion index *b* and stock market participation under hypotheses about reflection at the individual level

	Reference Independence	Reflection Neutrality	Partial Reflection	Complete Reflection
$b \Leftrightarrow$ stocks	strongly –	–	0	+

In Table WD.2.1 we summarize the possible relations between ambiguity attitudes for gains and for losses. Reference independence means that ambiguity aversion for gains is strongly positively related (even identical) to ambiguity aversion for losses. Virtually all ambiguity theories popular today make this assumption. In which case, our ambiguity aversion index *b* (which concerns gains) will be strongly negatively related to stock market participation. The other extreme is complete reflection. Then an individual with strong ambiguity aversion for gains will have equally strong ambiguity seeking for losses. Because of loss aversion, potential losses affect decisions more than potential gains do and, hence, we can even expect a paradoxical positive relation between our ambiguity aversion index and market participation. The other cases are in between.

Our empirical results best correspond with reflection neutrality (no relation between gain- and loss-ambiguity aversion), the finding of Cohen, Jaffray, and Said (1987). Since stock returns include the possibilities of both losses and gains, ambiguity aversion for gains and for losses are both relevant. Because of loss-aversion, however, ambiguity aversion for losses is relatively more important. Thus in our empirical findings, we fail to find a significant effect for ambiguity aversion for gains, except among those subjects who perceive stock returns as particularly ambiguous.

Because a-insensitivity concerns the overweighting of both the best and the worst outcomes (low likelihood events), reflection does not alter the predictions. The overweighting of the best gain corresponds with the overweighting of the worst loss, and the overweighting of the worst gain corresponds with the overweighting of the best losses. That is, extreme outcomes continue to be overweighted.[7] Abdellaoui, Vossmann, and Weber (2005) and Baillon and Bleichrodt (2013), the only two studies that measured event weighting for both gains and losses, confirmed correspondence between insensitivity for gains and losses. Because of loss aversion, the overweighting of the worst losses will affect decisions more than the overweighting of the best outcomes. This makes it plausible that the a-insensitivity index that we derived from gain choices will have a negative relation with stock market participation, consistent with our findings. The prediction is also consistent with Liu, Pan, and Wang (2005), who argue for ambiguity aversion for rare losses of extreme magnitudes, but no such aversion for non-rare losses of moderate magnitude (supported by Drechsler 2013; Liu, Pan, and Wang 2005; Pan 2002). Such differential ambiguity attitudes depending on likelihoods of events agree with a-insensitivity but not with universal ambiguity aversion. To summarize our conclusions:

OBSERVATION WD.2.1. A-insensitivity for gains will have a negative relation with stock market participation. The relation between ambiguity aversion for gains and stock market participation depends on the relation, at the individual level, between ambiguity aversion for gains and for losses, as in Table WD.2.1. □

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[7] In mathematical terms, the overweighting of the highest outcomes translates into an overweighting of the lowest outcomes, and the overweighting of the lowest outcomes translates into an overweighting of the highest outcomes (Goldsmith and Sahlin 1983 p. 464 3rd para). Reflection of insensitivity simply gives back insensitivity. This algebraic property corresponds well with a cognitive interpretation of insensitivity, prior to any evaluation of outcomes or their signs.

We next present a formal analysis of prospect theory with reference dependence and a simulation based on this model. The results, summarized in Observation WD.2.1, can explain our empirical findings. In the simulation, we assume a-neutral probabilities equal to historical probabilities. These are most plausible, satisfying the exchangeability properties of the historical probabilities (Chew and Sagi 2006, 2008). Our approach is a version of rational expectations with agents acting on the basis of probabilities. We emphasize, however, that in our approach the agents view these probabilities as uncertain. The latter point is modeled through matching probabilities (also called ambiguity functions) deviating from a-neutral probabilities. This modeling is alternative to Hansen and Sargent's (2001) robust model. Our simulations show that a classical expected utility maximizer should invest everything in stocks.

We will see that an ambiguity neutral decision maker with the most common risk attitude (deviating from expected utility) should invest 16% in stocks. The effect of ambiguity aversion varies as shown in Table WC.2.1. With ambiguity incorporated, a-insensitivity (index *a*) is strongly negatively related to the stock market weight. Under plausible a-insensitivity ($\alpha > 0.2$), the investor does not participate in the stock market. We conclude that prospect theory and reference dependence can explain our experimental findings. We now turn to our formal analysis and simulation.

We first extend prospect theory to multi-outcome prospects. Uncertainty is modeled through a *state space* S. Subsets of S are *events*. Outcomes are real valued, designating money. *Prospects* map states to outcomes. $(E_1{:}x_1, \ldots, E_n{:}x_n)$ denotes a prospect yielding outcome x_1 under event E_1, …, and x_n under event E_n. It is implicitly assumed that the E_j's partition S, and that

$$x_1 \geq \cdots \geq x_k \geq 0 \geq x_{k+1} \geq \cdots \geq x_n.$$

P denotes a-neutral probability. With p_j denoting $P(E_j)$, each prospect $(E_1{:}x_1, \ldots, E_n{:}x_n)$ generates a a-neutral probability distribution $(p_1{:}x_1, \ldots, p_n{:}x_n)$ over the outcomes. With the source understood, we often denote the prospect x by $(p_1{:}x_1,\ldots,p_n{:}x_n)$, suppressing the events. This prospect is evaluated by

$$PT(x) = \sum_{j=1}^{n} \pi_j U(x_j), \qquad \text{(WD.2.1)}$$

its *prospect theory value*, explained next. We assume:

$$U(\alpha) = \alpha^{\theta^+} \text{ if } \alpha \geq 0,$$
$$U(\alpha) = -\lambda(-\alpha)^{\theta^-}, \text{ if } \alpha < 0, \tag{WD.2.2}$$

with $0 < \theta^+ \leq 1$, $0 < \theta^- \leq 1$, and $\lambda \geq 1$ the loss aversion parameter, in agreement with Eq. WD.1.6. The *decision weights* π_j are nonnegative and are defined by

$$\pi_1 = w^+_{So}(p_1),$$
$$\pi_j = w^+_{So}(p_1 + \cdots + p_j) - w^+_{So}(p_1 + \cdots + p_{j-1}), \text{ for } 2 \leq j \leq k \text{ (gains)} \tag{WD.2.3}$$

and

$$\pi_n = w^-_{So}(p_n),$$
$$\pi_j = w^-_{So}(p_j + \cdots + p_n) - w^-_{So}(p_{j+1} + \cdots + p_n), \text{ for } k+1 \leq j \leq n-1 \text{ (losses).} \tag{WD.2.4}$$

The following two-parameter weighting function (Goldstein and Einhorn 1987; abbreviated GE) is useful for analyzing weighting functions:

$$p \ \rightarrow \ \frac{\delta p^\gamma}{\delta p^\gamma + (1\text{-}p)^\gamma}, \tag{WD.2.5}$$

with $\delta > 0$ and $\gamma > 0$. Linearity is the special case of all parameters equal to 1. Parameter δ affects the overweighting of probabilities, i.e., optimism, with larger δs generating more optimism. It is closely related to, but in the opposite direction from, the ambiguity aversion index *b* (reflecting pessimism) in the main text. If $\gamma = 1$ and $0 < \delta < 1$, then probabilities are underweighted, and for $\delta > 1$ probabilities are overweighted. Parameter γ controls likelihood sensitivity, again very similar to our parameter *a*, although again in the opposite direction. When $\delta = 1$ and $\gamma < 1$, then the decision maker overweights small probabilities and underweights large probabilities (inverse S-shape), whereas $\gamma > 1$ gives an S-shaped weighting function.

For probability weighting functions under risk, $w^+(p)$ and $w^-(p)$, the GE functions have been found to accommodate the data well. A general finding with ambiguity is that it amplifies the deviations from expected utility found under risk[8]. Hence, writing δ^+, γ^+, δ^-, and γ^- for the parameters of w^+ and w^- (concerning risk) and δ^+_{So}, γ^+_{So}, δ^-_{So}, and γ^-_{So} for the

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[8] See Abdellaoui, Vossmann, and Weber (2005), Chakravarty and Roy (2009), Hogarth and Einhorn (1990), Gayer (2010), Kahn and Sarin (1988 p. 270), Kahneman and Tversky (1979 p. 281), Kilka and Weber (2001), and Maafi (2011).

parameters of w^+_{So} and w^-_{So} (the source functions), the latter parameters can be expected to deviate more from linearity. We can model this through Eq. WD.1.1 using a convenient analytic property of the GE family, being that it is closed under composition.

OBSERVATION WD.2.2. If $w^+(p)$ and $m(p)$ in Eq. WD.1.1 are from the GE family, with parameters γ^+, δ^+, $\gamma^+_{m_{So}}$, and $\delta^+_{m_{So}}$ then so is the composition $w^+_{So} = w^+ \circ m^+_{So}$ with parameters $\gamma^+_{So} = \gamma^+\gamma^+_{m_{So}}$ and $\delta^+_{So} = \delta^+$. Similarly, for losses we get $\gamma^-_{So} = \gamma^-\gamma^-_{m_{So}}$ and $\delta^-_{So} = \delta^-(\delta^-_{m_{So}}{}^{\gamma^-})$.

PROOF: Follows from substitution. □

Thus we can let w^+ and w^- capture the deviations from expected utility under risk, let m^+_{So} and m^-_{So} capture the further deviations due to ambiguity, have the source functions as their compositions, and have all of these functions from the GE family.

For gains, the parameters $\gamma^+ = 0.69$ and $\delta^+ = 0.77$ best fit the current empirical findings (Wakker 2010 p. 208). The parameters in Eq. WD.2.5 that best fit the data of our experiment are $\gamma^+_{m_{So}} = 0.49$ and $\delta^+_{m_{So}} = 0.73$ (using pooled nonlinear regression). Observation WD.2.2 now suggests $\gamma^+_{So} = 0.34$ and $\delta^+_{So} = 0.62$.

We next analyze how ambiguity aversion and a-insensitivity affect the optimal stock market allocation of investors. Suppose an investor with initial wealth x can invest in the stock market. The investor is uncertain about the future returns over the investment horizon and, as is typically the case in practice, does not know the probability distribution of the future returns. We assume that the investor's a-neutral probabilities are drawn from the historical probabilities, for which we use the value-weighted total return on the aggregate U.S. stock market and the 1-month T-bill return as the risk-free asset (source: data library of Kenneth French). Following Polkovnichenko (2005), for the a-neutral probabilities we bootstrap 1,000 annual returns for the stock market and the risk-free asset from the historical monthly return series (July-1926 through May-2010; we sample with replacement, using a block-length of 12 months). Given a stock market allocation φ, we create a cumulative distribution for the investor's wealth, using 500 buckets ranging from –100% (return) to +200% (return), with a fixed 0.5% step-size. We use the cumulative wealth distribution to calculate the value of the portfolio for an investment horizon of one year ($T = 1$).

The investor invests a fraction φ of her wealth in the stock market and the remainder in a risk-free asset with sure payoff $r^f_j = r^f$. The index j denotes one of n (= 500) potential values of the investor's end-of-period possible wealth $x_j(\varphi)$

The investor's end-of-period possible wealth $x_j(\varphi)$ is given by:

$$x_j(\varphi) = \varphi(1 + r_j)x + (1 - \varphi)(1 + r^f)x = (1 + r^f)x + \varphi(r_j - r^f)x$$
$$\text{for all } j = 1, \ldots, n, \text{ and } 0 \le \varphi \le 1. \qquad \text{(WD.2.6)}$$

The investor finds the optimal stock market allocation φ^* by maximizing

$$\max_\varphi \sum_{j=1}^{n} \pi_j U(x_j(\varphi)),$$
$$\text{subject to } x_j(\varphi) = (1 + r^f)x + \varphi(r_j - r^f)x, \text{ for } j = 1, \ldots, n, \text{ and } 0 \le \varphi \le 1. \qquad \text{(WD.2.7)}$$

Finally, we determine the optimal portfolio allocation φ^* numerically by varying φ from 0% to 100% with steps of 1%.

The weighting functions $w^+_{So}(p)$ and $w^-_{So}(p)$ are GE functions modeling the combined effect of probability weighting due to risk and ambiguity. For probability weighting under risk, we follow the literature. For gains, the most common pattern of probability weighting results with $\delta^+ = 0.77$ and $\gamma^+ = 0.69$ (see above). For losses there have been fewer studies. It is plausible that insensitivity, a cognitive component prior to value or preference, is similar for losses as for gains. For pessimism, partial reflection is natural, where pessimism for gains changes into optimism for losses, but this change is muted, and closer to linearity and expected value. Hence, we take $\gamma^- = \gamma^+ = 0.69$ and $\delta^- = (1+\delta^+)/2 = 0.885$. This corresponds with common findings in the literature (Abdellaoui, Vossmann, and Weber 2005; Cohen, Jaffray, and Said 1987; Hogarth and Einhorn 1990; Mangelsdorff and Weber 1994).

For loss aversion and the curvature of the utility function we use $\lambda = 2.25$, $\theta^+ = 0.88$, and $\theta^- = 0.94$ in Eq. WD.2.2. Tversky and Kahneman (1992) found $\theta^+ = 0.88$ for gains. Although they found the same parameter for losses, suggesting complete reflection, subsequent studies and partial reflection suggest a parameter for losses closer to 1, which explains our choice.

We now turn to our main interest, the effects of ambiguity attitudes on stock market participation. We analyze this by varying the parameters of the GE functions: $\delta^+_{m_{So}}$ and $\gamma^+_{m_{So}}$ for gains and $\delta^-_{m_{So}}$ and $\gamma^-_{m_{So}}$ for losses. Figure WD.2.1 shows the optimal portfolio weight as a function of a-insensitivity (index *a*) in the main text. That is, for each GE function we calculated the parameters index *a* and index *b* from the main text, and vary these in the figures. We consider the indexes *a* and index *b* rather than γ and δ for the sake of easy comparison with the main text.

The dotted line in Figure WD.2.1 shows the optimal stock market allocation for an investor who does not apply any probability weighting (neither for risk, nor for ambiguity). That is, this is a classical homo economicus maximizing expected utility in agreement with rational expectations, although we keep the kink in utility at 0 generated by loss aversion. Then the allocation is 100%, implying that the investor invests all wealth in the stock market. The average excess stock market return of 8.1% is apparently sufficiently high to overcome loss aversion.[9]

The dashed line in Figure WD.2.1 is for an investor who applies probability weighting for risk ($\delta^+ = 0.77$, $\gamma^+ = 0.69$, $\delta^- = 0.885$, $\gamma^- = 0.69$), but applies no additional weighting due to ambiguity about returns ($\delta^+_{m_{So}} = \delta^-_{m_{So}} = \gamma^+_{m_{So}} = \gamma^-_{m_{So}} = 1$). In this case the stock market allocation is 16%, implying that probability weighting for risk makes the investor much more conservative, but she still participates in the stock market. The overweighting of small probability extreme returns, in combination with loss aversion, makes the investor more cautious.

Finally, the solid line in Figure WD.2.1 shows the optimal portfolio allocation as a function of a-insensitivity for gains (index *a*), by varying the parameter $\gamma^+_{m_{So}}$, while keeping $\delta^+_{m_{So}} = \delta^-_{m_{So}} = 1$. For losses we choose the same level of a-insensitivity, that is, $\gamma^-_{m_{So}} = \gamma^+_{m_{So}}$. This is, again, because insensitivity is a cognitive component prior to the consideration of preference or value, which can be expected to be the same for gains as for losses, in agreement with reflection. Figure WD.2.1 shows that there is a strong negative relation between a-insensitivity (index *a*) and the stock market allocation. When index *a* is larger than 0.2, the investor does not participate in the stock market. When a-insensitivity increases then the decision weights of large losses and large gains both increase, but because the impact of large losses is amplified by loss aversion, the overall effect on the stock market allocation is very negative.

Figure WD.2.2 shows the optimal portfolio weight as a function of ambiguity aversion (index *b*, measured for gains) by varying the parameter $\delta^+_{m_{So}}$, while keeping $\gamma^+_{m_{So}} = \gamma^-_{m_{So}} = 1$. We

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[9] The annual standard deviation of the excess returns is 21.4% and the Sharpe ratio is 0.38.

need to make some assumption about the relation between the ambiguity seeking parameters $\delta^{+}_{m_{So}}$ and $\delta^{-}_{m_{So}}$ at the individual level. We analyze the cases in Table WD.2.1.

For complete reflection we assume $\delta^{-}_{m_{So}} = \delta^{+}_{m_{So}}$. The dashed line in Figure WD.2.2 shows that the stock weight then is in fact increasing as a function of index *b* (measured for gains). Increased ambiguity seeking for losses then dominates increased ambiguity aversion for gains, which can be explained because losses receive more weight due to loss aversion. This explains the + sign in Table WD.2.1.

For partial reflection we assume $\delta^{-}_{m_{So}} = (1+\delta^{+}_{m_{So}})/2$, moving it twice as close to the neutral value 1. The dotted line in Figure WD.2.2 shows that the stock allocation decreases slightly as a function of index *b* (for gains), as the effect of increased ambiguity aversion for gains is not completely offset by the opposing force of ambiguity seeking for losses (reduced because reflection is only partial but is still amplified by loss aversion).

For anti-reflection we take $\delta^{-}_{m_{So}} = 1/\delta^{+}_{m_{So}}$, (which is equivalent to $m^{+}_{So}(p) = 1 - m^{-}_{So}(1-p)$ when $\gamma^{+}_{m_{So}} = \gamma^{-}_{m_{So}}$)[10]. The line with alternating dashes and dots in Figure WD.2.2 shows that the relation between ambiguity aversion (index *b*) and the optimal stock market allocation then is strongly negative, as was to be expected.

We also consider a case of partial anti-reflection, $\delta^{-}_{m_{So}} = 1/((1+\delta^{+}_{m_{So}})/2)$. The line with alternating long and short dashes in Figure WD.2.2 shows this case. Similarly to complete anti-reflection, we find a strong negative relation between index *b* and the optimal stock market allocation.

We finally consider the case of reflection neutrality, shown by solid. We again have a negative relation between index *b* and stock allocation, but slightly less strong than with anti-reflection.

[10] Regarding $m^{+}_{So}(p)$, because prospect theory weights losses dually to gains, taking a dual weighting function for losses as in this equation means in fact that losses are weighted the same way as gains in the sense of overweighting unfavorable outcomes versus overweighting favorable outcomes.

Figure WD.2.1: Stock Market Weight versus A-insensitivity

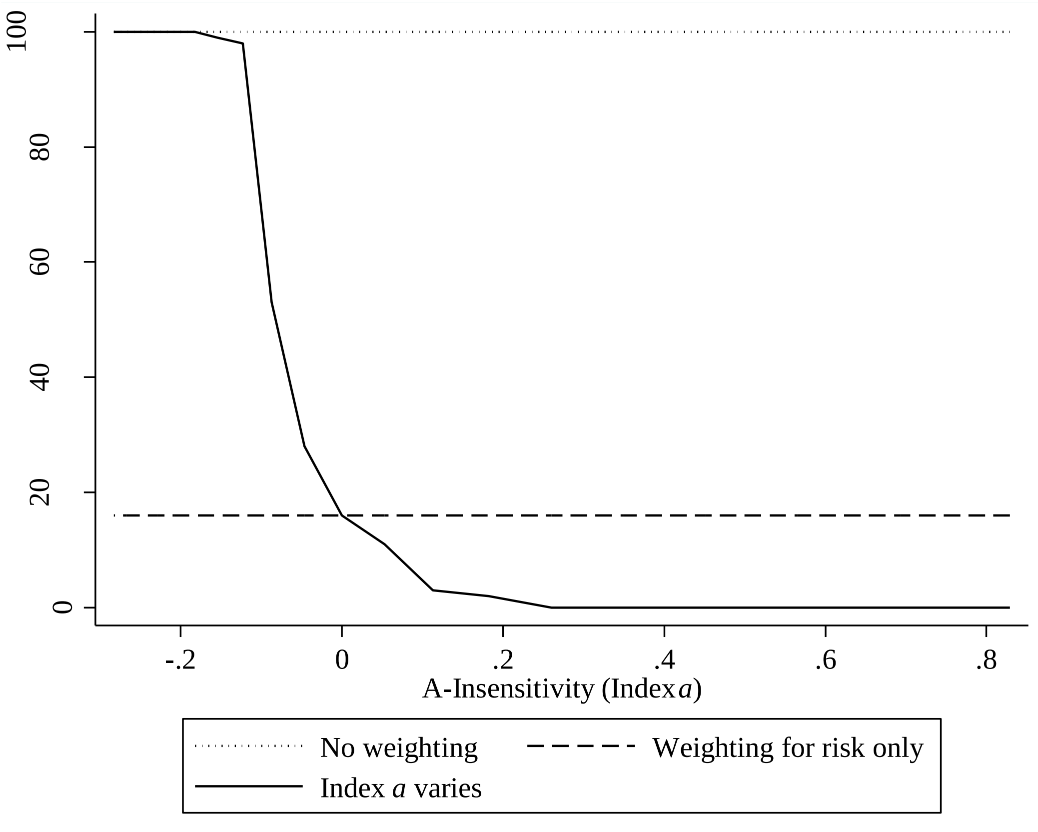
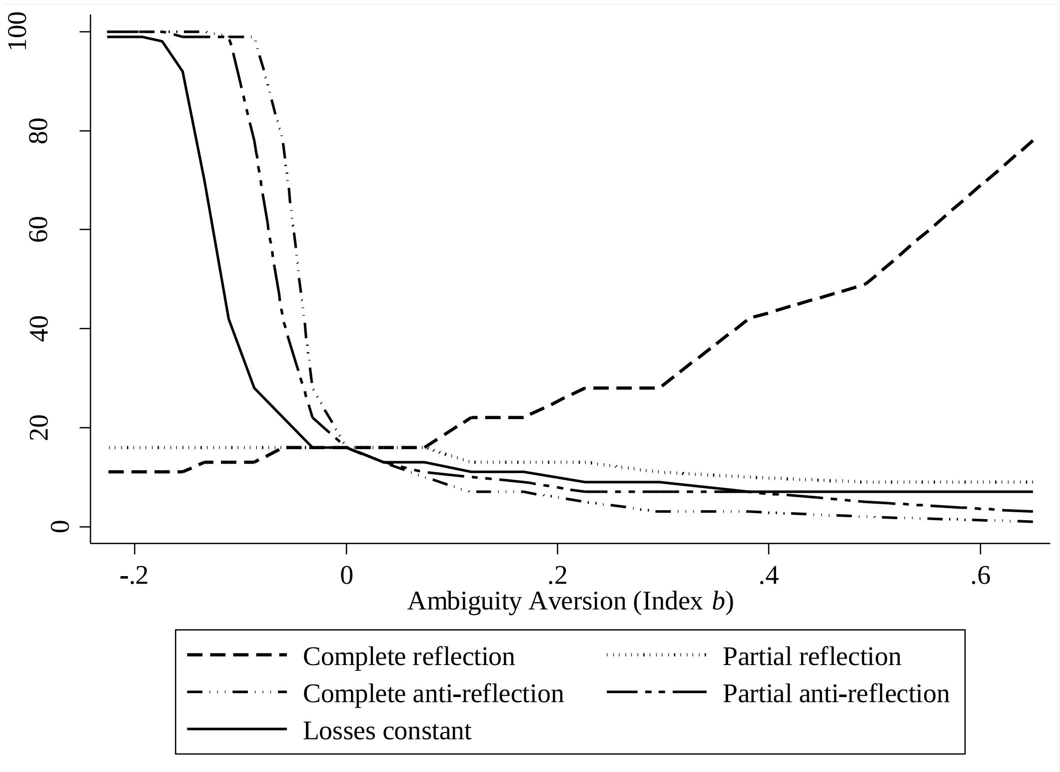


Figure WD.2.2 Stock Market Weight versus Ambiguity Aversion for Gains



Web Appendix E. Results for hypothetical choices

This Web Appendix explores the ambiguity attitudes of subjects facing hypothetical choices. There are two parts: First, we compare the ambiguity attitudes of subjects facing hypothetical choices to those of subjects making choices with real incentives. Second, we replicate all tables in the paper, but use only the subjects whose ambiguity attitudes were elicited using hypothetical choices.

WE.1 Comparison of ambiguity attitudes reported using hypothetical vs. real incentives

In this section we compare the ambiguity attitudes of subjects facing hypothetical choices to the ambiguity attitudes of subjects making choices with real incentives. We show that the elicited ambiguity attitudes are different in the two samples, and present evidence that suggests the ambiguity attitudes elicited using hypothetical choice are of lower quality than those elicited using real incentives. First, for hypothetical choice, ambiguity seeking is much stronger than with real incentives. Second, the effect of incentives on ambiguity attitudes is especially strong among subjects with low education levels. Third, we show that for hypothetical choice, trust (or suspicion) may partially confound the measurement of ambiguity aversion. Finally, in the second section of this web appendix we show that when explaining economic decisions, the ambiguity measurements in the hypothetical group are never significant, suggesting that they are noisier.

WE.1.A. Incentives and Ambiguity Attitudes

For all ambiguity attitude questions, Table WE.1.1 shows that the hypothetical choice group has lower rates of ambiguity aversion and higher rates of ambiguity seeking, but the difference is significant only for the low likelihood event ($AA_{0.1}$). The pattern is stronger when we consider the ambiguity attitude indexes in Table WE.1.2: the subjects with hypothetical incentives have lower ambiguity aversion for the 10% question ($AA_{0.1}$) and for the 50% question ($AA_{0.5}$). The point estimate for the 90% question ($AA_{0.9}$) indicates lower ambiguity aversion, but the difference is not significant.[11] The overall ambiguity aversion measure, index *b*, is 75% higher for the subjects with real incentives (b = 0.12) compared to

[11] For the responses to the three questions, we also conducted a joint test of the equality of means between the two samples. The Hotelling's test rejects the joint equality of means at the 5% level.

hypothetical choice (*b* = 0.07), a substantial difference.[12] The pattern of higher ambiguity seeking for the hypothetical choice group also carries over to the two consistency check questions: see Table WE.1.3 and Table WE.1.4. For both questions, a higher proportion of the hypothetical subjects chose the ambiguous urn instead of the known probability urn.

Table WE.1.1
Ambiguity attitudes revealed by first round choices: The effect of real incentives

The table shows the frequency distribution of subjects with ambiguity averse, ambiguity seeking and ambiguity neutral attitudes at a-neutral probabilities of 0.10, 0.50, and 0.90, separately for the groups with real and hypothetical rewards. The column 'p-value diff.' shows the p-value for testing the null hypothesis that proportions are equal in both groups.

		Real	Hypothetical	p-value diff.
p = 0.10	Averse	33.5%	29.5	0.106
	Neutral	17.1%	15.5	0.403
	Seeking	49.4%	55.0	0.034**
p = 0.50	Averse	68.3%	67.3	0.690
	Neutral	9.6%	8.2	0.351
	Seeking	22.1%	24.5	0.286
p = 0.90	Averse	53.2%	52.9	0.927
	Neutral	11.6%	9.1	0.131
	Seeking	35.3%	38.0	0.296

Table WE.1.2
Ambiguity attitude indexes: The effect of real incentives

The table shows the mean of the ambiguity attitude indexes, separately for the groups with real and hypothetical rewards. The column 'p-value diff.' shows the p-value for testing the null hypothesis that means are equal in both groups.

Variable	Real	Hypothetical	p-value diff.
$AA_{0.1}$	-12.1	-15.2	0.026**
$AA_{0.5}$	10.0	7.3	0.036**
$AA_{0.9}$	20.5	18.3	0.196
Index *b* (Ambiguity Aversion)	0.123	0.070	0.012**
Index *a* (A-insensitivity)	0.408	0.419	0.625

[12] For a-insensitivity, the higher ambiguity seeking reported by the hypothetical choice group on both the 10% and the 90% questions cancels out, and so a-insensitivity (index *a*) is not significantly different between the two groups.

Table WE.1.3
Check Question 1

(Known probability choice made more attractive; Averse correct choice)
The table shows the frequency distribution of subjects choosing the ambiguity averse, ambiguity seeking and ambiguity neutral options in the first consistency check question, separately for the groups with real and hypothetical rewards. The column 'p-value diff.' shows the p-value for testing the null hypothesis that proportions are equal in both groups.

	Real	Hypothetical	p-value diff.
Averse	71.0%	66.4	0.061*
Neutral	9.3%	7.9	0.356
Seeking	19.7%	25.7	0.007***

p-value of overall test of equality between groups = 0.025

Table WE.1.4
Check Question 2

(Known probability choice made less attractive; Seeking correct choice)
The table shows the frequency distribution of subjects choosing the ambiguity averse, ambiguity seeking and ambiguity neutral options in the second consistency check question, separately for the groups with real and hypothetical rewards. The column 'p-value diff.' shows the p-value for testing the null hypothesis that proportions are equal in both groups.

	Real	Hypothetical	p-value diff.
Averse	34.1%	30.0	0.091*
Neutral	13.1%	8.1	0.002***
Seeking	52.9%	62.0	0.001***

p-value of overall test of equality between groups < 0.001

WE.1.B The Effects of Education and Incentives on Ambiguity Attitudes

In contrast with the samples of undergraduate students typically used in laboratory studies, our representative sample includes many subjects with relatively low levels of education. Camerer and Hogarth (1999) show that incentives are particularly important for cognitively demanding tasks. Presumably, the cognitive demands of evaluating the risky vs. ambiguous urns in our experiment are greater for subjects with lower education. Thus, the extant literature suggests that the effect of incentives in our sample should be strongest for the subjects with low education. In Table WE.1.5, we compare the ambiguity attitudes of low and highly educated subjects in our sample, split by the incentive treatment (hypo and real). Low education is defined as having no post-secondary education.

We find that the differences between the hypothetical choice and real incentive groups are driven entirely by subjects with low education. For subjects with high education (at least some post-secondary education), there are no differences in ambiguity attitudes between the hypothetical and real choice groups. For subjects with low education, those in the hypothetical choice group are less ambiguity averse. These results show that real incentives matter most for nonacademic subjects.

Table WE.1.5
Ambiguity attitude indexes and education: The effect of real incentives

The table shows the mean of the ambiguity attitude indexes for the groups with real and hypothetical rewards, further split between subjects having low and high education (defined as having at least some post-secondary education), resulting in four groups. The p-values on the second line are for a test for differences in the mean between the real and hypothetical reward groups, with the *t*-test done for each education level separately.

	Low Education		High Education	
	Hypo	Real	Hypo	Real
$AA_{0.1}$	-19.4	-13.7	-11.4	-10.7
	p=0.014**		*p*=0.649	
$AA_{0.5}$	5.3	9.3	9.2	10.7
	p=0.053*		*p*=0.342	
$AA_{0.9}$	18.6	22.6	18.0	18.6
	p=0.122		*p*=0.812	
Index *b*	0.030	0.122	0.105	0.124
(Ambig. Aversion)	*p*=0.012**		*p*=0.500	
Index *a*	0.475	0.453	0.368	0.366
(A-insensitivity)	*p*=0.560		*p*=0.933	

WE.1.C The Effect of Trust and Incentives on Ambiguity Attitudes

The survey instructions for the hypothetical and real incentive groups had to differ in an important manner. For the real incentive group, the participants were informed about the incentives and also that LISS was responsible for calculating all prizes but the funds were provided by the research team. That is, the subjects were explicitly told that the calculation and administration of the rewards were separated from the funding of the rewards. For the hypothetical incentive group, there could be no explanation that LISS would calculate the actual prizes. Given that the rewards were hypothetical it would seem odd to discuss who would hypothetically calculate and allocate them, but this omission means that we could not reassure these subjects about the issue of trickery.

To investigate whether this difference in instructions affected the ambiguity attitude measurements, Table WE.1.6 below compares ambiguity attitudes between respondents with high and low trust in others (using the binary high/low trust classification of Guiso, Sapienza, and Zingales, 2008). The relation between trust and ambiguity attitudes is significant in the hypothetical group but not in the real incentive group. This is consistent with the instructions about LISS calculating prizes eliminating problems due to suspicion.

The main takeaway is that low trust subjects are more ambiguity averse in the hypothetical sample. Low and high trust subjects are not different in the real incentive sample. This suggests that the different instructions that the two groups received affected the responses.

Table WE.1.6
Ambiguity attitude indexes and trust: The effect of real incentives

The table shows the mean of the ambiguity attitude indexes for the groups with real and hypothetical rewards, further split between subjects having low and high trust in others (following the definition of Guiso, Sapienza, and Zingales, 2008). The p-value on the second line shows whether the reported mean is different from the other group with the same incentive structure (i.e., tests for difference in the means for low trust & hypo vs. high trust & hypo, and for low trust & real incentives vs. high trust & real incentives).

	Hypothetical choice		Real incentives	
	Low trust	High trust	Low trust	High trust
$AA_{0.1}$	-13.4	-15.4	-12.5	-12.3
	p=0.350		*p*=0.901	
$AA_{0.5}$	11.4	3.9	9.4	9.0
	p=0.0001***		*p*=0.833	
$AA_{0.9}$	22.1	15.4	22.8	18.3
	p=0.007***		*p*=0.108	
Index *b*	0.135	0.026	0.132	0.101
(Ambig. Aversion)	*p*=0.002***		*p*=0.381	
Index *a*	0.444	0.385	0.442	0.383
(A-insensitivity)	*p*=0.081*		*p*=0.117	

WE.2 Results for hypothetical choice

In this section, we replicated all tables from the main paper, except using the hypothetical incentives sample instead of the real incentives sample. The key finding is that ambiguity attitudes elicited with hypothetical choice are not related to economic choices, consistent with greater noise or bias in ambiguity preferences elicited without real incentives.

Table WE.2.1: Hypothetical Incentives Sample
Summary statistics

Income and total financial assets are reported at the household level. All other variables are reported at the individual level. The first three variables are dummy variables: Stock Market Participant indicates ownership of publicly traded stocks or equity mutual funds; Private Business Owner indicates ownership of equity of a private firm. Total Financial Assets is the sum of: bank accounts, investments, insurance, loans made to others, and other financial assets. Income is gross family income in euros per month. Risk Aversion is the CRRA coefficient derived from certainty equivalents. Trust refers to responses to a question that asks if others can be trusted (0-10 scale); high values indicate greater trust. Financial Literacy is a factor extracted from three questions measuring financial knowledge following van Rooij, Lusardi, and Alessie (2011); high values indicate greater knowledge. Don't Know Returns is a dummy variable for individuals who answer "Don't Know" to a question about historical asset returns. See Web Appendix A for detailed definitions.

Variable	All	Non-Participants	Stock Market Participants
Stock Market Participant	19.4%	0.0	100.0
Private Business Owner	6.0%	5.3	8.8
Total Financial Assets	51,882	40,159	100,450
Income	4,160	3,930	5,116
Age	48.9	48.1	52.0
Female	51.7%	55.2	37.4
Household Size	2.6	2.6	2.7
Live with Partner	75.5%	75.0	77.6
Education:			
Low	9.7%	11.5	2.0
Intermediate/Low	27.9%	30.4	17.7
Intermediate/High	10.3%	9.7	12.9
Vocational 1	21.7%	22.7	17.7
Vocational 2	22.6%	19.4	36.1
University	7.8%	6.4	13.6
Risk Aversion	0.16	0.17	0.15
Trust	6.16	6.16	6.18
Financial Literacy	0.06	-0.07	0.57
Don't Know Returns	24.3%	28.1	8.8

Table WE.2.2: Hypothetical Incentives Sample
Ambiguity attitudes revealed by first round choices

The table shows the frequency distribution of subjects with ambiguity averse, ambiguity seeking and ambiguity neutral attitudes at a-neutral probabilities of 0.10, 0.50, and 0.90.

A-neutral prob. p	0.10	0.50	0.90
Ambiguity Averse	29.5%	67.3	52.9
Ambiguity Seeking	55.0%	24.5	38.0
Ambiguity Indifferent	15.5%	8.2	9.1

Table WE.2.3: Hypothetical Incentives Sample
Statistics of ambiguity attitude indexes

Rows 1-3 show the matching probabilities for the three ambiguity questions (m(0.1), m(0.5), m(0.9)). Rows 4-6 show the three indexes of ambiguity attitudes based on the differences between the objective and matching probabilities: $AA_{0.1}$ (Eq. (6)); $AA_{0.5}$ (Eq. (7)); $AA_{0.9}$ (Eq. (8)). The last two rows show the overall indexes of ambiguity attitudes: Index *b*: Eq. (11) (ambiguity aversion); Index *a*: Eq. (10) (a-insensitivity).

Variable	Mean	Median	Std. Dev.	Min.	Max.
Matching Probability m(0.1)	0.25	0.11	0.27	0.01	0.99
Matching Probability m(0.5)	0.43	0.45	0.25	0.02	0.98
Matching Probability m(0.9)	0.72	0.89	0.31	0.01	0.99
$AA_{0.1}$	-0.15	-0.01	0.27	-0.89	0.09
$AA_{0.5}$	0.07	0.05	0.25	-0.48	0.48
$AA_{0.9}$	0.18	0.01	0.31	-0.09	0.89
Index *b* (Ambiguity Aversion)	0.07	0.05	0.43	-0.97	0.97
Index *a* (A-insensitivity)	0.42	0.35	0.43	-0.22	2.18

Table WE.2.4: Hypothetical Incentives Sample
Correlations between ambiguity attitudes, risk aversion, trust, and financial literacy

Variables 1-5 are defined in Table 3: Index *b*: Eq. (11) (ambiguity aversion); Index *a*: Eq. (10) (a-insensitivity); $AA_{0.1}$: Eq. (6); $AA_{0.5}$: Eq. (7); $AA_{0.9}$: Eq. (8). Variables 6-8 are defined in Table 1: Risk Aversion (CRRA coefficient), Trust, and Financial Literacy. Correlations that are *not* significant at the 0.10 level are italicized.

Variable	(1) *b*	(2) *a*	(3) $AA_{0.1}$	(4) $AA_{0.5}$	(5) $AA_{0.9}$
(1) Index *b* (Amb. Aversion)	1				
(2) Index *a* (A-insensitivity)	0.09	1			
(3) $AA_{0.1}$	0.77	-0.51	1		
(4) $AA_{0.5}$	0.80	*-0.06*	0.54	1	
(5) $AA_{0.9}$	0.77	0.66	0.31	0.40	1
(6) Risk Aversion	-0.18	-0.18	*-0.04*	-0.13	-0.23
(7) Trust	-0.12	*-0.06*	*-0.04*	-0.14	-0.10
(8) Financial Literacy	*-0.03*	-0.15	*0.05*	*0.01*	-0.12

Table WE.2.5: Hypothetical Incentives Sample
Regressions for demographics predictors of ambiguity attitudes

The dependent variables are defined in Table 3: index *b*: Eq. (11) (ambiguity aversion); Index *a*: Eq. (10) (a-insensitivity); $AA_{0.1}$: Eq. (6); $AA_{0.5}$: Eq. (7); $AA_{0.9}$: Eq. (8). The independent variables are defined in Table 1: Risk Aversion (CRRA coefficient), Trust, Financial Literacy, Don't Know Returns (proxy for perceived incompetence). The education controls are five dummy variables for highest level of education achieved (base category is primary school). The regressions include constants but these are not displayed for brevity's sake. The t-statistics are calculated using standard errors clustered by household. The symbols *, **, and *** indicate significance at the 0.10, 0.05, and 0.01 levels, respectively.

	Index *b*	Index *a*	$AA_{0.1}$	$AA_{0.5}$	$AA_{0.9}$
Risk Aversion	-0.199***	-0.14***	-0.076*	-0.159***	-0.221***
	[4.18]	[3.45]	[1.73]	[3.49]	[4.84]
Trust	-0.087**	-0.035	-0.025	-0.126***	-0.060
	[2.30]	[0.94]	[0.67]	[3.26]	[1.60]
Financial Literacy	-0.053	-0.139***	0.023	0.004	-0.133***
	[1.28]	[2.79]	[0.53]	[0.08]	[2.78]
Don't Know Returns	-0.28***	-0.103	-0.162	-0.236**	-0.253***
	[2.91]	[1.09]	[1.59]	[2.47]	[2.71]
Total Fin. Assets	-0.070	0.045	-0.095	-0.037	-0.033
	[0.79]	[0.50]	[1.04]	[0.41]	[0.39]
Total Fin. Assets Squ.	0.018	-0.065	0.074	-0.023	-0.008
	[0.26]	[0.78]	[0.93]	[0.30]	[0.12]
Income	0.004	-0.119	0.130	-0.108	-0.019
	[0.03]	[0.87]	[0.94]	[0.76]	[0.14]
Income Squared	-0.029	0.100	-0.146	0.105	-0.016
	[0.22]	[0.79]	[1.06]	[0.75]	[0.14]
Age	-0.268	0.345	-0.444**	-0.208	-0.005
	[1.35]	[1.60]	[2.22]	[1.10]	[0.02]
Age Squared	0.073	-0.298	0.262	0.032	-0.102
	[0.36]	[1.38]	[1.24]	[0.17]	[0.48]
Female	-0.011	-0.016	-0.027	0.051	-0.040
	[0.16]	[0.21]	[0.37]	[0.71]	[0.55]
Household Size	-0.026	-0.057	0.017	-0.025	-0.048
	[0.73]	[1.58]	[0.52]	[0.72]	[1.26]
Live with Partner	0.100	0.141	-0.034	0.140	0.126
	[0.94]	[1.26]	[0.32]	[1.33]	[1.09]
Educ. (joint p-value)	0.104	0.218	0.011**	0.161	0.892
Adjusted - R^2	0.083	0.050	0.055	0.065	0.066
No. of Observations	756	756	756	756	756

Table WE.2.6: Hypothetical Incentives Sample
Ambiguity attitudes and stock market participation

This table shows logit regressions with stock market participation as the dependent variable. The ambiguity attitude variables are defined in Table 3: Index *b*: Eq. (11) (ambiguity aversion); index *a*: Eq. (10) (a-insensitivity); $AA_{0.1}$: Eq. (6); $AA_{0.5}$: Eq. (7); $AA_{0.9}$: Eq. (8). The other independent variables are defined in Table 1. The regressions include constants but these are not displayed for brevity's sake. The t-statistics are calculated using standard errors clustered by household.

	(1)	(2)	(3)	(4)
Index *b* (Amb. Aversion)	0.0001	-0.004		
	[0.02]	[0.27]		
Index *a* (A-insensitivity)	0.001	0.008		
	[0.10]	[0.53]		
$AA_{0.1}$			-0.007	-0.010
			[0.49]	[0.66]
$AA_{0.5}$			0.010	0.002
			[0.67]	[0.14]
$AA_{0.9}$			-0.002	0.004
			[0.15]	[0.23]
Risk Aversion		-0.013		-0.013
		[0.95]		[0.94]
Trust		-0.023 *		-0.023
		[1.66]		[1.63]
Financial Literacy		0.062 ***		0.062 ***
		[3.25]		[3.19]
Total Financial Assets	0.113 ***	0.103 ***	0.113 ***	0.103 ***
	[3.89]	[3.58]	[3.88]	[3.57]
Total Fin. Assets Squ.	-0.070 **	-0.061 **	-0.070 **	-0.061 **
	[2.42]	[2.23]	[2.40]	[2.23]
Income	-0.011	-0.027	-0.009	-0.026
	[0.22]	[0.59]	[0.19]	[0.57]
Income Squared	0.040	0.056	0.038	0.055
	[0.97]	[1.39]	[0.93]	[1.38]
Age	0.191 **	0.171 *	0.189 **	0.171 *
	[2.07]	[1.83]	[2.06]	[1.83]
Age Squared	-0.143	-0.126	-0.142	-0.126
	[1.54]	[1.35]	[1.53]	[1.35]
Female	-0.080 ***	-0.056 **	-0.080 ***	-0.056 **
	[2.98]	[2.10]	[3.03]	[2.12]
Household Size	0.020	0.019	0.020	0.019
	[1.42]	[1.39]	[1.45]	[1.40]
Live with Partner	-0.074 *	-0.068 *	-0.076 **	-0.069 *
	[1.92]	[1.77]	[1.97]	[1.78]
Education (joint p-value)	0.002 ***	0.005 ***	0.002 ***	0.005 ***
Pseudo - R^2	0.144	0.162	0.144	0.162
No. of Observations	756	756	756	756

Table WE.2.7: Hypothetical Incentives Sample
Ambiguity attitudes, perceived incompetence, and stock market participation

This table shows logit regressions with stock market participation as dependent variable. The regressions include interaction terms of the ambiguity attitude variables with "Don't Know Returns". All other variables are the same as in Table 5.1. The regressions include constants but these are not displayed for brevity's sake. The t-statistics are calculated using standard errors clustered by household.

	(1)	(2)	(3)	(4)
Index *b* (Amb. Aversion)	-0.013	-0.015		
	[0.89]	[1.01]		
Index *b* × Don't Know	0.051	0.050		
	[1.13]	[1.06]		
Index *a* (A-insensitivity)	0.012	0.015		
	[0.83]	[1.00]		
Index *a* × Don't Know	-0.050	-0.045		
	[1.03]	[0.87]		
$AA_{0.1}$			-0.017	-0.018
			[1.06]	[1.09]
$AA_{0.1}$ × Don't Know			0.032	0.033
			[0.46]	[0.47]
$AA_{0.5}$			-0.002	-0.006
			[0.10]	[0.37]
$AA_{0.5}$ × Don't Know			0.056	0.050
			[0.77]	[0.67]
$AA_{0.9}$			0.003	0.007
			[0.21]	[0.40]
$AA_{0.9}$ × Don't Know			-0.028	-0.023
			[0.50]	[0.38]
Don't Know Returns	-0.115 ***	-0.078 *	-0.115 ***	-0.079 *
	[2.70]	[1.82]	[2.68]	[1.81]
Risk Aversion		-0.012		-0.011
		[0.85]		[0.81]
Trust		-0.022		-0.022
		[1.56]		[1.55]
Financial Literacy		0.046 **		0.045 **
		[2.32]		[2.28]
Controls and Constant	Yes	Yes	Yes	Yes
Pseudo - R^2	0.161	0.171	0.162	0.172
No. of Observations	756	756	756	756

Table WE.2.8: Hypothetical Incentives Sample
Ambiguity attitudes and stock market participation: subsamples

This table shows logit regressions with stock market participation as dependent variable. Columns (2), (4), and (6) include interaction terms with the "Don't Know" dummy and the ambiguity indexes. The independent variables are the same as in Table 5.1. The subsamples Tertiary Education (only subjects who have completed some form of tertiary education), Questions Were Clear (stated that the ambiguity attitude questions were clear or very clear), and Check Questions Not Inconsistent (did not violate their earlier choices when responding to the check questions). The regressions include constants but these are not displayed for brevity's sake. The t-statistics are calculated using standard errors clustered by household.

	Tertiary Education		Questions Were Clear		Check Questions Not Inconsistent	
	(1)	(2)	(3)	(4)	(5)	(6)
Index *b* (Amb. Aversion)	-0.029	-0.040	-0.010	-0.022	0.053	0.037
	[1.16]	[1.47]	[0.62]	[1.27]	[1.56]	[1.08]
Index *b* × Don't Know		0.022		0.063		0.065
		[0.29]		[0.98]		[0.66]
Index *a* (A-insensitivity)	0.017	0.028	0.002	0.009	-0.013	0.004
	[0.73]	[1.14]	[0.10]	[0.55]	[0.41]	[0.12]
Index *a* × Don't Know		-0.070		-0.052		-0.088
		[0.66]		[0.79]		[0.87]
Don't Know Returns		-0.065		-0.084 *		-0.068
		[0.91]		[1.76]		[0.93]
Risk Aversion	-0.012	-0.011	-0.012	-0.011	-0.044 *	-0.047 **
	[0.56]	[0.48]	[0.76]	[0.69]	[1.90]	[2.09]
Trust	-0.032	-0.033	-0.025	-0.023	-0.037 *	-0.036 *
	[1.64]	[1.64]	[1.63]	[1.50]	[1.73]	[1.72]
Financial Literacy	0.151 ***	0.143 ***	0.067 ***	0.050 **	0.041	0.033
	[3.47]	[3.32]	[2.93]	[2.12]	[1.35]	[0.98]
Controls and Constant	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo - R^2	0.195	0.199	0.189	0.200	0.196	0.202
No. of Observations	394	394	624	624	363	363

Table WE.2.9: Hypothetical Incentives Sample
Ambiguity attitudes, private business ownership and bank accounts

This table shows logit regressions. In the first two columns the dependent variable concerns ownership of equity in a private business. In the third and fourth columns the dependent variable concerns ownership of a bank account. The independent variables are the same as in Table B.2. The regressions include constants but these are not displayed for brevity's sake. The t-statistics are calculated using standard errors clustered by household.

	Private Business		Bank Account	
	(1)	(2)	(3)	(4)
Index *b* (Amb. Aversion)	0.006		-0.007	
	[0.60]		[0.62]	
Index *a* (A-insensitivity)	0.014		-0.015	
	[1.52]		[1.45]	
$AA_{0.1}$		0.006		0.007
		[0.49]		[0.64]
$AA_{0.5}$		-0.022 *		-0.001
		[1.93]		[0.06]
$AA_{0.9}$		0.024 **		-0.017
		[2.53]		[1.63]
Risk Aversion	0.017	0.015	0.016	0.016
	[1.42]	[1.30]	[1.52]	[1.51]
Trust	0.014	0.011	0.007	0.007
	[1.35]	[1.12]	[0.73]	[0.74]
Financial Literacy	0.016	0.019	0.013	0.013
	[1.31]	[1.46]	[1.06]	[1.04]
Controls and Constant	Yes	Yes	Yes	Yes
Pseudo - R^2	0.145	0.161	0.065	0.065
No. of Observations	756	756	756	756

Web Appendix F. Interactions between ambiguity attitudes and incorrect financial knowledge

Table WF.1
Ambiguity attitudes, incorrect financial knowledge, and stock market participation

This table shows logit regressions with stock market participation as dependent variable. The regressions include interaction terms of the ambiguity attitude variables with "Wrong Answer". All other variables are as in Table 5.1. The regressions include constants but these are not displayed for brevity's sake. The t-statistics are calculated using standard errors clustered by household.

	(1)	(2)	(3)	(4)
Index *b* (Amb. Aversion)	-0.008	-0.004		
	[0.38]	[0.16]		
Index *b* × Wrong Answer	0.041	0.037		
	[1.33]	[1.15]		
Index *a* (A-insensitivity)	-0.048 **	-0.045 **		
	[2.31]	[2.04]		
Index *a* × Wrong Answer	0.035	0.037		
	[1.08]	[1.11]		
$AA_{0.1}$			0.040	0.040
			[1.60]	[1.44]
$AA_{0.1}$ × Wrong Answer			0.001	-0.007
			[0.03]	[0.14]
$AA_{0.5}$			-0.018	-0.017
			[0.84]	[0.70]
$AA_{0.5}$ × Wrong Answer			0.004	0.010
			[0.12]	[0.25]
$AA_{0.9}$			-0.042 **	-0.037 *
			[2.04]	[1.77]
$AA_{0.9}$ × Wrong Answer			0.059 *	0.056 *
			[1.83]	[1.75]
Wrong Answer	0.004	0.003	0.001	0.001
	[0.14]	[0.10]	[0.04]	[0.02]
Risk Aversion		-0.003		-0.002
		[0.17]		[0.16]
Trust		0.027 *		0.026 *
		[1.85]		[1.80]
Financial Literacy		0.076 ***		0.076 ***
		[3.58]		[3.58]
Controls and Constant	Yes	Yes	Yes	Yes
Pseudo - R^2	0.199	0.227	0.202	0.229
No. of Observations	666	666	666	666

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