NBER WORKING PAPER SERIES

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Working Paper 18743
http://www.nber.org/papers/w18743

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
January 2013

This paper was previously circulated as "Ambiguity Attitudes and Economic Behavior". This paper is part of the NBER's Research Program on the Economics of Aging and the Working Group on Household Portfolios. The authors gratefully acknowledge support from Netspar, the National Institute on Aging, P30 AG-012836-18, the Pension Research Council/Boettner Center for Pensions and Retirement Security, and National Institutes of Health–National Institute of Child Health and Development Population Research Infrastructure Program R24 HD-044964-9, all at the University of Pennsylvania, and the ALP teams at RAND and the University of Southern California, as well as the Wharton Behavioral Labs. We thank Jawad Addoum, Sahil Bajaj, Nicola Gennaioli, Debrah Meloso, Arno Riedl, Stefan Trautmann, Martijn van den Assem, Peter Wakker, and numerous seminar and conference participants for helpful comments, and Tania Gutsche, Arie Kapteyn, Bart Orriens, and Bas Weerman for assistance with the survey. Yong Yu provided outstanding programming assistance. The content is solely the responsibility of the authors and does not necessarily represent the official views of the National Institute of Aging, the National Institutes of Health, the National Bureau of Economic Research or of the other institutions providing funding for this study or with which the authors are affiliated.

At least one co-author has disclosed a financial relationship of potential relevance for this research. Further information is available online at http://www.nber.org/papers/w18743.ack

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NBER Working Paper No. 18743
January 2013, Revised September 2013
JEL No. C83,D14,D81,G11

ABSTRACT

This paper tests the effects of ambiguity aversion on household portfolio choice. We measure ambiguity aversion with custom-designed questions based on Ellsberg urns, using a large representative survey of U.S. households. As theory predicts, ambiguity aversion is negatively associated with stock market participation and with the fraction of wealth allocated to stocks. Moreover, the effect is large: the participation rate is 4.3 percentage points lower among ambiguity averse respondents, compared to ambiguity neutral/seeking respondents. We also find that, conditional on prior stock ownership, ambiguity averse respondents were more likely to sell stocks during the financial crisis.

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People must consider both the *risk* and the *ambiguity* of future outcomes when making financial decisions. *Risk* refers to events for which the probabilities of the possible outcomes are known, while *ambiguity* refers to events for which the probabilities of the possible outcomes are unknown. Ellsberg (1961) argues that most people are *ambiguity-averse*, i.e., they prefer a lottery with known probabilities to a similar lottery with unknown probabilities, and numerous theoretical studies explore the implications of ambiguity for economic behavior. In particular, several theoretical papers link ambiguity aversion to household portfolio choice; however, empirical evidence derives mainly from laboratory experiments rather than actual portfolio choices. In this paper, we provide the first non-laboratory empirical evidence showing that ambiguity aversion is significantly and negatively associated with household investment in stocks. Specifically, in a nationally-representative sample of U.S. households, we use real rewards to elicit measures of individuals' ambiguity aversion and then demonstrate that these measures can explain actual portfolio choices.

We develop an internet survey module to elicit respondents' ambiguity aversion and implement it on more than 3,000 respondents in the American Life Panel (ALP). Following the classic Ellsberg urn problem, the module asks respondents to choose between a lottery with known probabilities (the drawing of a ball from a box with 100 colored balls in known proportions), versus a lottery with unknown probabilities. By varying the probability of winning in the lottery with known probabilities, we are able to measure individual respondents' ambiguity aversion. All of the respondents are eligible to win real monetary incentives (a total of $23,850 was paid to 1,590 of the respondents), which prior studies show is crucial for eliciting meaningful responses to questions involving economic preferences. Our results confirm that there is strong heterogeneity in ambiguity aversion: a large fraction of respondents (51%) is ambiguity *averse*, a small fraction (12%) ambiguity *neutral*, and the remainder (37%) ambiguity *seeking*. Having elicited ambiguity aversion, we then test whether it can help explain stock market participation.

The fact that a large proportion of the U.S. population does not participate in the stock market is puzzling, because models using standard expected utility functions predict that all individuals should participate (Merton, 1969). Several theoretical papers suggest that ambiguity aversion can explain this puzzle. Based on the assumption that investors view stock returns as ambiguous, Bossaerts et al. (2010), Cao, Wang, and Zhang (2005), Dow and Werlang (1992), Easley and O'Hara (2009), Epstein and Schneider (2010), and Peijnenburg (2012), among others, show that ambiguity aversion can cause non-participation. Garlappi, Uppal, and Wang (2007) and Peijnenburg (2012) show that ambiguity aversion can reduce the fraction of financial wealth allocated to equity. These theoretical models provide two empirically testable hypotheses: (1) People with higher ambiguity aversion are less likely to *participate* in the stock market; and (2) People with higher ambiguity aversion allocate a lower *fraction* of their financial wealth to equities.

Our tests of these hypotheses show that a one standard deviation increase in ambiguity aversion implies a 10% decrease in the probability of stock market participation and a 16% decrease in the fraction of financial wealth allocated to equity. The results are robust to controls for factors that previous studies show to affect household portfolio choice including wealth, income, age, education, risk aversion, trust, and financial literacy. The module also includes two check questions to assess whether a respondent's choices are consistent; we find stronger results for respondents whose choices are consistent.

In most models of ambiguity, the effect of ambiguity aversion is stronger when the perceived level of ambiguity is high. We therefore also test how equity owners reacted to the recent financial crisis, a period when the perceived ambiguity of future asset returns increased sharply (e.g., Bernanke, 2010; Caballero and Simsek, 2012). Our results show that respondents with higher ambiguity aversion were significantly more likely to actively sell equities during the crisis. To our knowledge, this is the first empirical test examining how ambiguity aversion affects active *changes* in household portfolios during times of market turmoil.

Furthermore we test Heath and Tversky's (1991) competence hypothesis, which predicts that ambiguity aversion depends on individuals' domain-specific knowledge. Although people are generally ambiguity averse for tasks where they do not feel competent (e.g., guessing the composition of an Ellsberg urn), people are often ambiguity seeking for tasks where they believe they have expertise. Hence, we expect that financial knowledge will moderate the relation between a respondent's ambiguity aversion towards Ellsberg urns and his ambiguity aversion towards financial decisions. We measure financial competence in two ways: financial literacy, and self-assessed knowledge about the stock market. For both measures, the effect of ambiguity aversion on portfolio choices is stronger for people with lower financial competence.

Recent laboratory studies report substantial differences in ambiguity aversion to gains versus to losses (e.g., Baillon and Bleichrodt, 2012). Accordingly, in our survey module we differentiate ambiguity aversion towards gains and losses. Consistent with the experimental literature, even within-subject we find substantial differences in ambiguity aversion towards gains and losses. To our knowledge, we are the first to elicit ambiguity aversion towards losses in the general population. We find, however, that ambiguity aversion towards losses is not related to portfolio choice. Also, drawing on recent experimental results (Abdellaoui et al., 2011), we measure ambiguity aversion for both low and high likelihood ambiguous events. Interestingly, these measures do not help explain peoples' portfolio choices in our sample. In contrast to the recent experimental findings, the basic models of ambiguity aversion used in the finance literature do not differentiate between ambiguity aversion towards *gains versus losses*, or *events of different likelihoods*. Thus the insignificance of our results for these alternative measures of ambiguity attitudes provides implicit support for the models used in the finance literature.

This paper contributes to the literature by testing the theoretical models that use ambiguity aversion to explain household portfolio choice. Aside from laboratory experiments (e.g., Bossaerts et al., 2010), we are the first to show a significant relation between ambiguity aversion and actual stock ownership.[1] Further the economic magnitude of this relation is large.

In a related study, Dimmock, Kouwenberg, and Wakker (2012) develop a method for eliciting ambiguity attitudes and apply it in a Dutch household survey. Although their primary focus is on developing the elicitation method, they also examine one of our two main hypotheses: whether ambiguity aversion is related to stock market participation. In their relatively small dataset, they do not find a significant relation except for a subsample of respondents with low perceived knowledge about future asset returns. Further, they focus on a particular model of ambiguity aversion, the source method of Abdellaoui et al. (2011) and Chew and Sagi (2008), which differs from the models of ambiguity aversion used in the finance literature. By contrast, we are agnostic about the “true” model of ambiguity aversion, and our key ambiguity aversion variables are consistent with nearly all underlying models of preferences,

[1] Although not their main focus, Guiso, Sapienza, and Zingales (2008) include a control variable for ambiguity aversion, measured using a hypothetical compound lottery with *known* probabilities, but do not find significant results.

making our results more generalizable. Our elicitation method builds on Dimmock et al. (2012), but extends their method to also measure ambiguity aversion for losses. We also have richer data on households' portfolios, which allows us to test how ambiguity aversion affected investors' behaviors during the financial crisis.

1. Theory and hypotheses

Models based on standard utility functions show that, in a frictionless world, all households will participate in the stock market (Merton, 1969). One branch of the literature attempts to explain non-participation based on market frictions, such as non-tradable labor income or stock market participation costs (e.g., Benzoni, Collin-Dufresne, and Goldstein, 2007; Cocco, Gomes, and Maenhout, 2005; Vissing-Jorgenson, 2002). But these frictions cannot explain the low fraction of financial wealth allocated to stocks, and as Campbell (2006) notes, cannot explain non-participation by the wealthy. Further, empirical tests by Andersen and Nielsen (2011) suggest that typical participation costs cannot explain most non-participation.

Another branch of the literature explains non-participation based on non-standard preferences such as ambiguity aversion. The first tractable method to model ambiguity aversion was the multiple prior model of Gilboa (1987), Schmeidler (1989), and Gilboa and Schmeidler (1989). In this setting, the agent does not know the true distribution of an uncertain event and evaluates multiple prior distributions using a maxmin approach (i.e., maximizing utility over the worst outcomes of the prior distributions). Using this model, Dow and Werlang (1992) show that if asset returns are ambiguous there is a range of prices for which the agent will not participate. Since Dow and Werlang (1992) model a single agent, they abstract from heterogeneity in ambiguity aversion; hence they do not directly explain why some participate and others do not. Cao, Tan, and Wang (2005), Easley and O'Hara (2009), Epstein and

Schneider (2010), and Peijnenburg (2012) extend the multiple prior approach to include heterogeneous agents with different priors over asset returns. They find that agents with more dispersed priors are less likely to participate in the stock market. Peijnenburg (2012) shows that the multiple prior model can simultaneously explain non-participation and the empirically observed low fraction of financial wealth allocated to stocks.

More recent models allow variation in both preferences towards and beliefs about ambiguity. In the α-maxmin model of Ghirardato, Maccheroni, and Marinacci (2004), agents have multiple priors and base decisions on a weighted average of utility across the minimum and the maximum possible outcomes. Their α parameter measures the weight on the minimum possible outcomes, and thus it quantifies the agent's dislike of ambiguity (preference) in a way that is separate from the agent's priors (beliefs about ambiguity). Bossaerts et al. (2010) show that agents with higher α parameters are less likely to participate in the stock market.

The ambiguity models just described imply a negative relation between ambiguity and *stock market participation*, although they differ in the precise mechanism generating the outcome. Moreover, several predict a negative relation between ambiguity and the *fraction of wealth allocated to stocks*. In this paper, we do not take a stand on which is the "correct" underlying model of ambiguity, nor do we test the different models against each other. Instead, we focus on testing whether stock market participation can be explained by variation in ambiguity aversion among respondents, regardless of whether this variation in ambiguity aversion is due to dispersion in preferences or dispersion in prior distributions.

2. Measuring ambiguity aversion

We developed a series of questions to elicit ambiguity aversion and implemented these questions using a special module in the ALP internet survey. Our questions are posed as choices between an *ambiguous* Box U (Unknown) and an *unambiguous* Box K (Known), similar to the famous Ellsberg (1961) two urn experiment.[2] As shown in Figure 1, both boxes contain exactly 100 balls, which can be purple or orange. One ball is randomly drawn from the box selected by the respondent; he wins $15 if that ball is purple and $0 if the ball is orange. For Box K, the number of purple balls is explicitly shown on the screen (50 purple balls), as well as the number of orange balls (50). For Box U, the number of purple balls is not given, and the respondent only knows it is between 0 and 100. A respondent who prefers Box K over Box U is ambiguity averse; that is, he prefers known probabilities to unknown probabilities. In the survey, a respondent can also choose “Indifferent” instead of Box K or Box U. A choice of “Indifferent” implies that the respondent considers Box K and Box U to be equally attractive, so he is ambiguity-neutral. An ambiguity-neutral subject treats the subjective probability of winning for Box U as if it were equal to the 50% known probability of winning for Box K. For this reason, we refer to 50% as Box U’s *ambiguity-neutral probability* of winning.

Figure 1 here

To more precisely measure the respondents’ ambiguity aversion, we follow an approach similar to that of Baillon and Bleichrodt (2012), Baillon, Cabantous, and Wakker (2012), and Dimmock, Kouwenberg, and Wakker (2012). Specifically, the question sequence has additional rounds that take the respondent through a series of choices, converging towards the point of indifference.[3] For example, suppose a respondent displays ambiguity aversion in the first round of the question, preferring Box K over Box U (see Figure 1). We then decrease Box K’s known probability of winning to 25% in the second round. Alternatively, if the respondent chooses Box

[2] Our survey module uses “box” instead of “urn,” as the word “urn” might be unfamiliar to some subjects.
[3] Kahn and Sarin (1988) measure ambiguity aversion by directly asking subjects for the known probability that makes them indifferent between a known and an unknown lottery. Our method differs, as prior studies show that discrete choices measure preferences more reliably than directly asking for an indifference value. e.g., Bostic, Herrnstein, and Luce (1990) and Noussair, Robbin, and Ruffieux (2004)

U in the first round, we then increase the known probability of winning to 75%. This process is repeated for up to four rounds, until the respondent's indifference point is closely approximated.[4] We refer to the known probability of winning for Box K at which the respondent is indifferent between Box K and Box U as the *matching probability* (Dimmock et al., 2012). For example, suppose the respondent is indifferent between drawing a purple ball from Box K with a known probability of winning equal to 40%, versus drawing a purple ball from Box U with an unknown probability. Then the matching probability is 40%.

A key appeal of this approach is that matching probabilities measure ambiguity aversion *relative* to risk aversion. As a result, all other features of utility, such as risk aversion or probability weighting, are differenced out of the comparison. For example, different subjects might receive different utilities from a prize of $15. But our matching probabilities measure a *within-subject* comparison between Box K and Box U, and because the prize is the same for both boxes, the utility of $15 is differenced out of the comparison. Accordingly, *cross-subject* differences in utility are irrelevant. Matching probabilities capture only *differential* preferences for ambiguity relative to risk.[5]

For the ambiguity question shown in Figure 1, a respondent with a matching probability below 50% is *ambiguity averse*. A respondent with a matching probability equal to 50% is *ambiguity neutral*, and a respondent with a matching probability above 50% is *ambiguity seeking*. In what follows, q^{50} denotes the matching probability for the question and we define $AA^{50} = 50\% - q^{50}$ as a measure of ambiguity aversion. Thus positive values of AA^{50} indicate ambiguity aversion, zero indicates ambiguity neutrality, and negative values indicate ambiguity seeking. In some of the empirical tests we use two additional measures of ambiguity aversion.

[4] Appendix A provides additional details about the approximation method.
[5] A proof is provided by Dimmock, Kouwenberg, and Wakker (2012, Theorem 6.1).

The first is simply an indicator variable equal to one if the respondent indicates ambiguity aversion for the first round of the question (i.e., if he selects Box K in the first round). The second is the rank transformation of AA^{50}, with zero indicating the lowest level of ambiguity aversion and one the highest.

Importantly, subjects have the possibility of receiving real rewards based on their choices, because prior studies show that this produces more reliable estimates of preferences (Smith, 1976). At the start of the survey, all subjects are told that one of their choices will be randomly selected and played for a chance to win $15.[6] We paid a total of $23,850 in real incentives to 1,590 of the 3,158 ALP subjects.[7] The RAND Corporation's ALP was responsible for determining the incentives won by respondents and making payments; so suspicion about the trustworthiness of the incentive scheme should therefore play no role, as subjects regularly participate in ALP surveys and frequently receive incentive payments from RAND.

In Ellsberg experiments respondents usually can choose the winning color, to rule out potential suspicion that the ambiguous urn was manipulated to contain fewer purple balls than orange balls. In our survey we chose not to add an option to change the winning color, as we wanted to keep the screen showing our ambiguity question as simple as possible for use in the general population. Further, the survey was administered by RAND Corporation's ALP, which should minimize distrust. Prior studies have also demonstrated overwhelmingly that subjects are indifferent between betting on either color (e.g., Abdellaoui et al. (2011); Fox and Tversky (1998)). To confirm this, we gave a separate group of 250 respondents the option to select the

[6] In theory, subjects can exhibit strategic behavior and positively influence their probabilities of receiving $15 by picking the ambiguous box, thereby increasing the known probability of winning in the risky box in subsequent steps. Nevertheless, our survey takes less than 10 minutes on average and only three sets of ambiguity questions are included, which limits the possibility of learning due to repetition of the task.

[7] Before including our survey module in the ALP panel, we piloted our questions in a laboratory experiment at the Wharton Behavioral Lab. Results of the lab experiment are available upon request.

winning color and we found no significant differences in ambiguity aversion from the main survey sample.[8]

Since elicited preferences likely contain measurement error,[9] we also include two check questions to test the consistency of subjects' choices. After each subject completes the ambiguity questions (including those described in Section 6), we estimate his matching probability: q^{50}. We then generate two check questions by changing the known probability of winning for Box K to q^{50} + 10% in the first question, and q^{50} − 10% in the second. Box U remains unchanged. A subject's response is deemed inconsistent if he prefers the ambiguous Box U in the first check question or the unambiguous Box K in the second check question. Appendix A details the ambiguity survey questions, including the consistency checks.

3. Data and variables

Our survey module to measure ambiguity aversion was implemented in the RAND American Life Panel.[10] The ALP consists of several thousand households that regularly answer Internet surveys. Households that lack Internet access at the recruiting stage are provided with a laptop and wireless service, so as to limit selection biases.[11] To further ensure the sample is representative of the U.S. population the ALP provides survey weights, which we use for all statistics reported in this paper. In addition to the ambiguity aversion variables derived from our

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[8] In August 2013 we fielded an additional survey with 500 respondents. In this survey, half of the respondents could choose the winning color (purple or orange), while the other half could not (all other aspects of this survey were identical to the original survey, including real incentives). The mean matching probabilities of the 'color choice' and 'no color choice' groups are 0.472 and 0.478, respectively, and the difference is not statistically significant. Furthermore, the average matching probability of the `color choice' group is not significantly different from that in the main survey sample.

[9] See Harless and Camerer (1994) and Hey and Orme (1994) for further discussion of measurement error in preference elicitation.

[10] See Appendix C for more information about the ALP.

[11] See https://mmicdata.rand.org/alp/index.php?page=comparison for a comparison of the ALP to alternative data sources.

module, we use additional variables from the ALP surveys. Table 1 defines these variables and Table 2 provides summary statistics; the last column of Table 2 also indicates the number of valid responses for each variable.

The first variable summarized in Table 2 is Stock Ownership, an indicator variable equal to one if a respondent holds stocks (either individual stocks or equity mutual funds) in his personal portfolio. The participation rate in our sample is 23%.[12] The second row shows that the unconditional average fraction of financial assets allocated to stocks is 12%; conditional on stock market participation, the average fraction is 52%.

Tables 1 and 2 here

In all empirical tests we control for several demographic and economic characteristics, including age, sex, ethnicity, marital status, education, household income and wealth, number of children, retirement plan type, and self-reported health status.[13] We include these variables to partial out any potential confounding effects that these factors might have on household portfolio choice, and thus to provide cleaner estimates of the effect of ambiguity aversion.

Our ALP survey module also incorporates additional questions to measure trust, risk aversion, and financial literacy. We include these variables to avoid omitted variable biases, as it is plausible that these variables affect portfolio choice and could measure something conceptually similar to ambiguity aversion. For example, it is possible that ambiguity aversion might be influenced by trust (i.e., people who distrust others may assume that ambiguous events

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

[13] For prior studies using these variables see, among others, Guiso, Sapienza, and Zingales (2008), Haliassos and Bertaut (1995), Rosen and Wu (2004), and Vissing-Jorgensen (2002).

are systematically biased against them). Following Guiso, Sapienza, and Zingales (2008), we use the trust question from the World Values Survey.[14]

Our methodology is designed to elicit ambiguity aversion in a manner unaffected by risk aversion, nevertheless we control for risk aversion for two reasons. First, to ensure that our ambiguity aversion variables capture a distinct component of preferences, separate from risk aversion. Second, ambiguity aversion and risk aversion could be correlated, in which case ambiguity attitudes might provide little incremental information about preferences. To measure risk aversion, we build on Tanaka, Camerer, and Nguyen's method (2010) which asks respondents to select from a list consisting of 14 tradeoffs between two gambles. We modify their approach and use a sequence of binary choices similar to the method for eliciting ambiguity aversion described previously, as illustrated in Figure 2. If a respondent selects the certain outcome, he is then shown another choice with a higher expected value for the risky outcome. If he selects the risky outcome, he is then shown another choice with a lower expected value for the risky outcome. This process is repeated until risk aversion is sufficiently well-approximated. We use the responses to estimate each respondent's risk aversion, measured as the coefficient of relative risk aversion assuming a power utility function.[15] Table 2 shows that the average ALP respondent is risk averse, but there is substantial variation and some people are risk-seeking.

Figure 2 here

[14] Although our question is the same as theirs, we use a different answer scale: we allow subjects to select a response along a 6-point Likert scale, with zero indicating a high level of trust in others and five indicating a high level of distrust, while Guiso, Sapienza, and Zingales (2008) use a binary variable indicating either agreement or disagreement with the statement that others can be trusted.

[15] As in Tanaka, Camerer, and Nguyen (2010), the payoffs of the gambles are not integrated with total wealth in the utility function, and the power coefficient is limited to the range from 0 to 1.5. Risk aversion is defined as: 1 – power function coefficient, and varies from -0.5 (risk seeking) to +1 (strongest level of risk aversion). A value of zero implies risk neutrality.

Finally, we control for financial literacy, as prior studies show it has a strong relation with financial decisions (c.f., Lusardi and Mitchell, 2007; van Rooij, Lusardi, and Alessie, 2011). To ensure that ambiguity aversion is not simply a proxy for low financial literacy, our survey module includes three questions similar to those devised by Lusardi and Mitchell (2007) for the Health and Retirement Study. Our index of financial literacy is the number of correct responses to these questions. Table 2 shows that, on average, respondents answer slightly more than two of the questions correctly. (Appendix C provides the exact wording of these questions.)

Table 3 summarizes ambiguity aversion in the ALP sample. Panel A shows that a 51% of the respondents are ambiguity averse, 12% are ambiguity neutral, and 37% are ambiguity seeking. These results are roughly consistent with the findings in a survey of Italian households by Butler, Guiso, and Jappelli (2011),[16] and they are within the range of results from a large number of studies summarized in Oechssler and Roomets (2013) and Trautmann and van de Kuilen (2013). Panel B summarizes the key ambiguity aversion measure: AA^{50}. On average, the respondents are ambiguity averse, but there is strong heterogeneity in ambiguity preferences. This finding is of importance for the finance literature, as Bossaerts et al. (2010) show that heterogeneity in investors' ambiguity aversion will result in equilibrium asset prices that cannot be replicated by a standard representative agent model with subjective expected utility.[17] Panel C shows the results for the two check questions: The percent of respondents giving inconsistent answers is 29.3% for the first question and 14.7% for the second. These rates are similar to those found in laboratory studies of preferences (e.g., Harless and Camerer, 1994). Table D-1 of Appendix D shows the results of regressing the ambiguity aversion measures on the control

[16] Butler, Guiso, and Jappelli (2011) elicit ambiguity aversion in a survey of Italian retail bank investors. Their goal is to link decision making styles to ambiguity and risk attitudes, in contrast with our goals in the present paper.
[17] The heterogeneity in ambiguity aversion is equally strong (comparable to full sample results in Table 3) among sub-groups that matter most for financial markets, namely stockholders and wealthy individuals.

variables. Naturally, these regressions do not imply causality; rather regression is a convenient tool to summarize the correlation structure of the data. We find that ambiguity aversion is largely uncorrelated with standard economic and demographic characteristics, and thus its effect on economic decisions is not subsumed by commonly used control variables.

Tables 3 here

4. Ambiguity aversion and household portfolio choice

This section tests the relation between ambiguity aversion and household financial behavior, in particular stock market participation and the fraction of financial wealth allocated to stocks. All models reported in this section include controls for financial literacy, risk aversion, trust, age, age squared, gender, White, Hispanic, married, education, employment status, (ln) family income, (ln) wealth, (ln) number of children, defined contribution plan and defined benefit plan participation dummies, self-reported health status, errors on the check questions, question order, missing data dummies,[18] and a constant term. For the sake of brevity, we do not report the coefficient estimates for most control variables (available upon request). For all models, we report robust standard errors clustered at the household level.

4.1. Ambiguity aversion and stock market participation

Panel A of Table 4 shows the results of probit models that test the relation between ambiguity aversion and stock market participation. The dependent variable is an indicator variable equal to one if the respondent owns individual stocks or equity mutual funds, and zero otherwise. In columns (1) and (2) the ambiguity aversion variable is AA^{50} Averse (Dummy): an indicator variable equal to one if the respondent's choice indicates ambiguity aversion in the

[18] Results are robust to excluding observations with missing data, rather than including these observations and using missing-data dummy variables.

first round of the question. We include this independent variable for two reasons. First, it is the simplest possible measure of ambiguity aversion from our survey, and it serves as a valid measure for any underlying model of ambiguity aversion. Second, because this variable depends only on the first response to the first question, it is not subject to concerns about strategic answering (as the subject could not know that the question had multiple linked rounds). In columns (3) and (4) the independent variable is the (rescaled) matching probability, AA^{50}. In columns (5) and (6), the independent variable is AA^{50} Rank, which is simply a rank transformation of AA^{50} (zero indicating the lowest level of ambiguity aversion and one the highest). We include this variable to show that the significance of our main ambiguity aversion variable, AA^{50}, is not driven by outliers. The results are similar for all three variables.

Table 4 here

Consistent with the predictions of theory, there is a significant negative relation between ambiguity aversion and stock market participation. Further, the economic magnitude is large. The coefficient reported in column (1) is the easiest to interpret: the estimated marginal effect implies that an ambiguity averse individual is 4.3 percentage points less likely to participate in the stock market (18.7% relative to the baseline rate of 23%). To put this in perspective, this economic magnitude is equivalent to a change in wealth of 0.74 standard deviations ($498,000).

The even numbered columns report results for a restricted sample, which includes only individuals with at least $500 in financial assets (as in Heaton and Lucas, 2000). We include these results because modest participation costs can account for a sizeable fraction of non-participation (Haliassos and Bertaut, 1995; Gomes and Michaelides, 2005; Vissing-Jorgensen, 2002). Such costs cannot, however, explain non-participation among those with moderate to large levels of financial assets. In our restricted sample, both the statistical and economic significance of ambiguity aversion rise. The marginal effect in column (2) implies that an ambiguity averse individual is 8.8 percentage points less likely to participate in the stock market (23.8% relative to the baseline participation rate in this subsample of 37.0%).

In addition to the standard demographic and economic control variables, Table 4 also includes some control variables of particular relevance for a study of ambiguity aversion: trust, risk aversion, and financial literacy.[19] Trust is important, as it is conceivable that the ambiguity aversion variables could measure subjects' distrust of the experiment: that is, subjects might believe that ambiguous situations are systematically biased against them. In our sample, the relation between trust and participation is directionally consistent with Guiso, Sapienza, and Zingales (2008). More importantly, the results for ambiguity aversion are robust to controlling for trust.

Another potential concern is that ambiguity aversion might be correlated with risk aversion, in which case our ambiguity aversion variables might capture little incremental information.[20] To control for this possibility, all specifications include our elicited measure of risk aversion. In the full sample, risk aversion is significant at the 10% level and positively related to equity market participation, but this effect dissipates in the subsample of subjects with at least $500 in financial wealth. Although this pattern seems somewhat counterintuitive,

[19] In Appendix Table D.2 we show results that also include a control variable for optimism. Similar to Puri and Robinson (2007), we measure optimism based on peoples' miscalibrations of their life expectancy. However, as we do not have all of the information available to Puri and Robinson, we can only use a dummy for individuals who overestimate their probability of living past age 75. Results for the estimated ambiguity effects are similar to those in Table 5.

[20] Although our elicitation method is designed to measure ambiguity aversion indepent of any effect from risk aversion, it is still possible for ambiguity aversion and risk aversion to be correlated, for instance, if individuals who are highly risk averse also have very strong preferences for risk over ambiguity.

it is generally consistent with Gomes and Michaelides (2005), who argue for a positive relation between risk aversion and participation because only the risk averse accumulate enough financial wealth to pay the participation costs (due to precautionary savings).

Another potential concern is that financial illiteracy might drive both non-participation and ambiguity aversion. *Ex ante*, this seems unlikely, as Table D.1 in Appendix D shows that education and financial literacy explain little of the variation in ambiguity aversion. But to guard against this possibility, in each specification we control for financial literacy. Consistent with previous studies, financial literacy has a highly significant and positive association with equity market participation (van Rooij, Lusardi, and Alessie, 2011). Controlling for financial literacy, however, does not diminish the negative relation between ambiguity aversion and stock market participation.

Overall, our results confirm the predictions of theory - higher ambiguity aversion is associated with lower stock market participation. Further, the results are stronger for households with at least moderate amounts of financial wealth, a group whose non-participation is particularly difficult to explain.

4.2. Ambiguity aversion and the fraction of financial wealth allocated to stocks

Panel B of Table 4 reports results from Tobit regressions that test the relation between ambiguity aversion and the fraction of financial wealth allocated to stocks. As in Panel A, the key independent variables are AA^{50} Averse (Dummy), AA^{50}, and AA^{50} rank. The odd numbered columns present results using the full sample; the even numbered columns exclude respondents with less than $500 in financial assets.

As predicted by theory (e.g., Garlappi, Uppal, and Wang, 2007; Peijnenburg, 2012), all of the columns show a negative relation between ambiguity aversion and the fraction of financial wealth allocated to equity.[21] In column (3), for an individual with non-zero ownership, the implied decrease in portfolio allocations to equity from a one standard deviation increase in ambiguity aversion is 8.2 percentage points (15.8% relative to the conditional average allocation of 51.8%). As in Panel A, the effect is larger for the subsample that has at least some minimum financial wealth. Overall, the results confirm a strong negative relation between ambiguity aversion and portfolio allocations to equity. Given that the three alternative measures of ambiguity aversion all give similar results, in the remainder of this section we report results only for AA^{50}.

4.3. Measurement error in preference elicitation and the effects of ambiguity aversion

A large literature beginning with Harless and Camerer (1994) and Hey and Orme (1994) shows that subjects often provide inconsistent responses to non-trivial questions about preferences. Our survey includes two check questions to test the consistency of respondents' choices, as there may be more measurement error in the estimates of ambiguity aversion for respondents whose answers are inconsistent. For this reason, the sample in Table 5 excludes the respondents who gave inconsistent answers to either check question.

Table 5 here

Interestingly, ambiguity aversion is significantly higher in this subsample: respondents who did not make errors on the check questions have matching probabilities 5.4 percentage

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[21] The estimated effects of ambiguity aversion are not significantly different if we estimate Tobit models using a restricted sample that only includes observations with non-zero equity ownership. We do not estimate Heckman style selection models as we do not have valid instruments to identify the first stage equation, and in the absence of valid instruments selection models are frequently severly misspecified (c.f., Lennox, Francis, and Wang, 2012).

points lower than the respondents who did make errors.[22] The implied economic magnitude of the effect of ambiguity aversion is also considerably larger in this subsample, consistent with attenuation bias due to measurement error in the independent variable. For instance, in column (1), the estimated marginal effect is nearly 35% larger than the corresponding marginal effect in column (3) of Panel A of Table 4. Finding stronger results for this subsample, in which our measure of ambiguity aversion is more reliable, suggests two things. First, this finding supports our interpretation of the main results, and it is inconsistent with alternative explanations based on misunderstandings of the elicitation questions. Second, our baseline estimates potentially understate the true economic magnitude of the relation between ambiguity aversion and household portfolio choice.

4.4. Ambiguity aversion and financial competence

The competence hypothesis of Heath and Tversky (1991) predicts that most people are ambiguity averse towards purely chance-based ambiguity (like an Ellsberg urn), but the effect of ambiguity aversion is reduced (or even reversed) for decisions in those areas where individuals see themselves as knowledgeable or competent. Hence, individuals with high financial knowledge would display less ambiguity aversion towards financial decisions, compared to Ellsberg urns (a low competence task). Conversely, individuals with low financial knowledge would display similar ambiguity aversion towards financial decisions and towards Ellsberg urns, as they do not feel competent in either setting. This implies that the relation between our measures of ambiguity aversion (based on Ellsberg urns) and portfolio choice should be stronger for those with relatively low financial competence.

[22] Errors in answering the ambiguity question should bias AA^{50} towards zero. Consistent with greater measurement error, AA^{50} is not significantly different from zero for the subsample of respondents who made errors answering the check questions.

We test the predictions of the competence hypothesis in two ways. First, in Panel A of Table 6 we split the sample into two groups: those who made mistakes on the financial literacy questions, and those who did not. In Table 4, we controlled for the effect of the *level* of financial literacy on household portfolio choice. By contrast, here we allow financial literacy to affect the *sensitivity* of the relation between ambiguity aversion and household portfolio choice. Second, in Panel B of Table 6 we again split the sample in two groups, but now based on self-assessed knowledge about the stock market.[23] In both panels, results for those with low financial competence are displayed in the odd-numbered columns, and results for the other subsample appear in the even-numbered columns. Aside from the sample split, these regressions use the same methods and control variables as in Table 4.

Table 6 here

Panel A of Table 6 shows that the effect of ambiguity aversion is always more statistically significant in the subsample with low financial literacy, both for stock market participation and the fraction allocated to stocks. Although the reported marginal effects in columns (1) and (2) appear similar, this is because the baseline participation rate is much smaller in the low financial literacy group than in the high literacy group. For a respondent with low financial literacy, a one standard deviation increase in ambiguity aversion implies a 20.7% decrease in the probability of participation (relative to this subsample's baseline participation rate of 11.1%). But for a respondent with high financial literacy, the implied decrease is only 4.4% (relative to this subsample's baseline participation rate of 37.9%).

Similarly, Panel B of Table shows that the effect of ambiguity aversion is mainly significant in the subsample with low self-assessed stock market knowledge. The marginal

[23] Our ALP survey includes the following question: "How would you rate your knowledge about the stock market?", with answers measured on a 5-point scale (very low, low, moderate, high, very high).

effect sometimes appears lower for the low competence group, however, once again, this is because the baseline participation rate is substantially smaller in this group. For example, comparing columns (3) and (4), the implied decrease in the probability of stock market participation due to a one standard deviation increase in ambiguity aversion is 21.6% for the low self-assessed knowledge subsample (whose baseline participation rate is 14.8%), compared to only 8.1% for the high self-assessed knowledge subsample (whose baseline participation rate is 43.7%). Overall, our results support the competence hypothesis of Heath and Tversky (1991).

5. Ambiguity aversion and investor behavior during the financial crisis

We next examine whether changes in the perceived ambiguity of equity returns affects investor behavior. Specifically, we test whether, conditional upon owning equities before the financial crisis, individuals with higher ambiguity aversion were more likely to actively sell equities during the financial crisis.[24] We use the financial crisis as numerous authors suggest that perceived ambiguity increased sharply during this period (e.g., Bernanke, 2010; Caballero and Simsek, 2013).

For these tests we use data from an ALP module titled “Effects of the Financial Crisis”, fielded in May 2009. The module asked several questions about active portfolio changes during the financial crisis. Unfortunately, only 43% of the respondents in our module also participated in the “Effects of the Financial Crisis” module, and we further limit the sample to include only

[24] These tests are conceptually similar to those in Butler, Guiso, and Jappelli (2011) who show that intuitive investors reacted differently to the financial crisis compared to deliberative investors. Antoniou, Harris, and Zhang (2013) show that the time-series of aggregate mutual fund flows has an inverse relation with time-varying uncertainty.

those respondents who owned equities outside of retirement accounts prior to the financial crisis. This leaves a final sample of 532 observations.[25]

The dependent variable in Table 7 is an indicator equal to one for respondents who actively sold equities during the financial crisis. For respondents who both bought and sold equities during this period, we count only the respondents who sold more than they bought. The regressions include the same control variables as in Table 4. We report marginal effects rather than coefficients and standard errors are clustered by household. Our results are consistent with theory: in all three columns respondents with higher ambiguity aversion were more likely to actively reduce their equity holdings during the financial crisis. The coefficient in the second column implies that a one standard deviation increase in ambiguity aversion is associated with a 3.3 percentage point increase in the probability of selling stocks (a 39% increase relative to the baseline probability of selling stocks of 8.4% percentage points).

Table 7 here

A growing literature shows that numerous asset pricing puzzles can be explained by time-varying uncertainty (e.g., Anderson, Ghysels, and Juergens, 2009; Drechsler, 2013). Our results compliment this literature by showing that, following an increase in perceived uncertainty, variation in ambiguity aversion can explain cross-sectional differences in portfolio changes.

6. Other ambiguity attitude measures and household portfolio choice

Until this section, we have used relatively simple measures of ambiguity aversion, derived from questions closely corresponding to the classical Ellsberg experiment with two colors. A key advantage of this approach is that it provides a valid measure of ambiguity

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[25] Although, the crisis module was completed nearly three years prior to our module, we believe that it is unlikely that investment choices made during the financial crisis would significantly affect respondents' ambiguity related choices three years later; as such, we do not believe reverse causality is a concern.

aversion for a wide range of underlying models of ambiguity aversion, and thus allows us to be agnostic regarding the "true" model of ambiguity aversion. Recent experimental studies, however, find empirical regularities that contradict many models of ambiguity. Specifically, as predicted by Ellsberg (1961), individuals tend to be ambiguity seeking for low likelihood ambiguous events (c.f., Abdellaoui et al., 2011). Also, individuals' preferences towards ambiguity depend on whether the outcomes involve gains or losses (Baillon and Bleichrodt, 2012; Chakravarty and Roy, 2009; Cohen, Jaffray, and Said, 1987).

Laboratory studies show that ambiguity aversion differs across likelihoods: most people are ambiguity seeking for low likelihood ambiguous events, but extremely ambiguity averse for high likelihood events (Abdellaoui et al., 2011). In other words, people tend to treat all ambiguous events as if they are 50-50%, displaying insensitivity to the likelihood of the event, a behavior termed ambiguity-generated likelihood insensitivity, or *a-insensitivity*.

To allow for this wider range of ambiguity attitudes, our survey includes three sets of ambiguity questions in addition to those already discussed. Two questions are similar to the traditional two-color Ellsberg (1961) urns, but the urns now have 100 balls of 10 different colors in unknown proportions. In the first question the respondent wins if one out 10 possible colors is drawn, while in the second question the respondent wins for nine out of 10 colors. Hence, the ambiguity-neutral probabilities of winning are 10% and 90%, respectively, and the measures of ambiguity aversion are $AA^{10} = q^{10}\% - 10\%$ and $AA^{90} = q^{90}\% - 90\%$, where q^{10} and q^{90} are the matching probabilities for the two questions.

The last question measures ambiguity aversion for losses. The respondent now loses $15 if a purple ball is drawn from the chosen box. As before, Box K contains 50 purple and 50 orange balls, and Box U contains purple and orange balls in unknown proportions. In this case,

$AA^{-50} = q^{-50}$ - 50%, where q^{-50} is the matching probability and 50% is the ambiguity-neutral probability. If AA^{-50} is positive, then the agent is ambiguity averse in the loss domain, that is, he is willing to accept a relatively high known probability of losing to avoid the ambiguous box.[26] Appendix A provides a description and screen shots of these three sets of additional questions.

As discussed earlier, in most of this paper we take an agnostic stance and do not commit to a specific model of ambiguity aversion. Yet for sensitivity analysis purposes and to compare with the stock market participation regressions in Dimmock, Kouwenberg, and Wakker (2012), we also calculate the ambiguity indexes proposed by Abdellaoui et al. (2011) based on a specific model of ambiguity: the source method. These indexes aggregate information from the first three ambiguity questions, with index *a* measuring a-insensitivity and index *b* measuring ambiguity aversion. Appendix B provides further explanation of these measures and of the source method.

Table 8 shows summary statistics for these alternative measures of ambiguity attitudes. Panels A and C reveal that ambiguity attitudes vary across likelihoods, even for the same person. For the low likelihood ambiguous event, winning if one of 10 ball colors is selected, 58% of the respondents are ambiguity *seeking*, while for the high likelihood ambiguous event, winning if nine of the 10 ball colors is selected, 56% of the respondents are ambiguity averse. Considering the responses to both questions simultaneously, Panel B shows that 78% of the respondents exhibit a-insensitivity. In the loss domain, represented by AA^{-50}, ambiguity aversion (32%), seeking (39), and neutrality (29%) are all common. Panel C summarizes the indexes of ambiguity aversion (index *b*) and a-insensitivity (index *a*) proposed by Abdellaoui et al. (2011). Consistent with the responses to the individual questions, these indexes show

[26] Because of the difficulty in implementing real losses in a household survey, we do not implement real losses in the ALP, instead telling the respondents that the losses are hypothetical for this question.

that, on average, respondents are ambiguity averse and a-insensitive, but there is substantial heterogeneity.

Table 8 here

Table 9 presents regression results that show how these alternative measures of ambiguity attitudes relate to household portfolio choice. Aside from the new ambiguity measures, these regressions are similar to those in Table 4. The main result is that ambiguity aversion, represented by AA^{50} and index *b*, has a significant negative relation with stock market participation and the equity fraction, confirming our previous findings. We next turn to the relation between household portfolio choice and a-insensitivity, shown by the coefficients for AA^{10} and AA^{90} in Panel A, and for index *a* (a-insensitivity) in Panel B. We lack clear theoretical predictions for these tests, as a-insensitivity implies investors overweight both good and bad extreme outcomes. Thus the effects of a-insensitivity will depend on risk aversion and the expected skewness of returns, so the net effect is unclear. In both panels, we fail to find a significant empirical relation between a-insensitivity and household portfolio choice. This differs from Dimmock, Kouwenberg, and Wakker (2012), who found a negative relation in a smaller Dutch sample of households.[27]

Table 9 here

Panel A of Table 9 also tests the relation between ambiguity aversion for losses, AA^{-50}, and household portfolio choice. Here we find no significant relation. This is potentially important because laboratory studies find substantial differences in ambiguity aversion for gains versus for losses, but theoretical studies in finance do not consider this distinction. Our results

[27] In additional robustness tests, not detailed here, we find a more complicated relation between a-insensitivity and investment. A-insensitivity is positively related to “small” fractional allocations to equities (i.e., greater than zero but below 20% of financial assets), but negatively related to “large” fractional allocations to equities. This non-linear relation between a-insensitivity and fractional allocations to equity highlights the difficulty of making predictions in the absence of theory.

therefore provide suggestive evidence supporting the current theoretical approaches. We do note, however, that this was the sole ambiguity question in our survey that was elicited without real rewards, and thus it might be measured with larger error than the other questions.

7. Conclusions

Using real incentives, we measure ambiguity aversion in a large representative survey of the U.S. population and test how ambiguity aversion relates to household portfolio choice. We find that most Americans are ambiguity averse, but there is substantial variation in ambiguity preferences, with 37% of the respondents making ambiguity seeking choices. This finding is of importance, as Bossaerts et al. (2010) show that equilibrium asset prices with ambiguity averse investors will only differ from a standard representative agent economy with subjective expected utility if there is sufficient heterogeneity in ambiguity aversion among market participants. We also find that ambiguity aversion is not highly correlated with other economic and demographic variables.

Our main empirical results demonstrate that ambiguity aversion is negatively associated with stock market participation and with the fraction of financial wealth allocated to equities, consistent with a large theoretical literature (Bossaerts et al., 2010; Cao, Wang, and Zhang, 2005; Dow and Werlang, 1992; Easley and O'Hara, 2009; Epstein and Schneider, 2010; Peijnenburg 2012). Our results are robust to controls for many factors that previous empirical studies suggest predict household portfolio choice. Additionally, we show that the relation between ambiguity aversion and household portfolio choice patterns is stronger for respondents with less financial knowledge, consistent with the competence hypothesis of Heath and Tversky (1991). We also find that, conditional on non-zero stock ownership before the financial crisis, individuals with greater ambiguity aversion were more likely to actively sell equities during the crisis. Additional tests examine the relation between household portfolio choice and alternative ambiguity measures, including ambiguity attitudes towards high and low likelihood events, as well as ambiguity aversion toward losses. Consistent with theoretical models commonly used in the finance literature, we find that ambiguity aversion as conventionally measured is significantly and negatively associated with stock ownership, but little additional information is gained from alternative measures of ambiguity aversion.

A related contribution is that we have created a new publicly available dataset that uses real monetary incentives to measure the ambiguity aversion of a nationally representative sample of Americans, linking preferences to actual economic choices. Overall, our results confirm that ambiguity remains a rich area for investigation, particularly regarding household finance and retirement planning. Moreover, our findings suggest that policies designed to increase financial literacy and financial competence could improve financial decision making, in part by reducing the effect of ambiguity aversion.

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Table 1. Variable Definitions

Stock Ownership	Indicator that respondent holds equities in his personal portfolio (stocks or stock mutual funds)
Fraction Allocated to Stocks	Equity holdings as a % of financial wealth (checking, saving, money market, bonds, CDs, and mutual funds)
Stock Sales during Crisis	Indicator if respondent actively sold stocks during financial crisis
Age	Age in years
Male	Indicator for male
White	Indicator if respondent considers himself primarily White
Hispanic	Indicator if respondent considers himself primarily Hispanic
Married	Indicator if respondent is married or has a partner
LT High School	Indicator if respondent did not complete high school
High School Graduate	Indicator if respondent completed high school, but no additional education
College+	Indicator if respondent completed college
Family Income	Total income for all household members older than 15, including from jobs, business, farm, rental, pension benefits, dividends, interest, social security, and other income
Household Wealth	The sum of net financial wealth, net housing assets, and imputed social security wealth using respondent self-reported claim ages, actual or estimated monthly benefits, and cohort life tables
Number of Children	Number of living children
Defined Contribution	Indicator if respondent has a defined contribution pension plan
Defined Benefit	Indicator if respondent has a defined benefit pension plan
Self-Reported Health	Self-reported health status ranging from 0-4, where 0 indicates “Poor” and 4 indicates “Excellent”
Question Order	Indicator if subject answered the risk aversion question before the ambiguity questions (the question order was randomized)
Trust	Ranges from 0 to 5, where 0 corresponds to "most people can be trusted" and 5 corresponds to "you can't be too careful"
Risk Aversion	Estimated coefficient of risk aversion based on lottery questions, > 0 if risk averse, = 0 if risk neutral, < 0 if risk seeking
Financial Literacy	Number of financial literacy questions answered correctly (out of 3 total; see Appendix C)
Optimism	Indicator if respondent overestimates their chance of living past age 75

Table 2. Summary Statistics of Outcome and Control Variables

This table reports summary statistics of the variables used in our study; variable definitions are provided in Table 1. The summary statistics for Fraction Allocated to Stocks are shown for all respondents and for the subsample of respondents with a non-zero allocation to equity. The last column shows the number of non-missing observations for each variable. All results use ALP survey weights and the sample omits 136 people who spent fewer than three minutes or more than two hours on the survey.

	Mean	*Std. Dev.*	*Min*	*Median*	*Max*	*N*
Stock Ownership (%)	0.23	0.42	0	0	1	3,078
Fraction Allocated to Stocks						
Unconditional (%)	0.12	0.27	0	0	1	3,083
Conditional (%)	0.52	0.33	0.001	0.55	1.00	758
Age	46.17	15.24	18	47	70	3,122
Male (%)	0.48	0.50	0	0	1	3,122
White (%)	0.81	0.39	0	1	1	3,118
Hispanic (%)	0.18	0.38	0	0	1	3,121
Married (%)	0.65	0.48	0	1	1	2,743
LT High School (%)	0.10	0.30	0	0	1	3,121
High School (%)	0.34	0.47	0	0	1	3,121
College+ (%)	0.56	0.50	0	1	1	3,121
Employed (%)	0.49	0.50	0	0	1	3,120
Family Income ($)	68,738	68,545	2,500	55,000	400,000	3,114
Wealth ($)	375,128	670,539	-74,981	150,000	4,917,981	2,317
Number of Children	1.66	1.61	0	2	13	3,077
Defined Contribution	0.48	0.50	0	0	1	3,038
Defined Benefit	0.11	0.31	0	0	1	3,038
Self-Reported Health	2.39	1.02	0	3	4	3,122
Question Order	0.51	0.50	0	1	1	3,122
Trust	3.18	1.44	0	3	5	3,122
Risk Aversion	0.33	0.45	-0.50	0.39	0.98	3,090
Financial Literacy	2.17	0.92	0	2	3	3,122
Optimism	0.30	0.46	0	0	1	3,122

Table 3. Ambiguity Aversion of the U.S. Population

This table shows ambiguity aversion in the U.S. population measured using our ALP survey module. Panel A shows the proportion of respondents who are ambiguity averse, ambiguity seeking, or ambiguity neutral, as revealed by their first-round choice between Box K and Box U (see text and Figure 1). Panel B summarizes the ambiguity aversion measure AA^{50}. We define $AA^{50} = 50\% - q^{50}$, where q^{50} denotes the matching probability for Box U in Figure 1 (with two ball colors, in unknown proportions). Panel C summarizes the percentage of respondents who gave inconsistent answers to the two check questions.

Panel A: Proportion of Respondents Ambiguity Averse, Neutral, and Seeking (%)	
Ambiguity Averse	0.51
Ambiguity Neutral	0.12
Ambiguity Seeking	0.37

Panel B: Summary Statistics Ambiguity Aversion Measure AA^{50}

	Mean	*Std. Dev.*	*Min*	*Median*	*Max*
AA^{50}	0.018	0.211	-0.440	0.030	0.470

Panel C: Check Question Responses

	Not Inconsistent	*Inconsistent*
Check Question 1	70.7%	29.3%
Check Question 2	85.8%	14.2%

Table 4. Ambiguity Aversion and Household Portfolio Choice

This table shows regression results for the dependent variables stock market participation and fraction allocated to stocks. Panel A shows probit regression results for stock market participation. Panel B shows Tobit regression results, in which the dependent variable is the fraction of financial wealth allocated to equities. In columns (2) and (3), the key independent variable is equal to one if the respondent is ambiguity averse. In columns (3) and (4), the key independent variable is the ambiguity aversion measure, AA^{50}. In columns (5) and (6) the key independent variable is the rank transformation of AA^{50} (see text). Columns (2), (4), and (6) exclude respondents who report financial wealth of less than $500. All models include a constant term and controls for age, age-squared, male, White, Hispanic, married, education, employment status, family income, wealth, number of children, participation in defined benefit or defined contribution plans, question order, check question score, and missing data dummies. The table reports marginal effects. Standard errors are clustered by household and appear in brackets.

Panel A: Ambiguity Aversion and Stock Market Participation

	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*
AA^{50} Averse (Dummy)	-0.043 **	-0.088 ***				
	[0.02]	[0.03]				
AA^{50}			-0.105 **	-0.212 ***		
			[0.05]	[0.08]		
AA^{50} Rank					-0.083 **	-0.167 ***
					[0.03]	[0.06]
Trust	-0.004	-0.004	-0.004	-0.004	-0.004	-0.003
	[0.01]	[0.01]	[0.01]	[0.01]	[0.01]	[0.01]
Risk Aversion	0.041 *	0.028	0.043 **	0.033	0.043 **	0.033
	[0.02]	[0.03]	[0.02]	[0.03]	[0.02]	[0.03]
Financial Literacy	0.081 ***	0.089 ***	0.080 ***	0.087 ***	0.080 ***	0.087 ***
	[0.02]	[0.03]	[0.02]	[0.03]	[0.02]	[0.03]
Financial Wealth ≥ $500	No	Yes	No	Yes	No	Yes
Controls and Constant	Yes	Yes	Yes	Yes	Yes	Yes
N	2,997	1,913	2,997	1,913	2,997	1,913

(continued)

Panel B: Ambiguity Aversion and the Fraction of Financial Wealth Allocated to Stocks						
	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*
AA^{50} Averse (Dummy)	-0.156 ***	-0.187 ***				
	[0.06]	[0.05]				
AA^{50}			-0.388 **	-0.457 ***		
			[0.15]	[0.15]		
AA^{50} Rank					-0.309 ***	-0.320 ***
					[0.11]	[0.09]
Trust	-0.012	-0.006	-0.011	-0.005	-0.011	-0.005
	[0.02]	[0.02]	[0.02]	[0.02]	[0.02]	[0.02]
Risk Aversion	0.142 **	0.074	0.150 **	0.084	0.151 **	0.083
	[0.06]	[0.06]	[0.06]	[0.06]	[0.06]	[0.05]
Financial Literacy	0.238 ***	0.142 ***	0.236 ***	0.139 ***	0.236 ***	0.129 ***
	[0.05]	[0.05]	[0.05]	[0.05]	[0.05]	[0.04]
Financial Wealth ≥ $500	No	Yes	No	Yes	No	Yes
Controls and Constant	Yes	Yes	Yes	Yes	Yes	Yes
N	2,997	1,913	2,997	1,913	2,997	1,913

Notes: * significant at the 10%; ** 5%; and *** 1% level.

Table 5. Ambiguity Aversion and Household Portfolio Choice: Check Questions

This table shows regression results for the dependent variables stock market participation and fraction allocated to stocks, and the dataset excludes respondents whose answers to the check question were inconsistent with their earlier choices. Columns (1) and (2) show probit regression results for stock market participation. Columns (3) and (4) show Tobit regression results where the dependent variable is the fraction of financial wealth that the subject allocates to equities. Columns (2) and (4) exclude respondents who report financial wealth of less than $500. All models include a constant term and controls for age, age-squared, male, White, Hispanic, married, education, employment status, family income, wealth, number of children, participation in defined benefit or defined contribution plans, question order, a check question score equal to one if the subject got either of the check questions wrong: meaning they chose Box U in the first check question or Box K in the second check question, and missing data dummies. The table reports marginal effects. Standard errors and are clustered by household and appear in brackets.

	Equity Market Participation		Fraction Allocated to Stocks	
	(1)	*(2)*	*(3)*	*(4)*
AA^{50}	-0.143 *	-0.286 **	-0.446 ***	-0.586 ***
	[0.08]	[0.12]	[0.17]	[0.18]
Financial Wealth ≥ $500	No	Yes	No	Yes
Controls and Constant	Yes	Yes	Yes	Yes
N	1,788	1,224	1,788	1,224

Notes: * significant at the 10%; ** 5%; and *** 1% level.

Table 6. Ambiguity Aversion and Financial Competence

This table shows regression results for the dependent variables stock market participation and fraction allocated to stocks, where respondents are split into two groups based on their financial competence. In Panel A, competence is measured as financial literacy, and in Panel B as self-assessed knowledge about the stock market. Respondents are allocated to the low literacy group if their answer to one or more of the three financial literacy questions is wrong. Respondents are put in the low knowledge group if they answered 'very low' to the question: "How would you rate your knowledge about the stock market?" Columns (1) - (4) show probit regression results for stock market participation. Columns (5) - (8) show Tobit regression results where the dependent variable is the fraction of financial wealth that the subject allocates to equities. Columns (3), (4), (7), and (8) exclude respondents who report financial wealth of less than $500. All models include a constant term and controls for age, age-squared, male, White, Hispanic, married, education, employment status, family income, wealth, number of children, participation in defined benefit or defined contribution plans, question order, check question score, and missing data dummies. The table reports marginal effects. Standard errors are clustered by household and appear in brackets.

Panel A: Ambiguity Aversion and Competence Measured as Financial Literacy

	Stock Market Participation				Fraction Allocated to Stocks			
	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*	*(8)*
	Low lit	High lit	Low lit	High lit	Low lit	High lit	Low lit	High lit
AA^{50}	-0.098 **	-0.079	-0.337 ***	-0.131	-1.007 ***	-0.223	-1.160 ***	-0.279 *
	[0.04]	[0.09]	[0.10]	[0.10]	[0.39]	[0.14]	[0.37]	[0.15]
Financial Wealth ≥ $500	No	No	Yes	Yes	No	No	Yes	Yes
Controls and Constant	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	1,465	1,532	672	1,241	1,465	1,532	672	1,241

Panel B: Ambiguity Aversion and Competence Measured as Self-Assessed Stock Market Knowledge

	Stock Market Participation				Fraction Allocated to Stocks			
	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*	*(8)*
	Low know	High know	Low know	High know	Low know	High know	Low know	High know
AA^{50}	-0.043 **	-0.090	-0.151 **	-0.168 *	-1.177 **	-0.249	-1.077 **	-0.329 **
	[0.02]	[0.07]	[0.08]	[0.09]	[0.52]	[0.15]	[0.53]	[0.15]
Financial Wealth ≥ $500	No	No	Yes	Yes	No	No	Yes	Yes
Controls and Constant	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	948	2,049	420	1,493	948	2,049	420	1,493

Notes: * significant at the 10%; ** 5%; and *** 1% level.

Table 7. Ambiguity Aversion and Reactions to the Financial Crisis

This table shows probit regression results in which the dependent variable equals one if the respondent actively sold equities during the financial crisis. The sample includes only those who owned equities prior to the crisis. All models include a constant term and controls for age, age-squared, male, White, Hispanic, married, education, employment status, family income, wealth, number of children, participation in defined benefit or defined contribution plans, question order, check question score, and missing data dummies. The table reports marginal effects. Standard errors are clustered by household and appear in brackets.

	(1)	*(2)*	*(3)*
AA^{50} Averse (Dummy)	0.034 *		
	[0.02]		
AA^{50}		0.156 ***	
		[0.05]	
AA^{50} Rank			0.113 **
			[0.05]
Controls and Constant	Yes	Yes	Yes
N	532	532	532

Notes: * significant at the 10%; ** 5%; and *** 1% level.

Table 8. Summary Statistics of Alternative Measures of Ambiguity Attitudes

This table shows descriptive statistics of alternative measures of ambiguity attitudes measured in our ALP survey module. Panel A displays the proportion of respondents who are ambiguity averse, ambiguity seeking, or ambiguity neutral, as revealed by their first-round choice in four different ambiguity questions. In the first three questions the ambiguity-neutral probabilities of winning $15 (gains) are 10%, 50%, and 90% (winning if 1 out of 10 colors, 1 out of 2 colors, and 9 out of 10 colors are drawn, respectively). In the fourth ambiguity question the ambiguity-neutral probability of losing $15 (losses) is 50%. Panel B shows the proportion of the ALP respondents who are a-insensitive, neutral, or a-oversensitive. A-insensitivity is defined as being more ambiguity averse for the 90% question than the 10% questions. Panel C shows summary statistics for the six ambiguity attitude measures (see text and Appendix B for definitions). Panel D presents correlations of these six measures.

Panel A: Ambiguity Attitudes (proportion of respondents for each question)

Ambiguity Question:	*gains 10%*	*gains 50%*	*gains 90%*	*losses 50%*
Ambiguity Averse	0.19	0.51	0.56	0.32
Ambiguity Neutral	0.23	0.12	0.16	0.29
Ambiguity Seeking	0.58	0.37	0.29	0.39

Panel B: Ambiguity-Generated Insensitivity to Likelihoods

		Proportion of respondents
A-Insensitive	($AA^{90} – AA^{10} > 0$)	0.78
Neutral	($AA^{90} – AA^{10} = 0$)	0.10
A-Oversensitive	($AA^{90} – AA^{10} < 0$)	0.12

Panel C: Summary of Ambiguity Measures

	Mean	*Std. Dev.*	*Min*	*Median*	*Max*
AA^{10}	-0.136	0.206	-0.750	-0.050	0.085
AA^{50}	0.018	0.211	-0.440	0.030	0.470
AA^{90}	0.184	0.256	-0.090	0.075	0.845
AA^{-50}	-0.015	0.195	-0.440	0.000	0.470
Index *b* (ambiguity aversion)	0.052	0.323	-0.853	0.033	0.933
Index *a* (a-insensitivity)	0.394	0.368	-0.219	0.350	1.994

Panel D: Correlations (Coefficients *not* significant at the 5% level in italics)

	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*
(1) AA^{10}	1.00					
(2) AA^{50}	0.41	1.00				
(3) AA^{90}	0.18	0.32	1.00			
(4) AA^{-50}	0.24	0.25	0.18	1.00		
(5) Index *b* (ambiguity aversion)	0.68	0.76	0.74	0.30	1.00	
(6) Index *a* (a-insensitivity)	-0.52	*0.002*	0.74	*-0.01*	0.18	1.00

Table 9. Alternative Measures of Ambiguity Attitudes and Household Portfolio Choice

This table shows regression results for the dependent variables stock market participation and fraction allocated to stocks. Panel A shows the results when including ambiguity measures AA^{10}, AA^{50}, AA^{90}, and AA^{50} Loss as independent variables. Panel B shows the results when including ambiguity measures index *b* (ambiguity aversion) and index *a* (a-insensitivity) as independent variables (see text). Columns (1) and (2) show probit regression results for stock market participation. Columns (3) and (4) show Tobit regression results where the dependent variable is the fraction of financial wealth that the subject allocates to equities. Columns (2) and (4) exclude respondents whose report financial wealth of less than $500. All models include a constant term and controls for age, age-squared, male, White, Hispanic, married, education, employment status, family income, wealth, number of children, participation in defined benefit or defined contribution plans, question order, check question score, and missing data dummies. The table reports marginal effects. Standard errors are clustered by household and appear in brackets.

Panel A: All Ambiguity Questions

	Stock Market Participation		Fraction Allocated to Stocks	
	(1)	*(2)*	*(3)*	*(4)*
AA^{10}	-0.054	-0.055	-0.145	-0.078
	[0.05]	[0.09]	[0.16]	[0.16]
AA^{50}	-0.088	-0.198 **	-0.355 *	-0.454 **
	[0.06]	[0.09]	[0.19]	[0.18]
AA^{90}	0.043	0.058	0.108	0.087
	[0.04]	[0.07]	[0.13]	[0.13]
AA^{50} Loss	-0.011	0.014	0.005	0.046
	[0.05]	[0.09]	[0.15]	[0.16]
Financial Wealth ≥ $500	No	Yes	No	Yes
Controls and Constant	Yes	Yes	Yes	Yes
N	2,962	1,895	2,962	1,895

Panel B: Ambiguity Attitude Indexes

	Stock Market Participation		Fraction Allocated to Stocks	
	(1)	*(2)*	*(3)*	*(4)*
Index *b* (ambiguity aversion)	-0.052 *	-0.096 *	-0.200 **	-0.223 **
	[0.03]	[0.05]	[0.09]	[0.09]
Index *a* (a-insensitivity)	0.044 *	0.058	0.125	0.099
	[0.03]	[0.04]	[0.08]	[0.08]
Financial Wealth ≥ $500	No	Yes	No	Yes
Controls and Constant	Yes	Yes	Yes	Yes
N	2,967	1,895	2,967	1,895

Notes: * significant at the 10%; ** 5%; and *** 1% level.

Figure 1. Choosing Between Two Boxes with Purple and Orange Balls, One Having a Known (50%) Chance of Winning and the Other Ambiguous

This figure shows a screen shot from our ALP module, representing the first question in the 50% ambiguity sequence. Box K is the box with 50% initial known probability of winning; Box U has an unknown mix of purple and orange balls. After answering this question, respondents are led to a next question. Selecting the "Indifferent" button takes the respondent to the next ambiguity sequence (in this case, the 10% ambiguity sequence). If the respondent selects "Box K", he gets a new question with a lower probability of winning in Box K (fewer purple balls), while if he selects "Box U", the next question has a higher winning probability of winning in Box K (more purple balls).

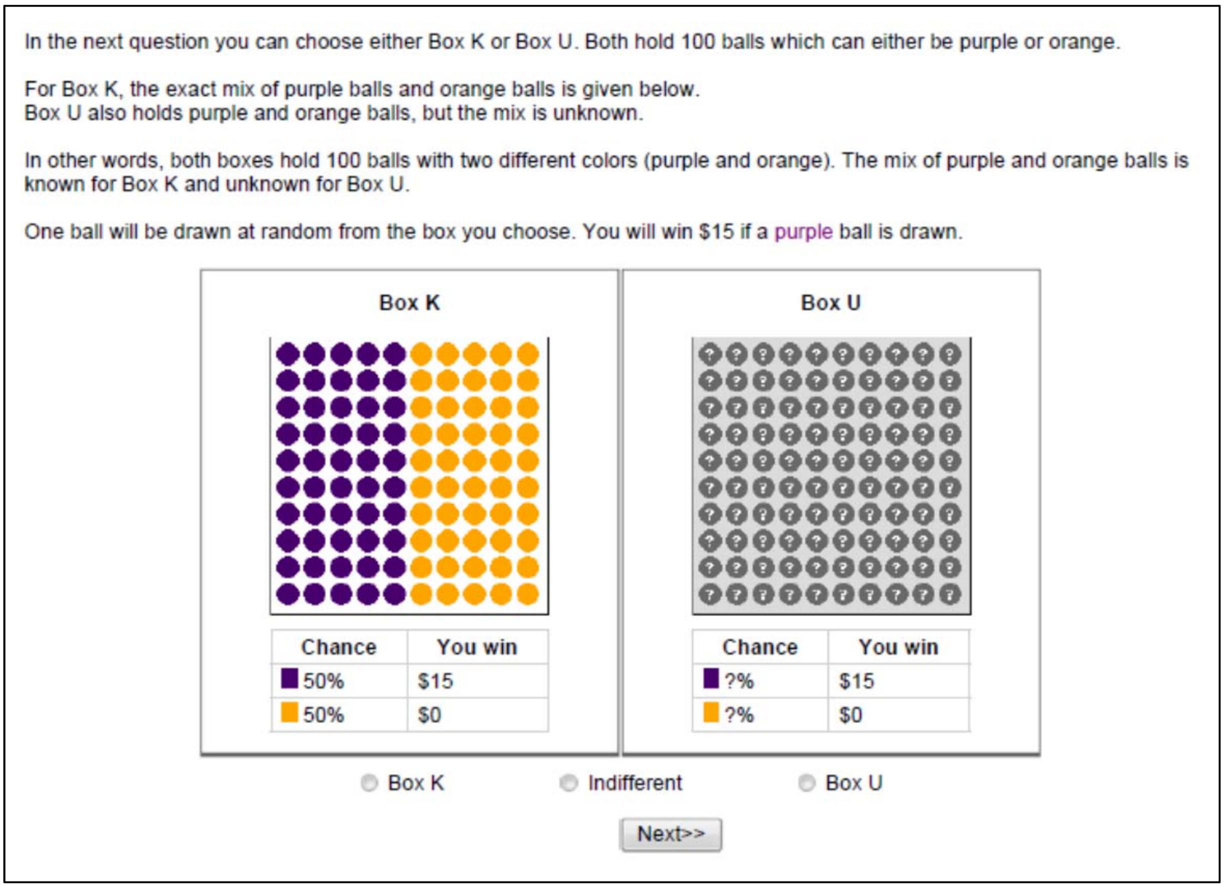
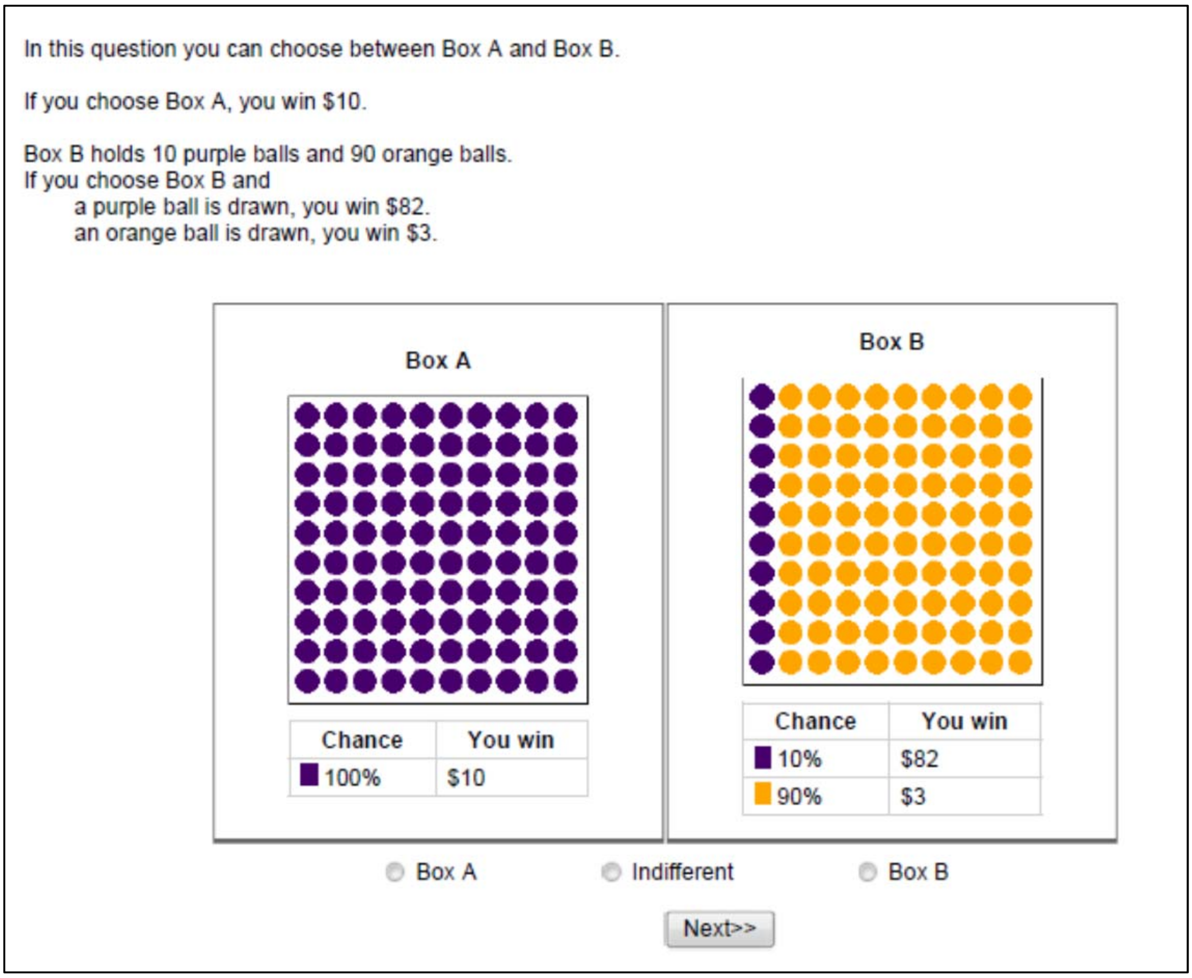


Figure 2. Choosing Between Two Boxes with Purple and Orange Balls, One Having a Sure (100%) Chance of Winning and the Other Having a Risky but Well-Defined Probability Distribution of Outcomes

This Figure shows a screen shot from our ALP module in the probability risk sequence. If the respondent chooses Box A, he wins with certainty; if he chooses Box B, winning is random. Selecting the "Indifferent" button takes the respondent to the next set of questions. If he selects "Box A", the respondent gets a new question with a higher probability of winning in Box B (more purple balls), while if he selects "Box B", the next question has a lower winning probability in Box B.



Appendixes for "Ambiguity Aversion and Household Portfolio Choice: Empirical Evidence"

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

Appendix A: Detailed Description of the Procedure for Eliciting Ambiguity Aversion

This Appendix describes our procedure for measuring ambiguity aversion in the ALP survey. The module starts with an introduction screen explaining the basic setup of the questions: see Figure A1-1. The introduction screen also explains that, after completing the survey, one of the respondent's choices in the set of thee ambiguity gain questions will be selected randomly by the computer and played for a real reward of $15.

Figure A1-1 here

1. First ambiguity question: two ball colors, 50% initial chance of *winning* for Box K

In the next screen, shown in Figure A1-2, the respondent is offered a choice between Box K, containing 50 purple and 50 orange balls, and Box U, containing an unknown mix of 100 purple and orange balls. Three response options are available: Box K, Box U, and Indifferent. If the respondent clicks the "Next" button before answering the question, the next screen shows a message that all responses are important and the respondent is asked to answer the question again.

If the respondent selects "Indifferent", the matching probability (q^{50}) is exactly 50% and the procedure continues with the second ambiguity question, described further on. If the respondent chooses Box K, she is ambiguity averse and we know that the matching probability is less than 50% ($0 \leq q^{50} < 50\%$). In the following round, the number of winning balls in Box K is reduced to 25: see Figure A1-2. If the respondent selected Box U in the first round instead, she is ambiguity seeking ($1 \geq q^{50} > 50\%$) and in the second round the number of winning balls in Box K is increased to 75.

Figure A1-2 here

The bi-section algorithm continues this way for an additional three rounds (four rounds in total). In every round of the bisection algorithm, the difference between the lower bound and the upper round on the matching probability is reduced by half. When the option "Indifferent" is chosen, the algorithm stops earlier, as then the upper and lower bounds are equal. After a maximum of four rounds, we take the average of the lower and upper bound, the midpoint, as the estimate of the matching probability (q^{50}). Table A1-1 shows all 27 possible outcome paths of the bisection algorithm, with corresponding matching probabilities. For two paths representing extremely ambiguity seeking attitudes ($q^{50} > 75\%$, paths UUK and UUU) we require less measurement accuracy and the algorithm stops after three rounds to save time.

Table A1-1 here

2. Second ambiguity question: 10 ball colors, 10% initial chance of *winning* for Box K

In the second ambiguity question respondents have to choose between two boxes containing 100 balls with 10 different colors: see Figure A1-3. The respondent can win a prize of \$15 if a purple ball is drawn from the box she chose. Box K contains 10 purple balls and Box U contains an unknown number of purple balls. Again, three response options are available: Box K, Box U, and Indifferent.

Figure A1-3 here

If the respondent selects "Indifferent", the matching probability for the second ambiguity question (q^{10}) is exactly 10% and the survey proceeds to the third ambiguity question, described further on. If the respondent chooses Box K, she is ambiguity averse and we know that the matching probability is less than 10% ($0 \leq q^{10} < 10\%$). In the next round the number of winning balls in Box K is reduced to 5. If, instead, the respondent selected Box U in the first round, she is ambiguity seeking ($1 \geq q^{10} > 10\%$) and in the second round the number of winning balls in Box K is increased to 20. The bi-section algorithm continues this way for an additional three rounds, or stops earlier if the respondent chooses "Indifferent". After four rounds, we take the average of the lower and upper bound (the midpoint) as the estimate of the matching probability (q^{10}). For choice sequences leading to low matching probabilities ($q^{10} < 20\%$), we reach sufficient accuracy after three rounds and the algorithm stops earlier to save time. Table A1-2 shows all 19 possible outcome paths of the bisection algorithm, with corresponding matching probabilities.

Table A1-2 here

3. Third ambiguity question: 10 ball colors, 90% initial chance of *winning* for Box K

In the third ambiguity question, respondents again must choose again between two boxes containing 100 balls with 10 different colors, but now the respondent can win a prize of \$15 if a purple ball is NOT drawn from the box she chose: see Figure A1-4. Box K contains 10 purple balls and Box U contains an unknown number of purple balls. Hence, the initial probability of winning the prize is 90% for Box K and unknown for Box U.

Figure A1-4 here

If the respondent selects "Indifferent", the matching probability for the second ambiguity question (q^{90}) is exactly 90% and the survey proceeds to the fourth ambiguity question, described further on. If the respondent chooses Box K, she is ambiguity averse and we know that the matching probability is less than 90% ($0 \leq q^{90} < 90\%$). In the second round the number of purple balls in Box K is increased to 55, reducing the chance of winning to 45%. If instead the respondent selected Box U in the first round, she is ambiguity seeking ($1 \geq q^{90} > 90\%$) and in the second round the number of purple balls in Box K is reduced to 5, increasing the chance of winning to 95%. The bi-section algorithm continues this way for an additional four rounds (five rounds in total), or stops earlier if the respondent chooses "Indifferent". After a maximum of five rounds, we take the average of the lower and upper bound as the estimate of the matching probability (q^{90}). In some cases, we reach sufficient accuracy after three of four rounds, and then the algorithm stops earlier to save time. Table A1-3 shows all 27 possible outcome paths, with corresponding matching probabilities.

Table A1-3 here

4. Fourth ambiguity question: 2 ball colors, 50% initial chance of *losing* for Box K

In the fourth ambiguity question, respondents again must choose again between two boxes containing 100 balls with 2 different colors, but now the respondent can lose a hypothetical prize of $15 if a purple ball is drawn from the box she chose: see Figure A-5. Box K contains 50 purple balls and Box U contains an unknown number of purple balls. Hence, the initial probability of losing the prize is 50% for Box K and unknown for Box U.

Figure A-5 here

If the respondent selects "Indifferent", the matching probability for the second ambiguity question (q^{-50}) is exactly 50% and the survey proceeds to the fifth ambiguity question, described further on. If the respondent chooses Box K, she is ambiguity averse and we know that the matching probability is more than 50% ($50\% < q^{-50} \leq 100\%$). In the second round the number of purple balls in Box K is increased to 75, increasing the chance of losing to 75%. If instead the respondent selected Box U in the first round, she is ambiguity seeking ($1 \geq q^{-50} > 50\%$) and in the second round the number of purple balls in Box K is reduced to 25, decreasing the chance of losing to 25%. The bi-section algorithm continues this way for an additional 3 rounds (four rounds in total), or stops earlier if the respondent chooses "Indifferent". After a maximum of 4 rounds, we take the average of the lower and upper bound as the estimate of the matching probability (q^{-50}). In some cases, we reach sufficient accuracy after three of four rounds, and then the algorithm stops earlier to save time. Table A-4 shows all 27 possible outcome paths, with corresponding matching probabilities.

Table A-4 here

5. Check questions to test for consistency of subjects' answers

To test for the consistency of the answers we included two check questions. Using the answers to the first ambiguity question (two ball colors, 50% ambiguity-neutral) we calculated the matching probability for each subject (q^{50}). To generate Check Question 1, we lowered the known probability of winning for Box K to each subjects' matching probability minus 10 percentage points ($q^{50} – 0.1$). In that case, the subject should choose the ambiguous Box U. To generate Check Question 2, we increased the known probability of winning of Box K to the matching probability plus 10 percentage points ($q^{50} + 0.1$). In that case, the subject should choose the unambiguous Box K. Note that the maximum known probability is set at 99 and the minimum is set at 1, to avoid certainty.

Table A-1: Responses and Matching Probabilities for the 1st Ambiguity Question

This table shows the possible outcomes in the four rounds of the 1st ambiguity question, with two ball colors and initial 50% chance of winning for Box K. Panel A shows the transitions of the bisection algorithm, starting at Q1a, offering a choice between Box K with known winning probability p=50% and ambiguous Box U. If the respondent chooses Box K, then next question round is Q1b (with p=75%), while round Q1i (with p=25%) follows after response Box U. After a choice of Indifferent, the algorithm always stops. Panel B shows the list of 27 possible response paths in the four question rounds. The letter combination in the column 'Response' summarizes one potential choices path, with K and U denoting the boxes, and I for Indifferent. The column q^{50} shows the corresponding matching probability, which is exact for paths ending with I and the average of the lower and upper bound for all other paths. For example, "KUUK" means the respondent chose Box K, followed by U twice, and then K. For this path the bounds on the matching probability are 38% and 44%, with midpoint q^{50} = 41%. The path "I" represents an Indifferent choice in the first round (q^{50} = 50%). For paths UUK, UUI and UUU, extreme ambiguity seeking, we require less accuracy and the algorithm stops after three rounds to save time.

Panel A: Probability of Winning for Box K and Transitions

Question Round	Purple balls in Box K (p)	Orange balls (100 - p)	Next round after response: Box K	Box U	Indifferent
Q1a	50	50	Q1b	Q1i	stop
Q1b	25	75	Q1c	Q1f	stop
Q1c	12	88	Q1d	Q1e	stop
Q1d	6	94	stop	stop	stop
Q1e	18	82	stop	stop	stop
Q1f	38	62	Q1g	Q1h	stop
Q1g	32	68	stop	stop	stop
Q1h	44	56	stop	stop	stop
Q1i	75	25	Q1j	Q1m	stop
Q1j	62	38	Q1k	Q1l	stop
Q1k	56	44	stop	stop	stop
Q1l	68	32	stop	stop	stop
Q1m	88	12	stop	stop	stop

Panel B: Outcome Paths

Response	q^{50}	Response	q^{50}	Response	q^{50}
KKKK	3	KUKI	32	UKKU	59
KKKI	6	KUKU	35	UKI	62
KKKU	9	KUI	38	UKUK	65
KKI	12	KUUK	41	UKUI	68
KKUK	15	KUUI	44	UKUU	71.5
KKUI	18	KUUU	47	UI	75
KKUU	21.5	I	50	UUK	81.5
KI	25	UKKK	53	UUI	88
KUKK	28.5	UKKI	56	UUU	94

Table A-2: Responses and Matching Probabilities for the 2nd Ambiguity Question

This table shows the transitions and possible outcomes in the four rounds of the 2nd ambiguity question, with ten ball colors. The respondent wins for 1 out of 10 ball colors, after one ball has been randomly drawn from the chosen box. Panel A shows the transitions of the bisection algorithm, starting at Q2a, offering a choice between Box K with known winning probability p=10% and ambiguous Box U. If the respondent chooses Box K, then next question round is Q2b (with p=5%), while round Q2e (with p=20%) follows after response Box U. After an Indifferent choice the algorithm always stops. Panel B shows the list of 19 possible response paths in the four rounds of the 2nd ambiguity question. The letter combination in the columns 'Response' summarizes one potential path of choices, with K denoting Box K, U for Box U, and I for Indifferent. The column q^{10} shows the corresponding matching probability. The matching probability is exact for paths ending with I, and the average of the lower and upper bound for all other paths. For all paths with q^{10} < 20%, the bounds are sufficiently tight after three rounds and the algorithm stops early to save time.

Panel A: Probability of Winning for Box K and Transitions

Question Round	Purple balls in Box K (p)	Other colors (100 - p)	Next round after response: Box K	Box U	Indifferent
Q2a	10	90	Q2b	Q2e	Done
Q2b	5	95	Q2c	Q2d	Done
Q2c	3	97	Done	Done	Done
Q2d	8	92	Done	Done	Done
Q2e	20	80	Q2f	Q2g	Done
Q2f	15	85	Done	Done	Done
Q2g	40	60	Q2h	Q2i	Done
Q2h	30	70	Done	Done	Done
Q2i	70	30	Done	Done	Done

Panel B: Outcome Paths

Response	q^{10}	Response	q^{10}	Response	q^{10}
KKK	1.5	I	10	UUKI	30
KKI	3	UKK	12.5	UUKU	35
KKU	4	UKI	15	UUI	40
KI	5	UKU	17.5	UUUK	55
KUK	6.5	UI	20	UUUI	70
KUI	8	UUKK	25	UUUU	85
KUU	9				

Table A-3: Responses and Matching Probabilities for the 3rd Ambiguity Question

This table shows the transitions and possible outcomes of the 3rd ambiguity question, with ten ball colors. The respondent wins for 9 out of 10 ball colors, after one ball has been drawn randomly from the chosen box. Panel A shows the transitions of the bisection algorithm, starting at Q3a, offering a choice between Box K with known winning probability p=90% and ambiguous Box U. If the respondent chooses Box K, then next question round is Q3b (with p=45%), while round Q3k (with p=95%) follows after response Box U. After an Indifferent choice the algorithm stops. Panel B shows the list of 27 possible response paths in the five rounds of the 3rd ambiguity question. The letter combination in the columns 'Response' summarizes one potential path of choices, with K denoting Box K, U for Box U, and I for Indifferent. The column q^{90} shows the corresponding matching probability. The matching probability is exact for paths ending with I, and the average of the lower and upper bound for all other paths. For some paths, the lower and bounds are sufficiently tight after three or four rounds, and the algorithm stops early to save time.

Panel A: Probability of Winning for Box K and Transitions

Question Round	Purple balls in Box K (1-p)	Other colors P	Next round after response: Box K	Box U	Indifferent
Q3a	10	90	Q3b	Q3k	stop
Q3b	55	45	Q3c	Q3e	stop
Q3c	78	22	Q3d	Q3j	stop
Q3d	89	11	Stop	stop	stop
Q3e	32	68	Q3f	Q3g	stop
Q3f	44	56	stop	stop	stop
Q3g	20	80	Q3h	Q3i	stop
Q3h	26	74	stop	stop	stop
Q3i	15	85	stop	stop	stop
Q3j	66	34	stop	stop	stop
Q3k	5	95	Q3l	Q3m	stop
Q3l	8	92	stop	stop	stop
Q3m	2	98	stop	stop	stop

Panel B: Outcome paths

Response	q^{90}	Response	q^{90}	Response	q^{90}
KKKK	5.5	KUKI	56	KUUUU	87.5
KKKI	11	KUKU	62	I	90
KKKU	16.5	KUI	68	UKK	91
KKI	22	KUUKK	71	UKI	92
KKUK	28	KUUKI	74	UKU	93.5
KKUI	34	KUUKU	77	UI	95
KKUU	39.5	KUUI	80	UUK	96.5
KI	45	KUUUK	82.5	UUI	98
KUKK	50.5	KUUUI	85	UUU	99

Table A-4: Responses and Matching Probabilities for the 4th Ambiguity Question

This table shows the possible outcomes in the four rounds of the 4th ambiguity question, with two ball colors (purple and orange). Now the respondent *loses* \$15 (hypothetically) if the color is purple, after one ball has been randomly drawn from the chosen box. Panel A shows the transitions of the bisection algorithm, starting at Q1a, offering a choice between Box K with known winning probability p=50% and ambiguous Box U. If the respondent chooses Box K, then next question round is Q1b (with p=75%), while round Q1i (with p=25%) follows after response Box U. After a choice of Indifferent, the algorithm always stops. Panel B shows the list of 27 possible response paths. The letter combinations in the columns 'Response' summarize potential choice paths, with K and U denoting the boxes, and I for Indifferent. The column q^{-50} shows the corresponding matching probability, which is exact for paths ending with I and the average of the lower and upper bound for other paths. For example, "KUUK" means the respondent chose Box K, followed by U twice, and then K. For paths UUK, UUI and UUU, extremely ambiguity seeking attitudes ($q^{50} > 75\%$), we require less accuracy and the algorithm stops after three rounds to save time.

Panel A: Probability of Winning for Box K and Transitions

Question Round	Purple balls in Box K (p)	Orange balls (100 - p)	Next round after response: Box K	Box U	Indifferent
Q4a	50	50	Q4b	Q4i	stop
Q4b	75	25	Q4c	Q4f	stop
Q4c	88	12	Q4d	Q4e	stop
Q4d	94	6	stop	stop	stop
Q4e	82	18	stop	stop	stop
Q4f	62	38	Q4g	Q4h	stop
Q4g	68	32	stop	stop	stop
Q4h	56	44	stop	stop	stop
Q4i	25	75	Q4j	Q4m	stop
Q4j	38	62	Q4k	Q4l	stop
Q4k	44	56	stop	stop	stop
Q4l	32	68	stop	stop	stop
Q4m	12	88	stop	stop	stop

Panel B: Outcome Paths

Response	q^{-50}	Response	q^{-50}	Response	q^{-50}
KKKK	97	KUKI	68	UKKU	41
KKKI	94	KUKU	65	UKI	38
KKKU	91	KUI	62	UKUK	35
KKI	88	KUUK	59	UKUI	32
KKUK	85	KUUI	56	UKUU	29.5
KKUI	82	KUUU	53	UI	25
KKUU	78.5	I	50	UUK	18.5
KI	75	UKKK	47	UUI	12
KUKK	71.5	UKKI	44	UUU	6

Figure A-1: Screen Shot: Text Introducing the Ambiguity Questions

You can win additional money on top of your regular payment for answering the survey, by answering the next questions.

You will be asked to choose between two boxes, Box K and Box U. Each box contains 100 balls of different colors. After you choose a box, one ball is drawn out of that box. If the ball is the right color, you could win $15. There are no right or wrong answers for these questions. If you feel both boxes are equally attractive, please choose Indifferent.

After completing the survey, one of the questions you answered will be selected randomly by the computer and played for real money. Your winnings will be based on the choices you made.

Next>>

RAND American Life Panel

Figure A-2: Screen Shot: Second Round of 1st Ambiguity Question (50%) after Choice K

This Figure shows a screen shot from our ALP module, representing the second question in the 50% ambiguity sequence. Box K is the box with now a 25% known probability of winning; Box U has an unknown mix of balls with two different colors. After answering this question, respondents are led to a next question. Selecting the "Indifferent" button takes the respondent to the next ambiguity sequence (in this case, the 10% ambiguity sequence). If the respondent selects "Box K", he gets a new question with a lower probability of winning in Box K (fewer purple balls), while if he selects "Box U", the next question has a higher winning probability of winning in Box K (more purple balls).

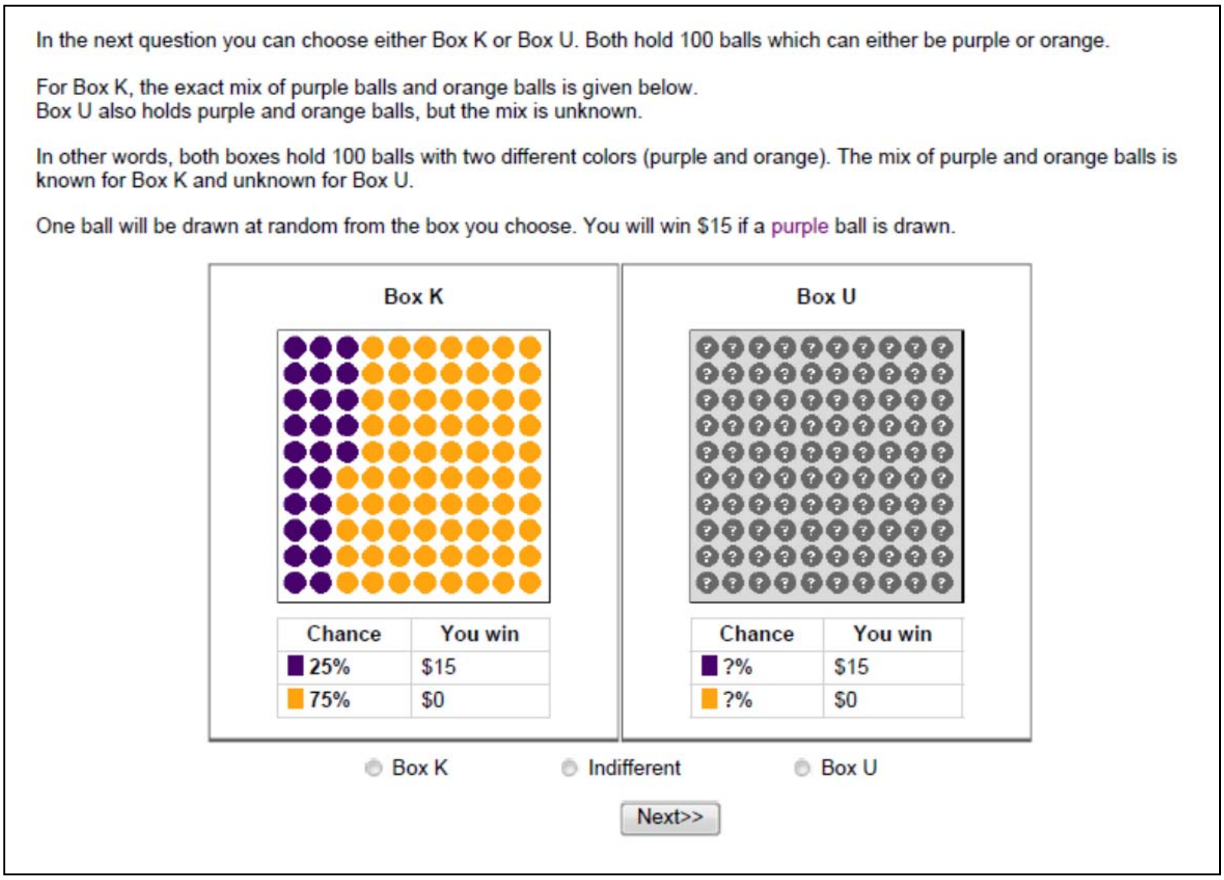


Figure A-3: Screen Shot: First Round of 2nd Ambiguity Question (10%)

This Figure shows a screen shot from our ALP module, representing the first question in the 10% ambiguity sequence. Box K is the box with 10% initial known probability of winning; Box U has an unknown mix of balls with 10 different colors. After answering this question, respondents are led to a next question. Selecting the "Indifferent" button takes the respondent to the next ambiguity sequence (in this case, the 90% ambiguity sequence). If the respondent selects "Box K", he gets a new question with a lower probability of winning in Box K (fewer purple balls), while if he selects "Box U", the next question has a higher winning probability of winning in Box K (more purple balls).

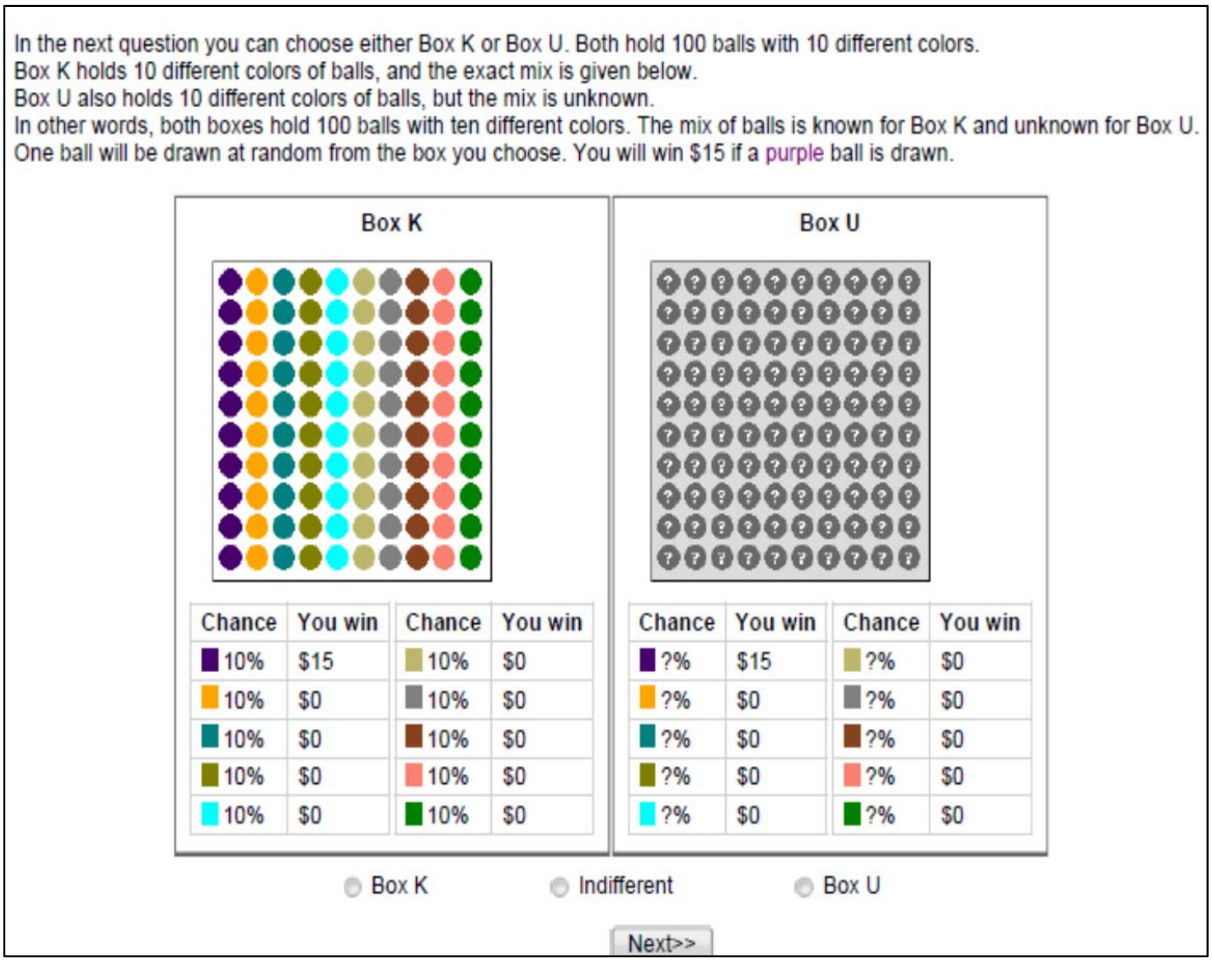


Figure A-4: Screen Shot: First Round of 3rd Ambiguity Question (90%)

This Figure shows a screen shot from our ALP module, representing the first question in the 90% ambiguity sequence. Box K is the box with 90% initial known probability of winning; Box U has an unknown mix of balls with 10 different colors. After answering this question, respondents are led to a next question. Selecting the "Indifferent" button takes the respondent to the next ambiguity sequence (in this case, the 50% chance of a loss ambiguity sequence). If the respondent selects "Box K", he gets a new question with a lower probability of winning in Box K (more purple balls), while if he selects "Box U", the next question has a higher winning probability of winning in Box K (less purple balls).

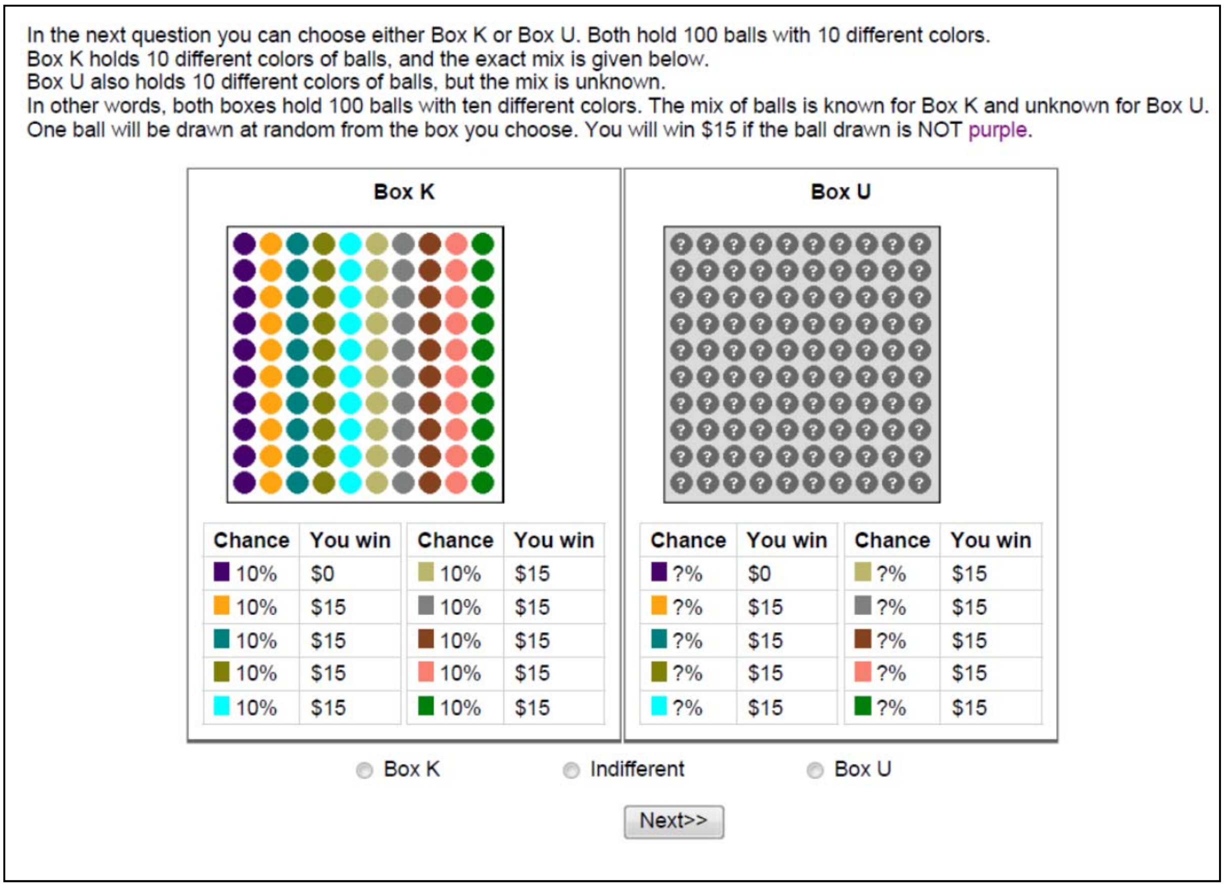
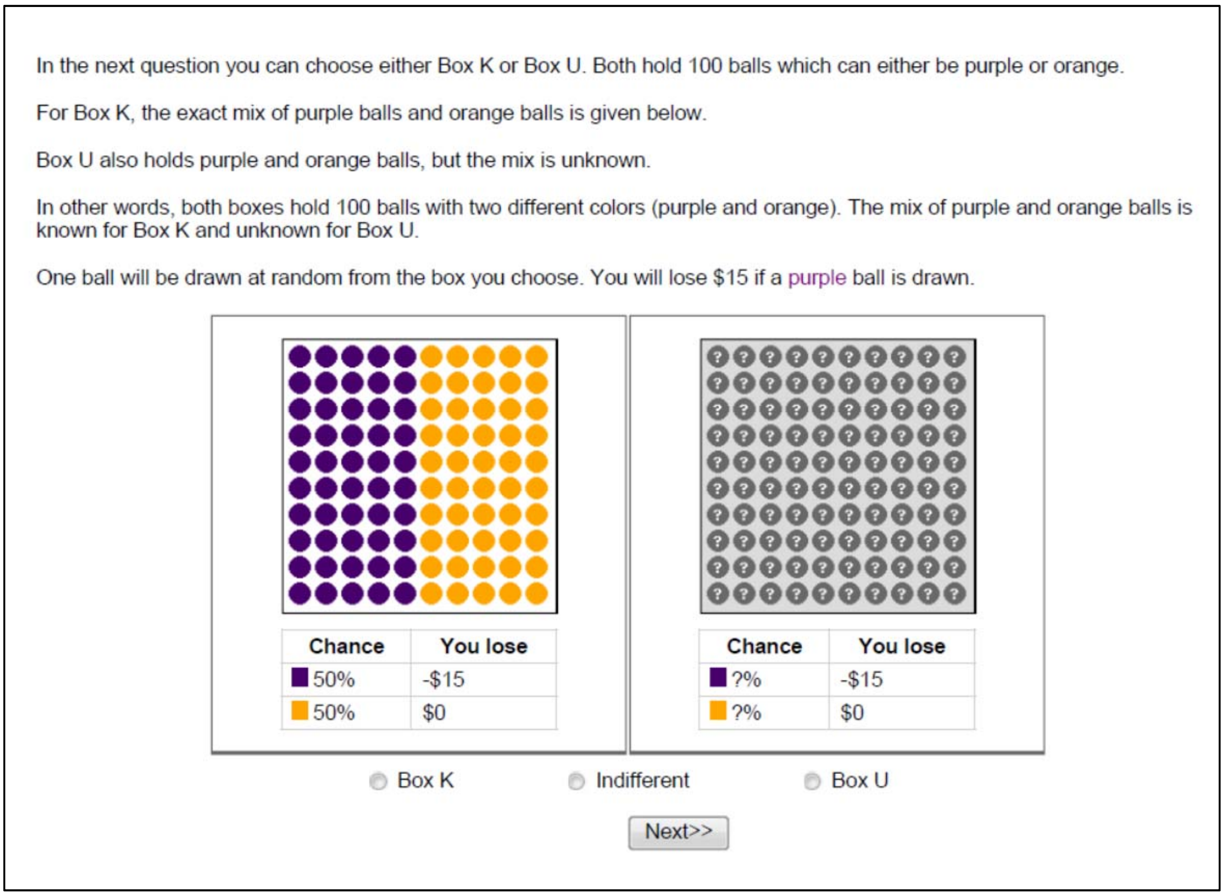


Figure A-5: Screen Shot: First Round of 4th Ambiguity Question (50% chance of loss)

This Figure shows a screen shot from our ALP module, representing the first question in the 50% chance of a loss ambiguity sequence. Box K is the box with 50% initial known probability of losing; Box U has an unknown mix of balls with two different colors. After answering this question, respondents are led to a next question. Selecting the "Indifferent" button ends the ambiguity sequence. If the respondent selects "Box K", he gets a new question with a higher probability of losing in Box K (more purple balls), while if he selects "Box U", the next question has a lower losing probability of winning in Box K (less purple balls).



Appendix B: Alternative Ambiguity Attitudes Measured in the ALP

This appendix describes the alternative measures of ambiguity attitudes. Based on our ALP ambiguity survey questions, we can also define measures of ambiguity aversion for ambiguous events of low and high likelihood (AA^{10} and AA^{90}), and for losses (AA^{-50}). Further, we describer two alternative measures of ambiguity aversion and a-insensitivity used by Abdellaoui et al. (2011) and Dimmock, Kouwenberg, and Wakker (2012).

Let q^i represent the respondent's matching probability for ambiguity gains question *i*, where *i* (=10, 50, or 90) represents the ambiguity-neutral chance of winning for Box U. The matching probability is the known probability of winning for Box K that makes the respondent indifferent between the ambiguous Box U and the unambiguous Box K. Similarly, let q^{-i} represent the respondent's matching probability for ambiguity *losses* question *i*, where *i* (=50) represents the ambiguity-neutral chance of *losing* for Box U.

We can summarize ambiguity attitudes in two ways. First, we simply rescale the matching probabilities solicited with the four ambiguity questions.

Question 1, winning for 1 out of 2 colors:	$AA^{50} = 50\% - q^{50}$	(A1)
Question 2, winning for 1 out of 10 colors:	$AA^{10} = 10\% - q^{10}$	(A2)
Question 3, winning for 9 out of 10 colors:	$AA^{90} = 90\% - q^{90}$	(A3)
Question 4, *losing* for 1 out of 2 colors:	$AA^{-50} = q^{-50} - 50\%$	(A4)

All four measures above are indexes of ambiguity aversion. Positive values of AA^{10}, AA^{50} and AA^{90} imply underweighting of ambiguous gains, indicating that the respondent is more pessimistic about the ambiguous Box U than the corresponding unambiguous Box K. Thus, positive values of AA^{10}, AA^{50}, and AA^{90} imply ambiguity aversion, negative values imply ambiguity seeking, and a zero value means ambiguity neutrality. Similarly, positive values of AA^{-50} imply overweighting of ambiguous *losses*, indicating that the respondent is more pessimistic about the ambiguous Box U than the unambiguous Box K with known probability of *losing i.*

Empirically, the prevalent pattern of ambiguity attitudes for gains is not universal ambiguity aversion ($AA^{10} > 0$, $AA^{50} > 0$ and $AA^{90} > 0$), but rather ambiguity *seeking* for unlikely events ($AA^{10} < 0$) and ambiguity *aversion* for likely events ($AA^{50} > 0$ and $AA^{90} > 0$), especially for highly likely events ($AA^{90} >> 0$). Abdellaoui et al. (2011) and Tversky and Wakker (1995) argue this is because ambiguity attitudes consist of two distinct components. The first component is ambiguity aversion, which refers to a general dislike of ambiguity, independent of the perceived likelihood of an event. The second component is ambiguity-likelihood insensitivity (a-insensitivity), which refers to individuals' tendency to overweight ambiguous events perceived as unlikely and underweight ambiguous events perceived as likely. Essentially, a-insensitivity is a tendency to treat all ambiguous events more as 50%-50% gambles. A simple measure of a-insensitivity is: $AA^{90} – AA^{10}$.

We now briefly describe decision theoretic frameworks that can replicate the prevalent pattern of ambiguity attitudes ($AA^{10} < 0$, $AA^{50} > 0$ and $AA^{90} > 0$), using weighting functions that transform the ambiguity-neutral probabilities of ambiguous events into decision weights. Both the rank-dependent utility model of Gilboa (1987) and Schmeidler (1989), and cumulative prospect theory of Tversky and Kahneman (1992), use weighting functions for ambiguous events to accommodate Ellsberg's (1961) paradox. The recently-introduced source method of

Abdellaoui et al. (2011) makes these models more tractable, allowing them to measure respondents' weighting functions for different sources of uncertainty. Abdellaoui et al. define a source of uncertainty as a group of events that is generated by the same mechanism of uncertainty. For example, an Ellsberg urn with purple and orange balls, the value of the S&P500 U.S. stock market index one year from now, or the temperature in Paris tomorrow, are three different sources of ambiguity. Chew and Sagi (2008) and Abdellaoui et al. (2011) show how subjective probabilities can be defined within each particular source of uncertainty (if the source has the technical property of 'uniformity'). They then introduce weighting functions that map the subjective probabilities into decision weights, which are called source functions.

To better understand these weighting functions for ambiguous events, consider Figure B-1. Each individual is assumed to have a source function that maps subjective probabilities, displayed on the x-axis, into decision weights, which are displayed on the y-axis. Empirically, Abdellaoui et al. (2011) show that elicited subjective probabilities for Ellsberg urns are equal to ambiguity-neutral probabilities, as people are indifferent about changing the winning color for Box U. Hence, for our questions, the x-axis displays ambiguity-neutral probabilities and the y-axis displays the corresponding matching probabilities. Panel A shows ambiguity neutrality; the matching probabilities are simply equal to the ambiguity-neutral probabilities. Panel B shows ambiguity aversion; the matching probabilities are always below the ambiguity-neutral probabilities. Panel C shows a-insensitivity; the ambiguity-neutral probabilities are transformed toward 50%, and the respondent is ambiguity seeking for low likelihoods and ambiguity averse for high likelihoods. Panel D shows the modal finding in the literature; the respondent is *both* ambiguity averse and a-insensitive.

Figure B-1 here

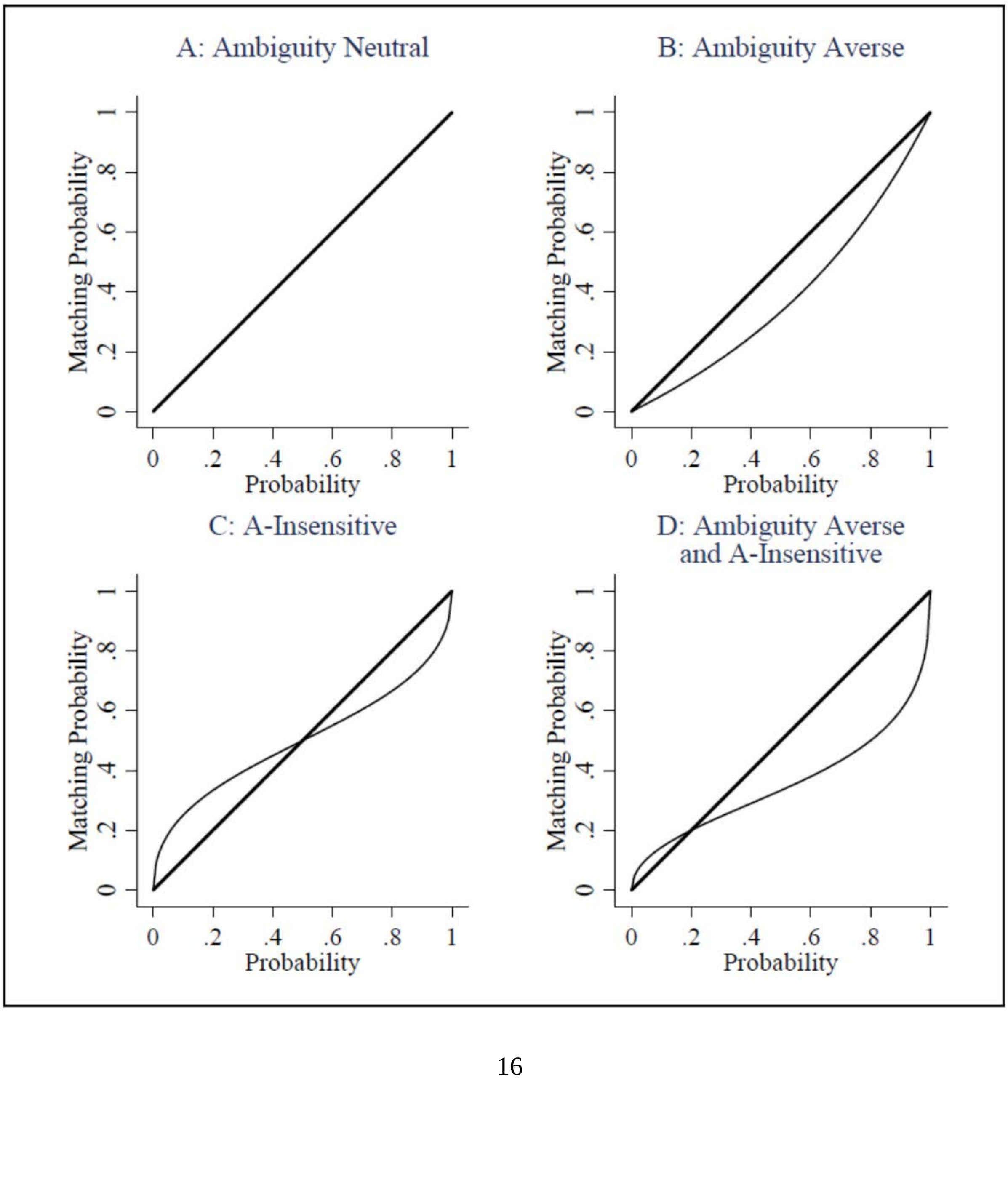
Based on Figure B-1, Abdellaoui et al. (2011) introduce two regression-based indexes to measure ambiguity aversion and a-insensitivity. Let q^p denote the matching probability for an ambiguous event with ambiguity-neutral probability of winning p. For each respondent separately, they regress q^p on p: $q^p = c + sp$, where c is a constant and s the slope coefficient. The measure of ambiguity aversion is defined as: index $b = 1 - s - 2c$. Index b is equal to the distance between 0 and the regression line at $p = 0$ (this distance $= 0 - c$), plus the distance between 1 and the fit line at $p = 1$ (this distance $= 1 - c - s$). Index b measures how far the regression line is below the diagonal line that represents ambiguity-neutrality. That is, positive values of index b indicate ambiguity aversion and negative values ambiguity seeking.

The measure of a-insensitivity is defined as: index $a = 1 - s$. Higher values of index a correspond to a flatter regression line, and a stronger tendency to treat all ambiguous events as 50%-50%. Positive values of index a designate a-insensitivity ($s < 1$), while negative values imply a-oversensitivity ($s > 1$).

Empirically, probability weighting does not only occur for ambiguous events, but also for events with known probabilities (see, e.g., Tversky and Kahneman, 1992). For example, consider Box K with 50 purple balls and chance of winning p=50%. A person can assign a decision weight $w(p)$ to Box K that is different from p=50%. For example, the average decision weight for p=50% measured by Tversky and Kahneman (1992) in a lab experiment is $w(0.50)=0.42$. Dimmock, Kouwenberg, and Wakker (2012) prove that matching probabilities q^i measure the *additional* probability weighting a respondent applies for ambiguous events, on top of any probability weighting $w(p)$ that already occurs for events with known probabilities, without the need to measure the respondent's utility function. Effectively, in the comparison between Box K and Box U, the curvature of the utility function and probability weighting for risk are both cancelled out.

Figure B-1: Ambiguity Attitudes and Matching Probabilities

This figure provides examples of different probability weighting functions for ambiguous events. Ambiguity-neutral probabilities for the ambiguous events are shown on the x-axis while the y-axis displays the corresponding matching probability. The matching probability *q* is the probability at which the subject is indifferent between winning when the ambiguous event occurs and winning with known probability *q*. The ambiguity-neutral probability is the matching probability of a decision maker with a neutral attitude towards ambiguity (as in the expected utility framework). Matching probabilities that are lower (higher) than the ambiguity-neutral probability reflect ambiguity aversion (seeking), the tendency to underweight (overweight) ambiguous events. Panel A shows the function consistent with the standard expected utility framework: no weighting. Panel B shows ambiguity aversion; the subject underweights all uncertain events. Panel C shows a-insensitivity, where all probabilities are transformed towards 50%. Panel D shows the most commonly observed pattern: both ambiguity aversion and a-insensitivity.



Appendix C: The ALP survey

This Appendix describes the American Life Panel (ALP) in more detail. The ALP is an Internet 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 from the Michigan monthly survey without Internet were provided with so-called WebTVs (http://www.webtv.com/pc/), which allows them to access the Internet using their television and a telephone line. The technology allows respondents who lacked Internet access to participate in the panel and furthermore use the WebTVs for browsing the Internet or email. 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.

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

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

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

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 Likert scale ranging from 0 to 5, whereas the Guiso, Sapienza, and Zingales (2008) study simply asked subjects to either agree or disagree with the statement.

Appendix D: Additional Results

To further explore ambiguity attitudes across demographic and economic characteristics, Column (1) of Table D-1 shows the results from regressing the ambiguity aversion measures on key control variables for the entire sample. Naturally the regressions do not imply any causal relation; rather, multiple regression is a convenient tool to concisely summarize the correlation structure of the data. In columns (2-4), we restrict the sample to certain groups of interest. Column (2) includes only respondents whose check question answers did not contradict their earlier choice. Column (3) includes only respondents with a college degree. Column (4) includes only respondents with at least $500 in financial assets. The results are similar across columns.

Table D-1 here

The results show that men are more ambiguity averse than women. College-educated respondents are more ambiguity averse than the less educated, suggesting that ambiguity aversion measures preferences rather than cognitive errors (i.e., such as cognitive errors due to using simplifying heuristics for complicated problems). There is also a positive relation between ambiguity aversion and risk aversion, consistent with Bossaerts et al. (2010).

We also find that the survey question order matters: that is, measured ambiguity aversion proves to be *higher* when the risk aversion questions are presented *before* the ambiguity aversion questions. Such an order effect is consistent with the "comparative ignorance" hypothesis of Fox and Tversky (1995), which posits that ambiguity aversion is magnified by comparisons to less ambiguous events (in this case, the preceding risk questions with known probabilities). Because of this issue, we randomized the order of the risk and ambiguity questions in the ALP survey, and we also include an indicator variable for question order in the empirical analyses.

Perhaps the most striking aspect of Table D-1 is that the adjusted R-square values are consistently low; the controls explain less than eight percent of the variance in ambiguity aversion. Even in column (2) where there is likely less measurement error in the dependent variable, the adjusted R-square is low. This suggests that our measure of ambiguity aversion captures new information about preferences which is not subsumed by standard demographic and economic controls.

Table D-1: Relation of Ambiguity Aversion with Economic and Demographic Variables

This table shows the results of OLS regressions in which the dependent variable is AA^{50}, defined in Table 3. The independent variables are defined in Table 1. Constant terms and retirement plan type indicator variables are included in the regressions, but not displayed in the interest of brevity. The coefficients are multiplied by 100 to enhance readability. Column (3) excludes respondents who gave inconsistent responses to either of the two check questions. Column (2) excludes respondents without a college degree. Column (4) excludes respondents with less than $500 in financial wealth. Standard errors are clustered by household and appear in brackets.

	Full Sample	Not Inconsistent	College Educated	Fin. Wealth ≥ $500
	(1)	(2)	(3)	(4)
Age	-0.343	-0.357	-0.604 *	-0.881 **
	[0.30]	[0.33]	[0.33]	[0.43]
Age^2	0.003	0.003	0.005	0.009 **
	[0.00]	[0.003]	[0.004]	[0.004]
Male	3.296 ***	3.562 ***	1.629	3.154 ***
	[0.99]	[1.03]	[1.19]	[1.15]
White	-2.593 *	-1.266	-3.382 **	-3.519 *
	[1.38]	[1.41]	[1.72]	[1.92]
Hispanic	0.494	1.070	4.976 **	-1.336
	[1.51]	[1.55]	[2.39]	[1.98]
Married	1.984	0.191	0.942	2.135
	[1.21]	[1.30]	[1.50]	[1.53]
High School	2.692	-1.270		3.645
	[2.12]	[2.29]		[4.36]
College	5.420 **	1.496		6.247
	[2.26]	[2.44]		[4.31]
Employed	-0.111	0.640	3.138 **	0.639
	[1.15]	[1.15]	[1.41]	[1.36]
ln(Family Income)	0.866	1.193	0.217	0.829
	[0.73]	[0.80]	[0.94]	[1.04]
ln(Wealth)	-0.217	-0.120	0.966 *	-0.353
	[0.51]	[0.47]	[0.51]	[0.65]
ln(# Children)	0.084	0.182	-0.258	-0.189
	[0.92]	[0.98]	[1.26]	[1.13]
Health	0.285	-0.786	0.541	0.599
	[0.57]	[0.62]	[0.63]	[0.81]
Question Order	6.747 ***	4.668 ***	6.116 ***	7.673 ***
	[0.99]	[1.03]	[1.18]	[1.18]
Trust	0.386	0.204	0.475	0.852 *
	[0.37]	[0.39]	[0.46]	[0.46]
Risk Aversion	8.803 ***	5.750 ***	7.730 ***	7.339 ***
	[1.23]	[1.22]	[1.48]	[1.49]
Financial Literacy	0.423	0.353	1.859 *	0.129
	[0.71]	[0.77]	[0.96]	[0.98]
Adjusted-R^2	0.072	0.049	0.076	0.065
N	3,026	1,808	1,209	1,916

Notes: * significant at the 10%; ** 5%; and *** 1% level.

Table D-2: Ambiguity Aversion and Household Portfolio Choice: Controlling for Optimism

This table shows regression results for the dependent variables stock market participation and fraction allocated to stocks, controlling for optimism. Columns (1) and (2) show probit regression results for stock market participation. Columns (3) and (4) show Tobit regression results where the dependent variable is the fraction of financial wealth that the subject allocates to equities. Columns (2) and (4) exclude respondents who report financial wealth of less than $500. All models include a constant term and controls for age, age-squared, male, White, Hispanic, married, education, employment status, family income, wealth, number of children, participation in defined benefit or defined contribution plans, question order, check question score, and missing data dummies. The table reports marginal effects. Standard errors are clustered by household and appear in brackets.

	Equity Market Participation		Fraction Allocated to Stocks	
	(1)	(2)	(3)	(4)
AA^{50}	-0.102 **	-0.201 **	-0.383 **	-0.446 ***
	[0.05]	[0.08]	[0.15]	[0.15]
Optimism	0.016	0.036	0.062	0.073
	[0.02]	[0.03]	[0.06]	[0.05]
Financial Wealth ≥ $500	No	Yes	No	Yes
Controls and Constant	Yes	Yes	Yes	Yes
N	2,997	1,913	2,997	1,913

Notes: * significant at the 10%; ** 5%; and *** 1% level.

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