Ambiguity Attitudes and Economic Behavior

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Abstract

We measure ambiguity attitudes for a representative sample of U.S. households using a custom-designed module in the American Life Panel. Ambiguity attitudes vary substantially across people: half are ambiguity averse, 12% ambiguity neutral, and 37% ambiguity seeking. Further, ambiguity attitudes depend on the likelihood of the ambiguous event: people tend to overweight low-likelihood ambiguous events and underweight high-likelihood events, a phenomenon called ambiguity-likelihood insensitivity. Consistent with theoretical predictions, higher ambiguity aversion is associated with less equity market participation, lower portfolio allocations to equities, and more retirement planning. High ambiguity-likelihood insensitivity is associated with a higher probability of being insured.

JEL Codes: G11, D81, D14, C83

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People must consider both the *risk* and the *ambiguity* of future outcomes when making 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) showed that people usually prefer risk rather than ambiguity, and he defined an *ambiguity-averse* individual as one who prefers a lottery with known probabilities over a similar lottery with unknown probabilities. Although many subsequent authors modeled the theoretical effects of ambiguity on economic behavior, empirical evidence on this phenomenon has come primarily from laboratory experiments. In fact, there is little evidence from outside the laboratory about the effect of ambiguity aversion on real-world economic behavior, a shortcoming we remedy in this paper. Specifically, using a nationally-representative sample of U.S. households we show that ambiguity attitudes have important explanatory power for key economic decisions including equity market participation, portfolio allocations, retirement planning, and insurance purchase.

Using the American Life Panel (ALP), we develop and implement a survey module for the general population that elicits respondents' ambiguity attitudes using questions based on the classic Ellsberg urn experiment. Our method has several attractive aspects. First, we test whether ambiguity attitudes can explain a rich variety of real-world economic behaviors. Second, our dataset captures a wider range of investment and insurance choices than previously examined. Third, we have a relatively large sample of over 3,000 respondents. Finally, we offer *all* survey respondents real monetary incentives (a total of $23,850 was paid to 1,590 subjects), which prior studies have found crucial for eliciting meaningful responses to questions involving economic decisions.

Our results confirm that many people are not ambiguity averse; indeed, a large fraction of respondents is ambiguity *seeking* or *neutral* (51% are ambiguity averse, 12% ambiguity neutral, and 37% ambiguity seeking). Moreover, we find that respondents' ambiguity attitudes depend on the perceived likelihood of the ambiguous event, consistent with predictions from psychological studies (Einhorn and Hogarth (1985)), and with experimental evidence (Abdellaoui et al. (2011)). For high likelihood events most people are ambiguity averse, while for low likelihood events most people are ambiguity seeking. This pattern in ambiguity attitudes is consistent with the concept of *Ambiguity-likelihood insensitivity* (or A-likelihood insensitivity; see Abdellaoui et al. (2011)). A-likelihood insensitivity implies that respondents tend to treat all ambiguous events as 50-50 gambles, implying that low likelihood ambiguous outcomes are overweighted, and high likelihood ambiguous outcomes are underweighted.

We next test whether ambiguity attitudes help to explain why a large fraction of the U.S. population does not participate in the equity market. This non-participation is a puzzle, as models using standard risk-averse utility functions predict that individuals will always wish to participate in the stock market (see Merton (1969)).[1] Several theoretical papers propose that ambiguity aversion can explain non-participation and the low fraction of financial wealth allocated to equities (low relative to the predictions of calibrated models).[2] These models argue that the distribution of future equity returns is ambiguous, and thus individuals who are sufficiently

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[1] A large number of theoretical studies proposes solutions to the non-participation puzzle based on frictions such as non-tradeable labor market risk and stock market participation costs (e.g., Benzoni, Collin-Dufresne, and Goldstein (2007); and Cocco, Gomes, and Maenhout (2005)). Empirical results in Andersen and Nielsen (2011), however, suggest that frictions cannot explain most non-participation.

[2] Key studies include Bossaerts et al. (2010); Cao, Wang, and Zhang (2005); Dow and Werlang, (1992); Epstein and Schneider (2010); Garlappi, Uppal, and Wang (2007); and Peijnenburg (2010).

ambiguity averse will not invest in equities. Our paper provides the first non-laboratory empirical evidence showing that ambiguity aversion is significantly and negatively associated with stock market participation and portfolio allocation to stocks. Specifically, we find that a one standard deviation increase in ambiguity aversion implies a 15% decrease in the probability of stock market participation and an 11% lower portfolio allocation to equity.

Additionally, we test whether ambiguity attitudes help explain individuals' decisions about retirement planning and insurance coverage. Brown and Finkelstein (2008, 2009) find that people fail to insure sufficiently against certain health risks. Theory argues that ambiguity aversion has an important effect on insurance coverage, although the direction of this effect differs across models (cf., Bewley (1989); and Castro and Chateauneuf (2012)). Turning to A-likelihood insensitivity, we expect it to have a positive relation with insurance ownership because people buy insurance to cover low likelihood ambiguous events, and insensitivity implies overweighting of such events. The results show that people with higher A-likelihood insensitivity are more likely to insure. Additionally, we demonstrate that individuals with higher ambiguity aversion are more likely to plan for retirement.

We make several contributions to the finance and economics literatures. First, although numerous laboratory studies have measured ambiguity aversion (c.f., Abdellaoui et al. (2011); and Bossaerts et al. (2010)), few studies measure ambiguity aversion in the broad population and, to our knowledge, no prior study measures ambiguity aversion for the general U.S. population. After measuring ambiguity attitudes in our large representative sample, we then show that ambiguity aversion is widespread but largely uncorrelated with standard economic and demographic characteristics. Moreover, we can link our measures of ambiguity attitudes to the subjects' actual economic behaviors outside the lab.

Second, despite a substantial theoretical literature relating ambiguity aversion to financial behaviors, there are few empirical tests of these models. Bossaerts et al. (2010) develop a model of stock market participation based on ambiguity aversion, and find empirical support in a laboratory test with university students as subjects. Our study, by contrast, tests the relation between ambiguity attitudes and actual stock market participation. To our knowledge, only two prior papers conduct similar tests. Although it is not their main focus, Guiso, Sapienza, and Zingales (2008) include a control variable for ambiguity aversion, based on a hypothetical compound lottery with known probabilities, but they fail to find significant results. More closely related to our work, Dimmock, Kouwenberg, and Wakker (2012) find no significant relation between ambiguity attitudes and stock market participation except for subjects who perceive stock returns as highly ambiguous. Guiso, Sapienza, and Zingales (2008) and Dimmock, Kouwenberg, and Wakker (2012) both use Dutch data, and so their results may not translate to other countries such as the U.S. In fact, a recent overview by Rieger and Wang (2012) notes that ambiguity aversion differs widely across countries: Americans are the least ambiguity averse among 45 nations (with 40% of people being ambiguity averse). Moreover, Dimmock, Kouwenberg, and Wakker (2012) primarily focus on eliciting and measuring ambiguity attitudes, rather than the relation between ambiguity attitudes and economic behavior as we do here. And our sample size is much larger than prior analyses, with over 3,000 respondents of all ages, allowing us to more precisely detect the effects of ambiguity attitudes on behavior.

Finally, our study tests the relation between ambiguity attitudes and a wider range of economic behaviors than those considered in prior studies. In addition to stock market participation, we also consider portfolio allocations, financial planning for retirement, and insurance decisions.

The remainder of the paper is structured as follows. Section I explains how we model and measure ambiguity attitudes. Section II discusses our hypotheses and the prior literature. Section III describes our survey, and Section IV summarizes the estimates of ambiguity attitudes. Section V presents the main empirical results about the impact of ambiguity attitudes on economic behaviors. A final section concludes.

I. Measuring Ambiguity Attitudes

We develop three sets of questions to measure ambiguity attitudes.

I.A The Elicitation Procedure

The 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.[3] As shown in Figure 1, both boxes contain exactly 100 balls, which can be purple or orange. One ball will be randomly drawn from the box selected by the respondent; he wins $15 if that ball is purple. 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. In an experimental setting, if a respondent prefers Box K over Box U, it implies he displays ambiguity aversion (a dislike of making decisions with unknown probabilities).[4]

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[3] In our survey module, unlike in Ellsberg (1961), we use the word "box" instead of "urn," as the word "urn" might be unfamiliar to some subjects.

[4] A preference for Box K over Box U in itself is not a violation of the standard expected utility model, as the subject might believe there are fewer purple balls than orange balls in the urn. The famous Ellsberg (1961) paradox arises when the same subject is also indifferent between betting on drawing a purple ball from Box U and betting on drawing an orange ball from Box U. In that case the subject's choice reveals that he treats drawing a purple ball or an orange ball from Box U as equally likely events (50-50%). Given the revealed 50% subjective probability of winning for Box U, a preference of K over U can no longer be explained in the expected utility framework. Given the time constraints in our survey, we do not elicit the subjects' preferences for drawings of both colors, and instead rely on prior studies that

Figure 1 here

In our experiment, respondents can choose not only Box K or Box U, but they can also choose "Indifferent". In case of indifference, we first randomly determine whether a ball will be drawn from Box K or Box U with equal probability (50-50%). One ball is then drawn randomly from that box, and the respondent wins $15 if the ball is purple. A choice of "indifferent" implies that the respondent considers Box K and Box U to be equally attractive, so he has a neutral attitude towards ambiguity. An ambiguity-neutral subject treats Box U as if the subjective probability of winning is 50%, 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, following the terminology of Dimmock, Kouwenberg, and Wakker (2012).

Suppose a respondent has displayed ambiguity aversion in the first round of the first question, preferring Box K over Box U (see Figure 1). We then lower Box K's known probability of winning until the respondent eventually becomes indifferent between Box K and Box U.[5] Kahn and Sarin (1988) directly ask respondents for the known probability of winning that makes them indifferent between the two boxes.[6] However, instead of directly asking for an indifference probability, we present subjects with a series of binary choices converging to the point of indifference, as prior studies show this produces more reliable measures of preferences.[7]

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overwhelmingly demonstrate that, in such situations, subjects do in fact assign equal subjective probabilities to each color (e.g., Abdellaoui et al. (2011); Fox and Tversky (1998)).

[5] In a classroom experiment using a similar elicitation methodology, Dimmock, Kouwenberg, and Wakker (2012) elicited ambiguity attitudes using an ambiguous Urn U, and an unambiguous Urn K, where the initial known probability of winning for Urn K was randomly determined for half the subjects, and was set at 50% for the other half. There was no significant difference in elicited ambiguity aversion for the two groups. Hence, the particular value shown for the known probability of winning of Urn K does not affect respondent's assessment of the ambiguous urn U.

[6] This approach is similar to that of Baillon and Bleichrodt (2011), Baillon, Cabantous, and Wakker (2011), Dimmock, Kouwenberg, and Wakker (2012), and Kahn and Sarin (1988).

[7] See for example, Bostic, Herrnstein, and Luce (1990); Fischer et al. (1999); Noussair, Robbin, and Ruffieux (2004).

For example, if the respondent chooses Box K in Figure 1, the known probability of winning is then reduced to 25% in the next round; if he chooses Box U in Figure 1, the known probability of winning is instead increased to 75%. This process is repeated for up to four rounds, until the respondent's indifference point is closely approximated.[8]

We use the term *matching probability* to refer to the known probability of winning for Box K that makes the respondent indifferent between Box K and Box U. 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%. For the ambiguity question shown in Figure 1 with two colors of balls (purple and orange), a respondent with a matching probability below the ambiguity-neutral probability of 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 Question 1 and we define $\text{AA}^{50} = 50\% - q^{50}\%$ as a measure of ambiguity aversion. Thus positive values of AA^{50} indicate ambiguity aversion, zero values indicate ambiguity neutrality, and negative values indicate ambiguity seeking.

The key advantage of this approach is that matching probabilities measure ambiguity attitudes *relative* to risk attitudes. 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 in our experiment 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. Similarly, differences in risk

[8] Appendix A provides additional details about the approximation method.

aversion are also irrelevant: since the matching probabilities measure each subject's attitude towards an ambiguous choice relative to a risky choice, risk aversion affects the valuation of both boxes in the same manner. Matching probabilities capture only *differential* preferences for ambiguity relative to risk.

Eliciting preferences is sensitive to measurement error,[9] and so we also include two check questions to test the consistency of the subjects' choices. After all rounds of each of the three main questions (the remaining two questions are described in the next subsection), we estimate each subject's matching probability for the first question. We then increase (decrease) each subject's elicited matching probability by 10 percentage points to generate the two check questions. A subject's response is deemed inconsistent if he prefers the ambiguous Box U in the first check question and/or the unambiguous Box K in the second check question.

Importantly, we provide real rewards to subjects based on their choices, since prior studies have found that this helps focus participant attention (Smith 1976). At the outset of our survey module, *all* subjects are told that one of their choices will be randomly selected and played for a chance to win \$15.[10] In total, we paid real incentives worth \$23,850 to 1,590 of the 3,158 ALP subjects.[11] The RAND Corporation's ALP was responsible for determining the incentives won by respondents and making payments; RAND is credible because it regularly pays compensation to all ALP survey respondents. Because the subjects regularly participate in

[9] For further discussion of measurement error in the elicitation of preferences see Harless and Camerer (1994) and Hey and Orme (1994).
[10] 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 repitition of the task.
[11] Prior to including our survey module in the ALP panel, we piloted our questions in a laboratory experiment using the Wharton Behavioral Lab. Results of the lab experiment are available upon request.

ALP surveys and frequently receive incentive payments from RAND, suspicion about the trustworthiness of the incentive scheme should therefore not play a role.[12]

I.B Measuring ambiguity-likelihood insensitivity

The example in the previous subsection discussed ambiguity attitudes for an uncertain event of moderate likelihood, namely with an ambiguity-neutral probability of 50%. But prior studies show that ambiguity attitudes differ across likelihoods: people tend to be ambiguity seeking for low likelihood events, and extremely ambiguity averse for high likelihood events. That is, people tend to transform all likelihoods towards 50% (Abdellaoui et al. (2011); Dimmock, Kouwenberg, and Wakker (2012)). This produces an inverse S-shaped weighting function for ambiguity, overweighting small likelihoods and underweighting high likelihoods, similar to what Tversky and Kahneman (1992) found for probability weighting under risk (for events with known probabilities). Following the terminology of Abdellaoui et al. (2011), we refer to this effect as *ambiguity-likelihood insensitivity* (A-likelihood insensitivity).

To measure A-likelihood insensitivity, we included two additional sets of questions in our survey, similar to the one just discussed, but with ambiguity-neutral probabilities of winning of 10% and 90%, respectively. For instance, Figure 2 shows the second question with 10 different colors of balls, including purple, in both boxes: the mixture is known for Box K, and unknown for Box U. Respondents win $15 if a purple ball is drawn from the box of their choice. Here Box K offers an initial known probability of winning of 10%, given that it contains 10 purple balls. Ambiguity-neutral subjects are indifferent between betting on Box K and Box U, so the

[12] For this reason we did not offer the option to change the winning ball color, as in Dimmock, Kouwenberg, and Wakker (2012), who report that only a handful of respondents change the color (less than 2% of the sample). Furthermore, suspicion of Box U would have produced higher ambiguity aversion (a stonger preference for Box K), but actual responses in our ALP survey prove to be less ambiguity averse, suggesting this was not an issue.

ambiguity-neutral probability of winning for Box U is 10%. A-likelihood insensitivity predicts that subjects will prefer to bet on Box U for this choice, implying ambiguity-seeking.

Figure 2 here

The third question is similar, but with the outcomes reversed: now, the respondent wins if any of the nine colors *other than* purple is drawn, and thus for Box K the initial known probability of winning is 90%. A-likelihood insensitivity predicts that subjects will be particularly ambiguity averse for this question. We define the ambiguity aversion measures for the 10% and 90% question as: $AA^{10} = 10\% - q^{10}\%$, and $AA^{90} = 90\% - q^{90}\%$, where q^{10} and q^{90} are the matching probabilities, while 10% and 90% are the ambiguity-neutral probabilities for the second and third ambiguity questions.

We use the matching probabilities for these three questions to create measures of the two distinct components of ambiguity attitudes, namely ambiguity aversion and A-likelihood insensitivity. To do so, we combine the three ambiguity measures just described to create an overall *Ambiguity Aversion* index we define as: $\frac{AA^{10}+2\times AA^{50}+AA^{90}}{4}$. More weight is attached to the 50% question because this measure is less responsive to A-likelihood insensitivity.[13] We measure the level of ambiguity-likelihood insensitivity by taking the ambiguity aversion measure for the 90% question (AA_{90}) and subtracting the ambiguity measure for the 10% question (AA_{10}). That is, the *A-Likelihood Insensitivity* index is equal to: $AA^{90} - AA^{10}$. Table I summarizes these measures and their implications for ambiguity attitudes.

Table I here

[13] See Appendix B for additional discussion. An alternative but related way of defining the two ambiguity attitude measures was applied by Abdellaoui et al. (2011) and Dimmock, Kouwenberg, and Wakker (2012). Their ambiguity aversion and ambiguity likelihood insensitivity measures are nearly perfectly corrected with ours, and our method is simpler.

Figure 3 displays the relations between ambiguity-neutral probabilities, matching probabilities, and ambiguity attitudes. The x-axis displays ambiguity-neutral probabilities, while the y-axis displays corresponding matching probabilities. Panel A shows the case of ambiguity neutrality; here, 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 illustrates A-likelihood insensitivity where the ambiguity-neutral probabilities are transformed towards 50%; the subject is ambiguity seeking for low likelihood events and ambiguity averse for high likelihood events. Panel D illustrates the modal finding in the data, that of *both* ambiguity aversion and A-likelihood insensitivity. We discuss the empirical results in more detail in Section III.

Figure 3 here

II. Hypotheses: Ambiguity Attitudes and Economic Behaviors

Numerous prior studies develop theoretical models of the effect of ambiguity aversion on equity market participation, and argue that stock returns are ambiguous since their true probability distribution is unknown. Given this assumption, Bossaerts et al. (2010), Cao, Wang, and Zhang (2005), Dow and Werlang (1992), Easley and O'Hara (2009), Epstein and Schneider (2010) and Peijnenburg (2010), among others, show that a sufficiently ambiguity-averse agent will not participate in the equity market. Garlappi, Uppal, and Wang (2007) and Peijnenburg (2010) show that ambiguity aversion will reduce portfolio allocations to equity. Based on these theoretical models, we predict:

1a. People with higher ambiguity aversion are less likely to participate in the equity market.

2a. People with higher ambiguity aversion allocate a lower fraction of their wealth to equities.

The only theoretical work on the relation between A-likelihood insensitivity and stock market participation is Dimmock, Kouwenberg, and Wakker (2012), who show that A-likelihood insensitivity predicts lower allocations to stocks. The intuition is that A-likelihood insensitive individuals overweight the low likelihood event of extremely negative stock market returns, which in combination with risk aversion (or loss aversion), makes stocks less attractive. Accordingly, we predict:

1b. People with higher A-likelihood insensitivity are less likely to participate in the equity market.

2b. People with higher A-likelihood insensitivity allocate a lower fraction of their wealth to equities.

Next we turn to the relation between ambiguity attitudes and financial planning for retirement. We hypothesize that higher ambiguity aversion will lead to more retirement planning, as planning could reduce the ambiguity associated with retirement. There is no clear prediction regarding the relationship between A-likelihood insensitivity and retirement planning. To summarize:

3. People with higher ambiguity aversion devote more effort to financial planning for retirement.

Our final hypotheses focus on the relation between ambiguity attitudes and insurance coverage decisions. For most people, purchasing insurance involves multiple sources of ambiguity. First, as noted by Alary, Gollier, and Triech (2010), the probability of having health problems and needing care is ambiguous for most people, which implies a positive relation between ambiguity aversion and health insurance coverage. Second, as modeled by Bryan (2010) and de Castro and Chateauneuf (2012), the probability that an insurance company actually honors a claim is also ambiguous, which implies a negative relation between ambiguity aversion and insurance coverage. Thus the relation between ambiguity attitudes and insurance coverage is unclear; there are theoretical arguments to support either a positive or a negative relation.

To our knowledge, there are no theoretical models of the effect of A-likelihood insensitivity on insurance choice. Since insurance is usually purchased for low likelihood events, and A-likelihood insensitivity implies such events are typically overweighted, we anticipate a positive relation. Specifically, we predict:

4. People with higher A-likelihood insensitivity are more likely to purchase insurance.

III. Methodology

To measure ambiguity attitudes in the U.S. population, we designed and implemented a survey module for the RAND American Life Panel (ALP).[14]

III.A Measuring ambiguity attitudes in the American Life Panel

The ALP consists of several thousand households that regularly answer surveys over the Internet. To allow the ALP to be representative of the U.S. population, if a selected household lacked Internet access at the recruiting stage, it was provided with a laptop and wireless service.[15]

III.B Outcomes and explanatory variables

In addition to the ambiguity attitude variables derived from our module, we use additional variables from the ALP surveys. Table II defines these variables and Table III provides summary statistics; the last column of Table III also indicates the number of valid responses for each variable. In both tables, Panel A describes the dependent variables, while Panel B describes the control variables.

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[14] See Appendix C for a more detailed description of the ALP.

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

Tables II and III here

The first dependent variable summarized in Table III is Equity Ownership. This is an indicator variable equal to one if a respondent holds equities (either individual stocks or equity mutual funds) in her personal portfolio. Overall, 23% of our sample holds equities.[16] The second row shows that the unconditional average fraction of financial assets allocated to equity is 12%; conditional on stock market participation the average fraction is about 52%. The third row shows summary statistics for Retirement Planning, which measures respondents' financial planning for retirement; a value of one indicates very little and four indicates a high level of planning. Overall, the average reported level of retirement planning is just less than three.

The final two dependent variables in Table III are insurance choices. Long-Term Care Insurance equals one if the respondent has purchased long-term care insurance. Health Insurance equals one if the respondent has never been without health insurance. The primary difference between long-term care insurance and regular health insurance is that, as their names suggest, long-term care insurance covers the costs associated with nursing home needs, while health insurance covers medical costs (other than long-term care). Furthermore, many people have regular health insurance from their employers when young and from Medicare during retirement. Yet Medicare does not generally cover long-term care costs, so people must buy private long-term care insurance, pay for long-term care out of pocket, or rely on Medicaid after exhausting their assets. Because long-term care insurance is rarely provided by employers, having long-term care insurance involves a more active choice by an individual compared to general health

[16] Our respondents have a lower equity participation rate than that reported in some other studies, since 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).

insurance. Table III shows that only 8% of the ALP sample has long-term care insurance, while 78% has generally been covered by health insurance.

In the empirical tests presented in the next section, all models control for several demographic and economic characteristics, including: age, sex, ethnicity, marital status, education, household income and wealth, number of children, and retirement plan type (Table II provides variable definitions and Table III provides summary statistics). Additionally, in our ALP survey module we included additional questions to control for financial literacy, risk aversion, and trust. We do so since prior studies have shown these variables have an important effect on household portfolio choice.

Lusardi and Mitchell (2007) and van Rooij, Lusardi, and Alessie (2011), among others, show that financial literacy is an important determinant of economic decision making. To ensure that ambiguity attitudes are 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 III shows that, on average, respondents answer slightly more than two of the questions correctly, with substantial variation across people (Appendix C provides the exact wording of these questions).

The survey module also includes a set of questions intended to elicit risk aversion. Although our methodology for eliciting ambiguity attitudes is designed to minimize any influence of risk aversion, we nonetheless include this control variable for two reasons. First, we seek to ensure that our ambiguity attitude variables capture a distinct component of preferences, separate from risk attitudes. Second, it is possible that ambiguity attitudes and risk aversion are highly correlated, in which case ambiguity attitudes might provide little incremental information about preferences. To measure risk aversion, we build on Tanaka, Camerer, and Nguyen (2010) who asked respondents to choose 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 attitudes described previously, as illustrated in Figure 4. If the 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 this sequence of questions to estimate subjects' risk aversion, which we measure as the coefficient of relative risk aversion assuming a power utility function.[17] Table III shows that the average subject in our sample is risk averse, but there is substantial variation in risk aversion, including people who are risk-neutral and risk-seeking.

Figure 4 here

Finally, we measure trust to control for the possibility that attitudes toward ambiguity might be influenced by suspicion of others (i.e., people who do not trust others may assume that ambiguous events are systematically biased against them). Specifically, we use a question from the World Values Survey which Guiso, Sapienza, and Zingales (2008) suggest relates to economic decisions involving trust. 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 they employ a binary variable indicating either agreement or disagreement with the statement. Table III shows that the mean level of trust is 3.18.

[17] 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, as defined '1 – power function coefficient,' varies from -0.5 (risk seeking) to +1 (strongest level of risk aversion), and a value of zero implies risk neutrality.

IV. Ambiguity Attitudes in the General Population

Table IV provides an overview of the ambiguity attitudes in our sample. Panel A reports the proportion whose responses are consistent with ambiguity aversion, ambiguity seeking, and ambiguity neutrality. Panel B shows the proportion whose responses are consistent with A-likelihood insensitivity, A-likelihood neutrality, and the small group that is not A-likelihood insensitive (that is, these last respondents' preferences are the opposite of A-likelihood insensitivity, they underweight unlikely events and overweight likely events). Panel C shows summary statistics for the question-specific ambiguity measures, as well as for the ambiguity aversion index and the A-likelihood insensitivity index. Finally, Panel D shows correlations between the ambiguity attitude measures and the financial literacy, risk aversion, and trust variables.

Table IV here

The ALP respondents display a wide dispersion of ambiguity attitudes, although on balance, people are ambiguity averse for events of moderate and high likelihood (50% and 90%), as indicated in Panel A. The question which most closely matches Ellsberg's (1961) experiment, AA^{50}, involves an uncertain outcome with an ambiguity-neutral probability of 50%. For this question, 12% of the respondents are ambiguity neutral, 51% ambiguity averse, and 37% ambiguity seeking. The results are roughly consistent with Butler, Guiso, and Jappelli (2011) and within the range of results from several studies summarized by Akay et al. (2012).[18] The statistics in Panel C for AA^{50} and the ambiguity aversion index show a similar pattern: the

[18] Butler, Guiso, and Jappelli (2011) use survey data on Italian retail bank investors along with experimental data to elicit ambiguity aversion, but their goal is to link decision making styles to ambiguity and risk attitudes, in contrast with our goals in the present paper.

average subject is ambiguity averse, but there is also substantial cross-sectional variability in ambiguity aversion.

Turning to A-likelihood insensitivity, respondent attitudes toward ambiguity vary across different likelihoods—even for the same person. As Panel B of Table IV shows, 78% of the respondents exhibit A-likelihood insensitivity, overweighting low uncertain likelihoods and underweighting high uncertain likelihoods, and the summary statistics for individual questions (in Panels A and C) show a similar pattern. For the question with the 10% ambiguity-neutral probability of winning, ambiguity seeking is the modal response: the median respondent is indifferent between betting on one of 10 colors in the ambiguous box versus a 15% known probability of winning.[19] For the question with the 90% ambiguity-neutral probability of winning, a majority of respondents is ambiguity averse (56%). Moreover, the matching probabilities indicate that, on average, respondents are indifferent between betting on nine of 10 colors in the ambiguous urn, versus an 81.6% known probability of winning.

Panel D of Table IV reports positive and significant correlations across the three question-specific measures of ambiguity attitudes, though the magnitude of the correlation between the ambiguity aversion index and the A-likelihood insensitivity index is small. This implies that the two indexes contain independent information, consistent with prior studies (Abdellaoui et al. (2011); Dimmock, Kouwenberg, and Wakker (2012); and Tversky and Fox (1995)). Moreover, the ambiguity measures are relatively uncorrelated with financial literacy, risk aversion, and trust, which suggests that our ambiguity attitude variables measure different attributes from those explored in previous studies.

Comparing our results for the U.S. population to those in the Dutch ambiguity study of Dimmock, Kouwenberg, and Wakker (2012), we find a similar overall pattern: the typical

[19] The median of AA^{10} is -0.05, hence the matching probability q^{10} is 0.1-(-0.05)=0.15.

respondent displays ambiguity aversion and A-likelihood insensitivity, but there is substantial between-subject heterogeneity. The fraction of people who are ambiguity averse for the first question ($AA^{50} > 0$) is considerably lower in the U.S. at 51%, versus 68% in the Netherlands, suggesting that the U.S. population is less ambiguity averse. This is consistent with Rieger and Wang's (2012) finding that Americans are the least ambiguity averse among 45 nations. A-likelihood insensitivity is similar in the U.S. and in the Netherlands: that is, 78% of the respondents is A-likelihood insensitive in the ALP versus 75% in the Dutch survey.

To provide further insight into the relations between ambiguity attitudes and the demographic/economic characteristics of the U.S. sample, Table V regresses the five measures of ambiguity attitudes on the key control variables. These regressions do not imply any sort of causal relation between the independent and dependent variables; rather we use regression as a convenient tool to concisely summarize the correlation structure of the data. Results indicate that men have higher ambiguity aversion and higher A-likelihood insensitivity, and Whites are less ambiguity averse but more A-likelihood insensitive. We also find a positive relation between ambiguity aversion and risk aversion, consistent with Bossaerts et al. (2010). College-educated respondents have higher ambiguity aversion than other groups, a finding that is inconsistent with a potential alternative explanation of the ambiguity aversion variable: that it might capture ignorance or low cognitive ability. The positive relation with college-education suggests that ambiguity aversion measures preferences, rather than cognitive errors.

Table V here

We also find that the question order in the survey matters: that is, measured ambiguity aversion is *higher* when the risk aversion questions are presented *before* the ambiguity attitude questions. This order effect is consistent with the "comparative ignorance" hypothesis of Fox and

Tversky (1995) which states that ambiguity aversion is magnified by a comparison to less ambiguous events (in this case, the preceding risk questions with known probabilities). To test this effect, we randomized the order of the risk and ambiguity questions in the ALP survey and control for this effect in the empirical analyses with an indicator variable.

Perhaps the most striking aspect of the table, however, is the consistently low R-squared values; at most, the R-squared reaches 0.046. This suggests that our measures of ambiguity attitudes capture new information about preferences not subsumed by standard demographic and economic characteristics.

V. Ambiguity Attitudes and Economic Behaviors

In this section, we test the relation between ambiguity attitudes and four categories of economic behaviors: equity market participation, the fraction of financial wealth allocated to equity, financial planning for retirement, and insurance purchases. All models include a constant term and controls for age and age-squared, male, White, Hispanic, married, education, employment status, (ln) family income, (ln) wealth, (ln) number of children, defined contribution plan and defined benefit plan participation dummies, financial literacy, risk aversion, trust, question order, and missing data dummies.[20] Tables provide coefficient estimates for the ambiguity attitude variables, financial literacy, risk aversion, and trust; results for other variables are suppressed in the interest of brevity (and are available on request). Standard errors are clustered by household and reported below the coefficient estimates (or below the marginal effects, in the case of logit models).

[20] The results are robust to excluding observations with missing data, rather than including these observations and using missing-data dummy variables. We added the questions for risk aversion, trust, and financial literacy to our own survey so we have no missing data for these controls. All results reported in this section are estimated using sample weights provided by ALP to ensure that the results are representative of the general population.

V.A Ambiguity attitudes and equity market participation

Table VI shows the first set of results linking ambiguity attitudes and economic behavior. Here, the dependent variable is an indicator variable equal to one if the respondent owns individual stocks or equity mutual funds, and zero otherwise. We report results from logit models and display marginal effects rather than coefficients. The results in column (1) are estimated using the full sample, whereas the other columns use different subsets described below.

Table VI here

Consistent with the predictions of theory, the results in column (1) show a negative relation between ambiguity aversion and equity market participation, which is significant at the 10% level. The estimated marginal effects imply that a one standard deviation increase in the ambiguity aversion index (0.167) results in a 1.6 percentage point lower probability of participating in the stock market (a 6.9% decrease relative to the baseline probability of 23%). The coefficient on A-likelihood insensitivity is not statistically significant.

The results in column (2) are estimated using a similar model, but here the sample includes only individuals with at least $500 in financial assets. As noted by Haliassos and Bertaut (1995), Gomes and Michaelides (2005), and Vissing-Jorgensen (2002), modest costs of participating in the stock market can explain a large fraction of non-participation. Participation costs, however, would not explain non-participation among those with moderate to large levels of financial assets. After restricting the sample using a cutoff of $500 (as in Heaton and Lucas (2000b)), both the statistical and economic significance of ambiguity aversion increases. The marginal effect in column (2) now implies that a one standard deviation increase in ambiguity aversion results in a 3.4 percentage point decrease in the probability of participation (an 8.8% decrease relative to the baseline participation rate in this subsample of 38.5%).

Columns (3) and (4) restrict the sample to exclude respondents whose responses to one or both of the ambiguity check questions violated their earlier stated choices; column (4) also omits respondents with less than $500 in financial assets. A 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. By removing respondents who provided inconsistent responses, we may reduce measurement error in the elicited ambiguity attitudes. Consistent with the effects of attenuation bias due to measurement error in the independent variable, the economic magnitude of the effect of ambiguity aversion proves to be considerably larger in these subsamples. For instance, in column (4), the estimated marginal effect implies that a one standard deviation increase in ambiguity aversion results in a 5.8 percentage point decrease in the probability of participation (a 14.2% decrease relative to this subsample's baseline participation probability of 40.8%).

All the regressions in Table VI include many control variables, for two reasons. First, to show that the effect of ambiguity aversion on equity market participation is not subsumed by variables identified in previous studies. Second, some of the control variables are included to guard against the possibility that our measures of ambiguity attitudes inadvertently capture some other concept. For example, it is plausible that a lack of education or financial illiteracy might drive both non-participation and ambiguity aversion. *Ex ante*, this seems unlikely, as Table V shows that education and financial literacy explain very little of the variation in ambiguity attitudes. But to further protect against this possibility, we include control variables for education and financial literacy in all regressions. Consistent with prior studies, we find that financial literacy has a highly significant and positive association with equity market participation (van

Rooij, Lusardi, and Alessie 2011). Including this variable, however, does not diminish the effect of ambiguity aversion.

Another potential concern is that ambiguity aversion might be correlated with risk aversion, and thus contains little incremental information. To control for this possibility, we include our elicited measure of risk aversion. In column (1), but not in the remaining columns, risk aversion is significant at the 10% level and positively related to equity market participation. This weak and inconsistent relation between risk aversion and equity market participation suggests that our measure of ambiguity aversion is not simply a proxy for risk aversion (consistent with Guiso, Sapienza, and Zingales (2008), who also find little relation between participation and risk aversion).[21]

Another potential concern is that the ambiguity aversion index could measure subjects' distrust of the experiment: that is, subjects might believe that ambiguous situations are systematically biased against them. To control for this possibility, we include a variable measuring trust in all specifications. In our sample, the relation between trust and participation is directionally consistent with the findings of Guiso, Sapienza, and Zingales (2008), although the estimates are not statistically significant.[22] More importantly, the results of ambiguity aversion are robust to the inclusion of this control variable.

Our results for stock market participation are consistent with the experimental asset market results of Bossaerts et al. (2010), but they differ somewhat from those in the Dutch survey by Dimmock, Kouwenberg, and Wakker (2012). The latter authors report a significant negative relation between ambiguity aversion and stock market participation, but only for

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[21] It is worth noting that non-participation is a puzzle precisely because it cannot be explained by reasonable levels of risk aversion.

[22] As noted above, we use the same trust question but we allow subjects to select a response along a 6-point Likert scale, while Guiso, Sapienza, and Zingales (2008) employed a binary variable indicating either agreement or disagreement with the statement.

subjects who perceived stock returns to be highly ambiguous. They also find a significant negative relation between A-likelihood insensitivity and stock market ownership. Of course we do not expect the results in these two studies to be identical, *a priori*, since the U.S. and the Netherlands have different institutional structures and people in different counties may have different perceptions about stock market ambiguity. The Dutch stock market experienced three extreme negative annual returns in 2001, 2002 and 2009, in each case considerably more severe than the U.S. stock market.[23] For this reason we might expect a larger impact of A-likelihood insensitivity in the Netherlands, because the size of low-likelihood events is larger. Dimmock, Kouwenberg, and Wakker (2012) do not test the relation of ambiguity attitudes with other financial behaviors, such as portfolio allocations, due to data limitations.

V.B Ambiguity attitudes and the fraction of financial wealth allocated to equities

Next we test the relation between ambiguity attitudes and portfolio allocations. Table VII reports results from Tobit regressions in which the dependent variable is the fraction of the respondent's financial wealth allocated to equities (all columns report marginal effects rather than coefficient estimates). The samples in the four columns match those in the previous table: Column (1) includes the full sample, columns (2) and (4) exclude respondents with less than \$500 in financial assets, and columns (3) and (4) exclude respondents who gave inconsistent responses to the check-questions.

Table VII here

All columns of Table VII confirm a significant negative relation between ambiguity aversion and portfolio allocations to equity. This result is consistent with theoretical models of

[23] In 2001, 2002, and 2009 the Amsterdam Stock Exchange experienced an annual return of -21%, -36%, and -52% respectively, compared to -13%, -23%, and -38% for the S&P500. Furthermore, when looking at monthly returns, the AEX four times fell more than -15% in one month, compared to only one time for the S&P500.

ambiguity aversion and stock allocations (e.g., Garlappi, Uppal, and Wang (2007); Peijnenburg (2010)). The implied decrease in portfolio allocations to equities from a one standard deviation increase in ambiguity aversion varies from a low of 6.5 percentage points in column (1), to a high of 11.5 percentage points in column (4). As with stock market participation, A-likelihood insensitivity has no significant association with portfolio allocation to equity.

V.C Ambiguity attitudes and financial planning for retirement

To examine the relation between ambiguity attitudes and financial planning for retirement, the first two columns of Table VIII show results from an ordered logit regression where the dependent variable ranges in value from one to four, with higher values indicating the household has made a greater effort to financially plan for retirement. We include the same control variables as in the previous two tables, and results are reported as marginal effects for the highest outcome (i.e., for the case in which the dependent variable equals four). Column (1) shows results for the full sample, while in column (2) the sample excludes subjects who provided inconsistent answers to the check questions.

Table VIII here

The marginal effect of ambiguity aversion is positive and significant at the 10% level in column (1), indicating that ambiguity aversion is associated with higher financial planning activities. This is consistent with the hypothesis that ambiguity-averse individuals use planning as a tool to reduce concerns about ambiguity. For the restricted sample reported in column (2), however, the marginal effect of ambiguity aversion is not statistically significant. Accordingly, while the results are directionally consistent with our hypothesis, the statistical evidence is weak.

V.D Ambiguity attitudes and insurance choices

Columns (3) through (6) of Table VIII show the results of logit models that test the relation between ambiguity attitudes and insurance choices. For all columns, the dependent variable equals one if the respondent is covered by insurance and zero otherwise. In columns (3) and (4), the dependent variable equals one if the respondent holds long-term care insurance; in columns (5) and (6), the dependent variable equals one if the respondent has always had health insurance coverage. As before, we report marginal effects rather than coefficients, and we suppress results for most control variables. For each outcome of interest, the first column reports results for the full sample, while the second column reports results for the restricted sample excluding subjects who gave inconsistent responses to the check questions.

Columns (3) and (4) show that there is a positive and significant relation between holding long-term care insurance and A-likelihood insensitivity. This is of interest since insurance typically provides protection against severe but low likelihood events. Thus it is reasonable to expect that, for insurance purchases, A-likelihood insensitivity is more relevant than ambiguity aversion. Individuals with high A-likelihood insensitivity overweight small likelihoods (such as requiring long-term care) and underweight high likelihoods (such as not requiring long-term care).[24] For this population, we find that relatively few (8%) have long term care insurance, since the elderly are the main purchasers of coverage and it is not routinely provided by employers. The economic significance of the effect is large: a one standard deviation higher level of ambiguity-likelihood insensitivity implies a 1% percentage point higher probability of having long-term care insurance (an increase of 12.5% relative to the baseline probability of 8%). The effect of ambiguity aversion is not statistically significant.

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[24] Even though insurance purchases cover the loss domain and our measures are for gains, this measure is still valid as there is correspondence between A-likelihood insensitivity for both gains and losses (see Baillon and Bleichrodt (2011)). Extreme events continue to be overweighted in both domains.

Column (5) indicates similar conclusions for the case of always having health insurance, though in column (6) results are not statistically significant. The relatively weaker results for health insurance are intuitive, since this is not an active choice for most individuals as health insurance for the non-elderly is often provided by employers.

In a previous subsection we reported that stock market participation is negatively related to ambiguity aversion, but it is unrelated to A-likelihood insensitivity. The opposite holds for insurance ownership, where A-likelihood insensitivity is significant but ambiguity aversion is not. This pattern of results is consistent with the different underlying distributions of events for stocks and insurance. For stock market participation, the full range of possible outcomes is relevant and affects the participation decision. For insurance ownership, however, only low likelihood events are relevant.

VI. Conclusions

Using real incentives, we measure ambiguity attitudes in a representative survey of the U.S. population and explore how ambiguity attitudes relate to economic behaviors. We show that ambiguity attitudes vary strongly across people: for an ambiguous event of moderate likelihood (winning if one out of two outcomes occurs), 51% of people are ambiguity averse, 12% ambiguity neutral, and 37% ambiguity seeking. Yet for *low likelihood* events (winning if one out of 10 outcomes occurs), most people are ambiguity seeking, while for *high likelihood* events (winning if any of nine out of 10 outcomes occurs), people are especially ambiguity averse. These findings are consistent with ambiguity attitudes having two distinct components: ambiguity aversion, and ambiguity-likelihood insensitivity (the tendency to transform all ambiguous likelihoods towards 50%). We find little correlation between these two components of ambiguity attitudes and conventionally measured risk aversion, or with other control variables.

Having developed the methodology, we next show that ambiguity-averse individuals are less likely to participate in the stock market and allocate less of their wealth to stocks, consistent with an extensive theoretical literature on this topic (cf., Bossaerts et al. (2010); Cao, Wang, and Zhang (2005); Dow and Werlang (1992); Easley and O'Hara (2009)). Equity market participation and portfolio allocations to equities are not, however, associated with A-likelihood insensitivity. The relation between insurance ownership and ambiguity attitudes proves to be different: ambiguity aversion is not significantly related to insurance coverage, but A-likelihood insensitive persons are more likely to be covered. Our interpretation is that A-likelihood insensitive respondents overweight the unlikely future event of incurring large health costs; accordingly, they are more likely to purchase insurance now, compared to others who do not overweight such unlikely events.

Finally, we confirm that ambiguity attitudes have an important effect on economic behaviors. This implies that further research may be warranted on policies that reduce ambiguity, in order to enhance financial decision making. Education regarding the advantages and risks inherent in investing in stocks could also reduce ambiguity, which would be predicted to boost individuals' stockholdings. And finally, regulation that reduces the ambiguity associated with equity investing - such as the provision of clearer information regarding risk and return - might also increase participation. For instance, Easley and O'Hara (2010) show that ambiguity about the stock market can be reduced by changing microstructure features of the exchange.

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Table I: Matching Probabilities and Implications for Ambiguity Attitudes

This table outlines the ambiguity attitudes implied by different matching probabilities. Here q^{10}, q^{50}, and q^{90} refer to the matching probabilities for the 10%, 50%, and 90% ambiguity questions. In the 50% ambiguity question, there are two possible outcomes (a purple or an orange ball is drawn) occurring with unknown probability, and the respondent wins if one particular outcome happens (a purple ball is drawn). In the 10% question, there are 10 possible outcomes with unknown probability, and the respondent wins when one particular outcome occurs. In the 90% question, there are 10 possible outcomes, and the respondent wins when any outcome occurs, except one. AA^{10}, AA^{50}, and AA^{90} are the ambiguity aversion measures for the 10%, 50%, and 90% questions.

$q^{10} = 10\%$	$AA^{10}=0$	Ambiguity neutral for low likelihoods
$q^{10} > 10\%$	$AA^{10}<0$	Ambiguity seeking for low likelihoods
$q^{10} < 10\%$	$AA^{10}>0$	Ambiguity averse for low likelihoods
$q^{50} = 50\%$	$AA^{50}=0$	Ambiguity neutral
$q^{50} > 50\%$	$AA^{50}<0$	Ambiguity seeking
$q^{50} < 50\%$	$AA^{50}>0$	Ambiguity averse
$q^{90} = 90\%$	$AA^{90}=0$	Ambiguity neutral for high likelihoods
$q^{90} > 90\%$	$AA^{90}<0$	Ambiguity seeking for high likelihoods
$q^{90} < 90\%$	$AA^{90}>0$	Ambiguity averse for high likelihoods
	$AA^{90}-AA^{10} > 0$	Ambiguity-likelihood insensitivity
	$\frac{AA^{10} + 2 \times AA^{50} + AA^{90}}{4} > 0$	Ambiguity aversion

Table II: Variable Definitions

This table provides definitions for the variables used in this paper.

Panel A: Outcome Variables	
Equity Ownership	Indicator that respondent held equities in his personal portfolio (stocks or stock mutual funds)
Equity Allocation	Respondent equity holdings as a % of financial wealth (checking, saving, money market, bonds, CDs, and mutual funds)
Retirement Planning	Ordinal variable ranging from 1 to 4, with higher values indicating more retirement planning activities
Long-Term Care Insurance	Indicator that respondent had purchased long-term care insurance
Health Insurance	Indicator that respondent had never been without health insurance
Panel B: Control Variables	
Age	Age in years
Male	Indicator for male
White (Hispanic)	Indicator if respondent considers herself primarily White (Hispanic)
Married	Indicator if respondent is married or has a partner
LT High School	Indicator is respondent did not complete high school
High School Graduate	Indicator if respondent completed high school, but no additional educations
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 (including 2nd homes if any), and imputed social security wealth using respondents' 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
Question Order	Indicator if subject answered the risk aversion question before the ambiguity questions (the question order was randomized)
Financial Literacy	Number of financial literacy questions answered correctly (out of 3 total; see Appendix C)
Risk Aversion	> 0 if risk averse, = 0 if risk neutral, < 0 if risk seeking
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"

Table III: 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 2. Panel A describes the outcome variables. The summary statistics for Equity Allocation are shown only for respondents with a non-zero allocation to equity. Panel B displays economic and demographic controls. 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 devoted fewer than three minutes or over two hours to the survey.

Panel A: Outcome Variables						
	Mean	*Std. Dev.*	*Min*	*Median*	*Max*	*N*
Equity Ownership	0.23	0.42	0	0	1	3,029
Equity Allocation	0.12	0.27	0	0	1	3,034
Retirement Planning	2.95	1.01	1	3	4	1,848
Long-Term Care Insurance	0.08	0.27	0	0	1	2,843
Health Insurance	0.78	0.41	0	1	1	2,842
Panel B: Control Variables						
	Mean	*Std. Dev.*	*Min*	*Median*	*Max*	*N*
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
Question Order	0.51	0.50	0	1	1	3,122
Financial Literacy	2.17	0.92	0	2	3	3,122
Risk Aversion	0.33	0.45	-0.50	0.39	0.98	3,090
Trust	3.18	1.44	0	3	5	3,122

Table IV: Ambiguity Attitudes of the U.S. Population

This table shows ambiguity attitudes in the U.S. population measured using our ALP survey module. Panel A displays ambiguity attitudes revealed by matching probabilities. The numbers represent the proportion of respondents who are ambiguity averse, ambiguity seeking, or ambiguity neutral. We report ambiguity attitudes for the three questions with ambiguity-neutral probabilities of 10%, 50%, and 90% for the ambiguous event. Panel B displays the proportions of our sample that are ambiguity-likelihood insensitive, ambiguity-likelihood neutral, and not ambiguity-likelihood insensitive. Panel C shows summary statistics for five ambiguity attitude measures (see text for definitions). Panel D presents correlations of these five measures.

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

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

Panel B: Ambiguity-Likelihood Insensitivity

	% of Respondents
Ambiguity-Likelihood Insensitive	78
Ambiguity-Likelihood Neutral	10
Not Ambiguity-Likelihood Insensitive	12

Panel C: Summary of Ambiguity Attitude 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
Ambiguity Aversion	0.021	0.167	-0.430	0.014	0.468
A-Likelihood Insensitivity	0.320	0.298	-0.175	0.280	1.600

Panel D: Correlations (Coefficients *not* significant at the 0.05 level are in italics)

	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*	*(8)*
(1) Ambiguity Aversion	1.00							
(2) A-Likelihood Insensitivity	0.09	1.00						
(3) AA^{10}	0.65	-0.54	1.00					
(4) AA^{50}	0.88	*-0.03*	0.43	1.00				
(5) AA^{90}	0.63	0.73	0.18	0.31	1.00			
(6) Financial Literacy	0.06	0.11	*-0.03*	0.05	0.10	1.00		
(7) Risk Aversion	0.16	*0.02*	0.08	0.17	0.08	0.09	1.00	
(8) Trust	*0.02*	-0.04	0.05	*0.01*	*-0.01*	-0.17	*0.03*	1.00

Table V: Relation Ambiguity Attitudes with Economic and Demographic Variables We show OLS regression results where the dependent variables are the ambiguity attitude measures from Table I and independent variables are defined in Table II. Constant terms and retirement plan type indicator variables are not displayed in the interest of brevity. Robust standard errors, clustered by household, are shown in parentheses beneath the coefficient estimates. Coefficients multiplied by 100 to enhance the readability of the table.

	AA^{10}	AA^{50}	AA^{90}	AA index	A-Insens.
	(1)	(2)	(3)	(4)	(5)
Age	-0.357	-0.313	-0.077	-0.294	0.305
	(0.29)	(0.30)	(0.37)	(0.25)	(0.41)
Age^2	0.004	0.003	-0.001	0.002	-0.005
	(0.003)	(0.003)	(0.004)	(0.002)	(0.004)
Male	0.043	3.320***	5.516***	2.969***	5.560***
	(1.00)	(0.99)	(1.19)	(0.78)	(1.45)
White	-5.189***	-2.306	-1.283	-2.756**	3.994*
	(1.36)	(1.40)	(1.608)	(1.09)	(2.02)
Hispanic	1.798	0.551	0.647	0.874	-1.123
	(1.55)	(1.53)	(1.81)	(1.23)	(2.23)
Married	1.844	2.413	0.618	1.835	-1.318
	(1.27)	(1.25)	(1.48)	(1.01)	(1.78)
High School	2.393	2.453	0.694	1.767	-3.048
	(2.79)	(2.18)	(2.62)	(1.91)	(3.31)
College	5.812	5.112*	4.562	5.240**	-1.077
	(3.02)	(2.32)	(2.84)	(2.07)	(3.59)
Employed	-0.659	-0.074	0.414	-0.020	1.022
	(1.10)	(1.12)	(1.30)	(0.88)	(1.60)
ln(Family Income)	-0.046	0.712	-0.098	0.293	-0.099
	(0.70)	(0.73)	(0.76)	(0.55)	(0.95)
ln(Wealth)	-0.579	-0.453	0.226	-0.315	0.805
	(0.53)	(0.54)	(0.58)	(0.43)	(0.75)
ln(# Children)	-1.424	-0.033	1.378	0.047	2.822*
	(0.96)	(0.93)	(1.11)	(0.77)	(1.29)
Question Order	2.793***	6.685***	3.780***	4.942***	0.917
	(1.04)	(1.00)	(1.20)	(0.81)	(1.45)
Financial Literacy	-0.247	0.587	2.256**	0.814	2.447
	(0.77)	(0.72)	(0.81)	(0.60)	(0.96)
Risk Aversion	4.000***	8.151***	4.588***	6.262***	0.659
	(1.29)	(1.24)	(1.43)	(1.04)	(1.68)
Trust	0.465	0.246	0.287	0.307	-0.161
	(0.39)	(0.37)	(0.46)	(0.31)	(0.54)
R^2	0.026	0.038	0.027	0.046	0.020
N	3,024	3,026	3,024	3,005	3,015

Notes: * significant at the 10%; ** 5%; and *** 1% level. AA index denotes the Ambiguity Aversion index, and A-Insens. the A-Likelihood Insensitivity measure. Variable definitions are provided in Table II.

Table VI: Ambiguity Attitudes and Equity Market Participation

We show Logit regression results for stock market participation; 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 and missing data dummies. The table reports marginal effects; standard errors appear in parentheses and are clustered by household. Columns (2) and (4) exclude respondents whose reported financial wealth is less than $500. Columns (3) and (4) exclude respondents whose answers to the check question were inconsistent with their earlier choices.

	(1)	(2)	(3)	(4)
Ambiguity Aversion	-0.095*	-0.201**	-0.180*	-0.347**
	(0.06)	(0.10)	(0.10)	(0.15)
A-Likelihood Insensitivity	0.050	0.071	0.021	0.009
	(0.03)	(0.05)	(0.05)	(0.07)
Financial Literacy	0.084***	0.098***	0.098***	0.102***
	(0.02)	(0.03)	(0.02)	(0.04)
Risk Aversion	0.035*	0.031	0.043	0.042
	(0.02)	(0.04)	(0.03)	(0.05)
Trust	-0.005	-0.006	-0.007	-0.009
	(0.01)	(0.01)	(0.01)	(0.01)
Financial Wealth ≥ $500	No	Yes	No	Yes
Exclude Errors on Checks	No	No	Yes	Yes
Controls and Constant	Yes	Yes	Yes	Yes
Pseudo-R^2	0.209	0.114	0.201	0.114
N	2,938	1,884	1,765	1,207

Notes: * coefficient significant at the 10%; ** 5%; and *** 1% level. Variable definitions are provided in Table II.

Table VII: Ambiguity Attitudes and Portfolio Allocations to Equities

We show Tobit regression results where the dependent variable is the fraction of financial wealth that the subject allocates to equities. 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 and missing data dummies. Standard errors appear in parentheses beneath the coefficient estimates, clustered by household. Columns (2) and (4) exclude respondents whose reported financial wealth is less than $500. Columns (3) and (4) exclude respondents whose answers to the check question were inconsistent with their earlier choices.

	(1)	(2)	(3)	(4)
Ambiguity Aversion	-0.391**	-0.464***	-0.582***	-0.691***
	(0.18)	(0.18)	(0.22)	(0.23)
A-Likelihood Insensitivity	0.152	0.114	0.051	0.006
	(0.10)	(0.10)	(0.12)	(0.12)
Financial Literacy	0.251***	0.155***	0.238***	0.151***
	(0.05)	(0.05)	(0.06)	(0.06)
Risk Aversion	0.149**	0.077	0.106	0.058
	(0.06)	(0.06)	(0.07)	(0.08)
Trust	-0.016	-0.009	-0.018	-0.013
	(0.02)	(0.02)	(0.02)	(0.02)
Financial Wealth ≥ $500	No	Yes	No	Yes
Exclude Errors on Checks	No	No	Yes	Yes
Controls and Constant	Yes	Yes	Yes	Yes
Pseudo-R^2	0.152	0.069	0.150	0.072
N	2,950	1,888	1,768	1,209

Notes: *coefficient significant at the 10%; ** 5%; and *** 1% level. Variable definitions are provided in Table II.

Table VIII: Ambiguity Attitudes, Retirement Planning, and Insurance Choices

We show results of OLS regressions for retirement planning behavior and insurance purchase; columns report marginal effects and not coefficient estimates. Columns (1) and (2) show the results of ordinal logit models. The dependent variable is higher for respondents who spend more time on financial planning for retirement. Columns (3) and (4) show the results of logit models in which the dependent variable equals one if the respondent owns long-term care insurance. Columns (5) and (6) show the results of logit models in which the dependent variable equals one if the respondent has always had health insurance. All models include a constant term and controls including age, age-squared, male, White, Hispanic, married, education, employment status, family income, wealth, number of children, and missing data dummies. Standard errors are shown in parentheses beneath the marginal effects, and are clustered by household.

	Retirement Planning		Long-Term Care Insurance		Have Health Insurance	
	(1)	(2)	(3)	(4)	(5)	(6)
Ambiguity Aversion	0.160*	0.180	-0.027	-0.015	-0.056	-0.111
	(0.09)	(0.13)	(0.03)	(0.03)	(0.07)	(0.10)
A-Likelihood Insensitivity	0.001	-0.036	0.032**	0.029*	0.057*	0.006
	(0.05)	(0.07)	(0.02)	(0.02)	(0.03)	(0.04)
Financial Literacy	0.054***	0.068***	-0.0002	-0.006	0.019*	0.012
	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)
Risk Aversion	-0.027	0.018	-0.006	-0.012	0.010	0.051*
	(0.03)	(0.05)	(0.01)	(0.01)	(0.02)	(0.03)
Trust	0.017	0.015	-0.004	-0.005	-0.008	-0.013*
	(0.01)	(0.01)	(0.003)	(0.003)	(0.007)	(0.008)
Exclude Errors on Checks	No	Yes	No	Yes	No	Yes
Controls and Constant	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo-R^2	0.085	0.080	0.111	0.192	0.197	0.217
N	1,808	1,104	2,783	1,669	2,784	1,671

Notes: * coefficient significant at the 10%; ** 5%; and *** 1% level. Variable definitions are provided in Table II.

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).

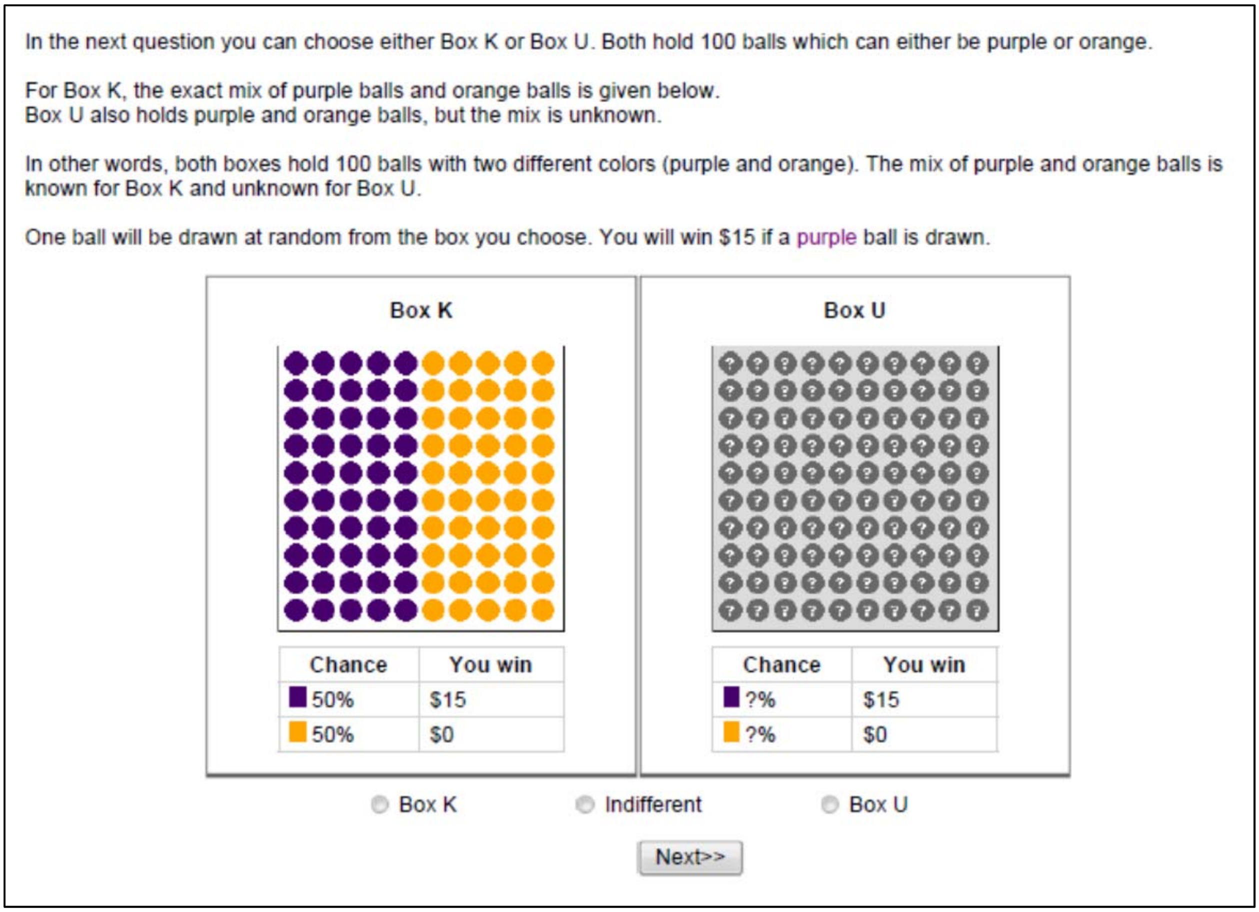


Figure 2. Choosing Between Two Boxes with Purple and Orange Balls, One Having a 10% Chance of Winning and the Other Ambiguous with 10 Possible Outcomes

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).

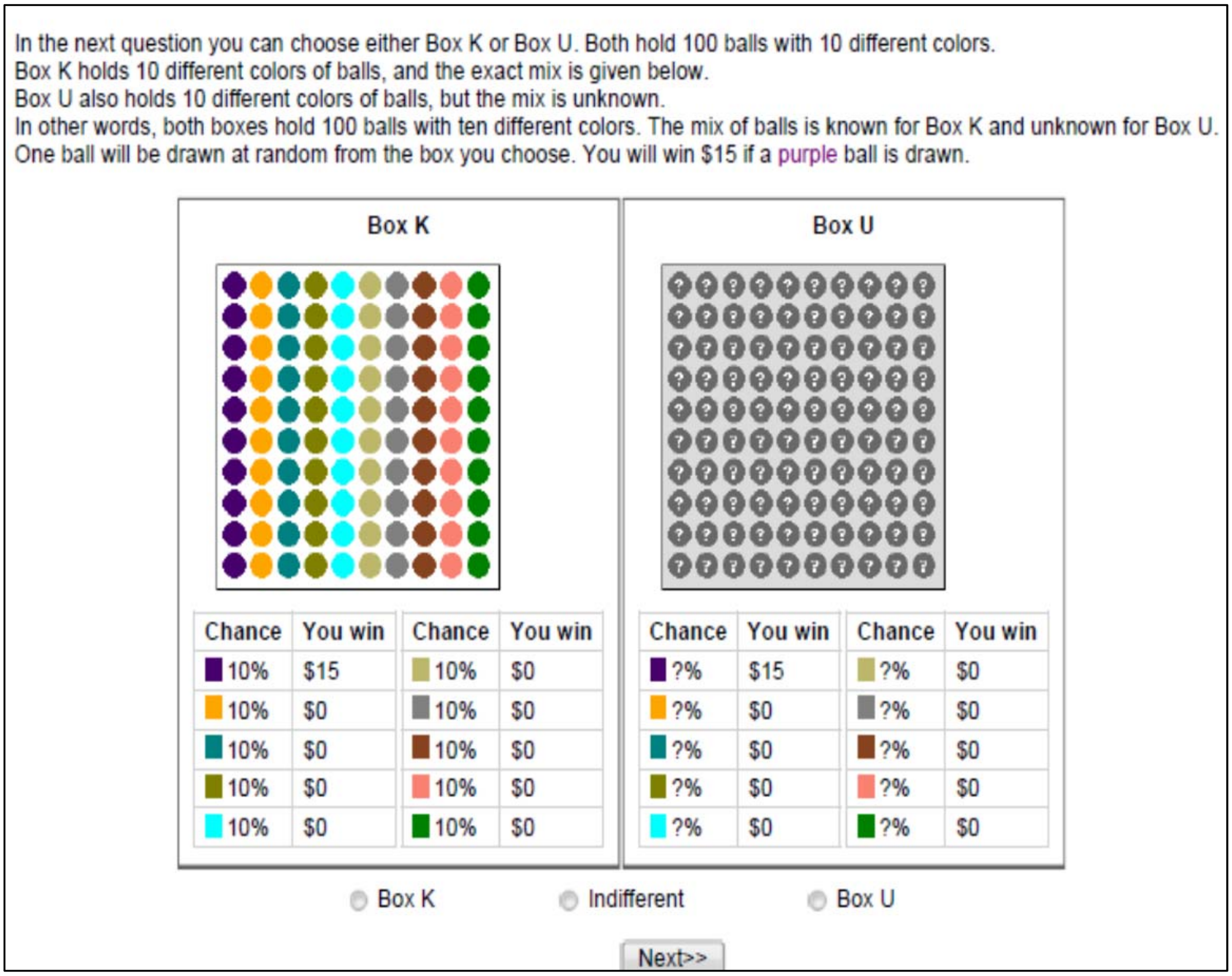


Figure 3. Ambiguity Attitudes and Matching Probabilities

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 *m* is the probability at which the subject is indifferent between winning when the ambiguous event occurs and winning with known probability *m*. The ambiguity neutral probability is the matching probability of a decision maker with a neutral attitude towards ambiguity (like 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-likelihood insensitivity, where all probabilities are transformed towards 50%. Panel D shows the most commonly observed pattern: both ambiguity aversion and A-likelihood insensitivity.

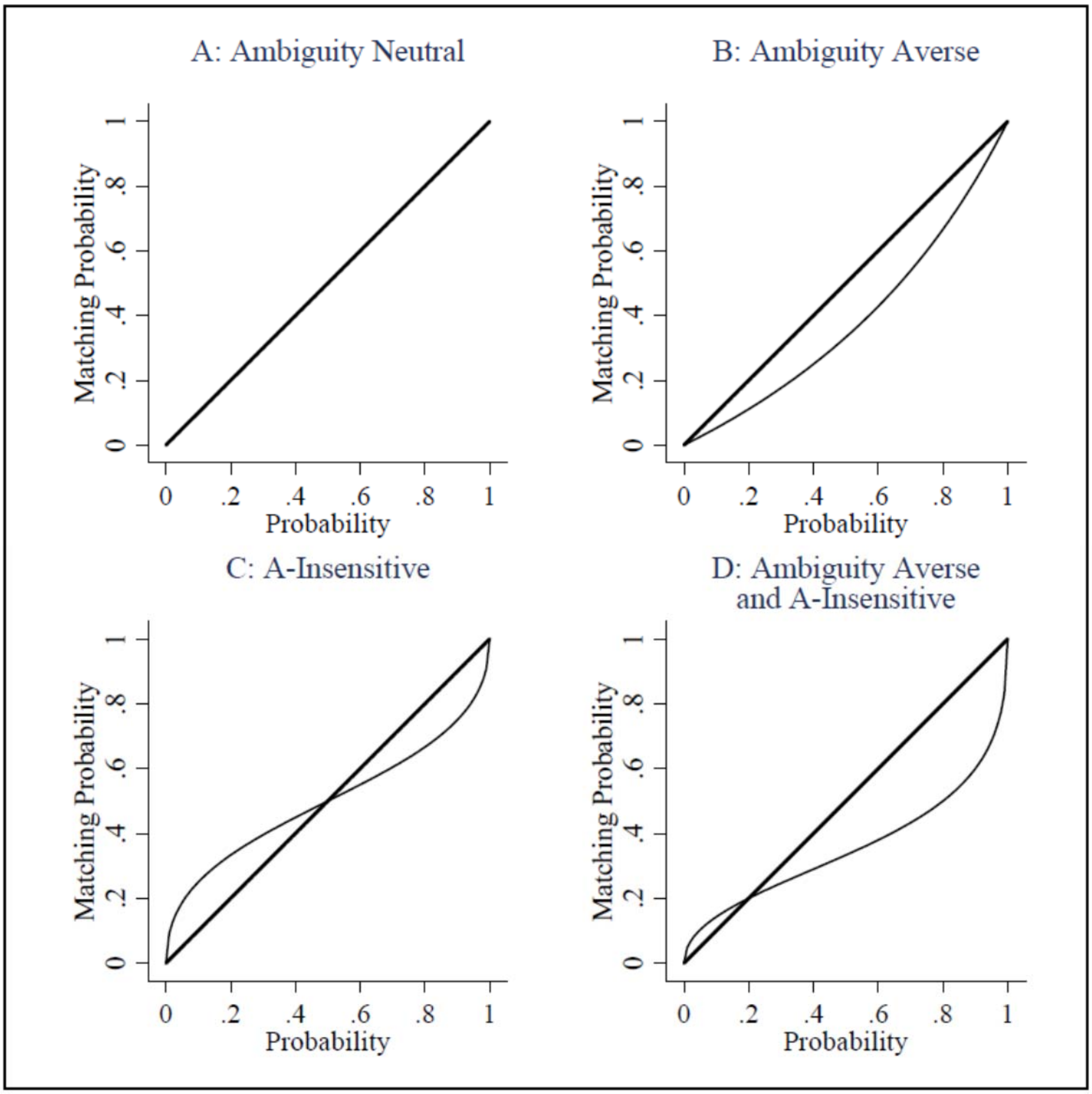
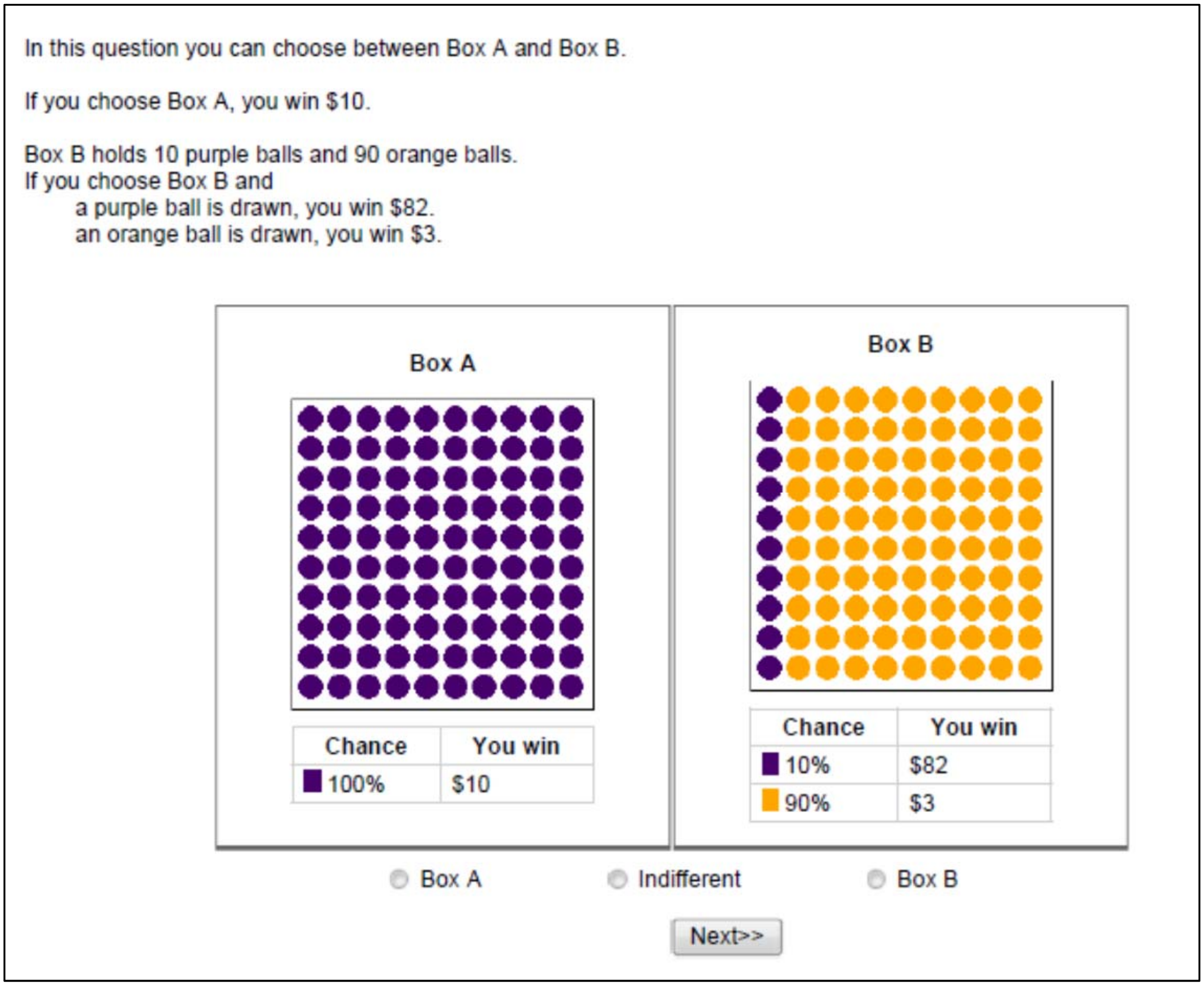


Figure 4. Choosing Between Two Boxes with Purple and Orange Balls, One Having a Sure (100%) Chance of Winning and the Other Having a Risky but Well-Defined Probability Distribution of Outcomes

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.



Appendix A: Detailed Description of the Ambiguity Attitudes Elicitation Procedure

This Appendix describes our ALP survey approach for measuring ambiguity attitudes. 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 indifference 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 2 in the main text. 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.

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 A1-3. 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 A1-3 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. 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 50% initial chance of winning questions, we calculated the matching probability for each subject. To generate check question 1, we lowered the known probability of winning to each subjects' matching probability minus 10. In that case, the subject should choose the ambiguous box. To generate check question 2, we increased the known probability of winning to the matching probability plus 10. In that case, the subject should choose the unambiguous box. Note that the maximum known probability is 100 and the minimum is 1.

Table A1-1: 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 rounds of the 1st 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^{50} 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 example, "KUUK" means the respondent chose Box K, followed by U twice, and then K. For this path the lower and upper bound on the matching probability are 38% and 44%, with midpoint q^{50} = 41%. The path "I" means the respondent chose Indifferent in the first round (with q^{50} = 50%). For paths UUK, UUI and UUU, representing 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
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 A1-2: 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 and initial 10% chance of winning for Box K. 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 A1-3: 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 and initial 90% chance of winning for Box K. 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 always 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

Figure A1-1: 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 A1-2: Screen Shot: Second Round of 1st Ambiguity Question (50%) after Choice K

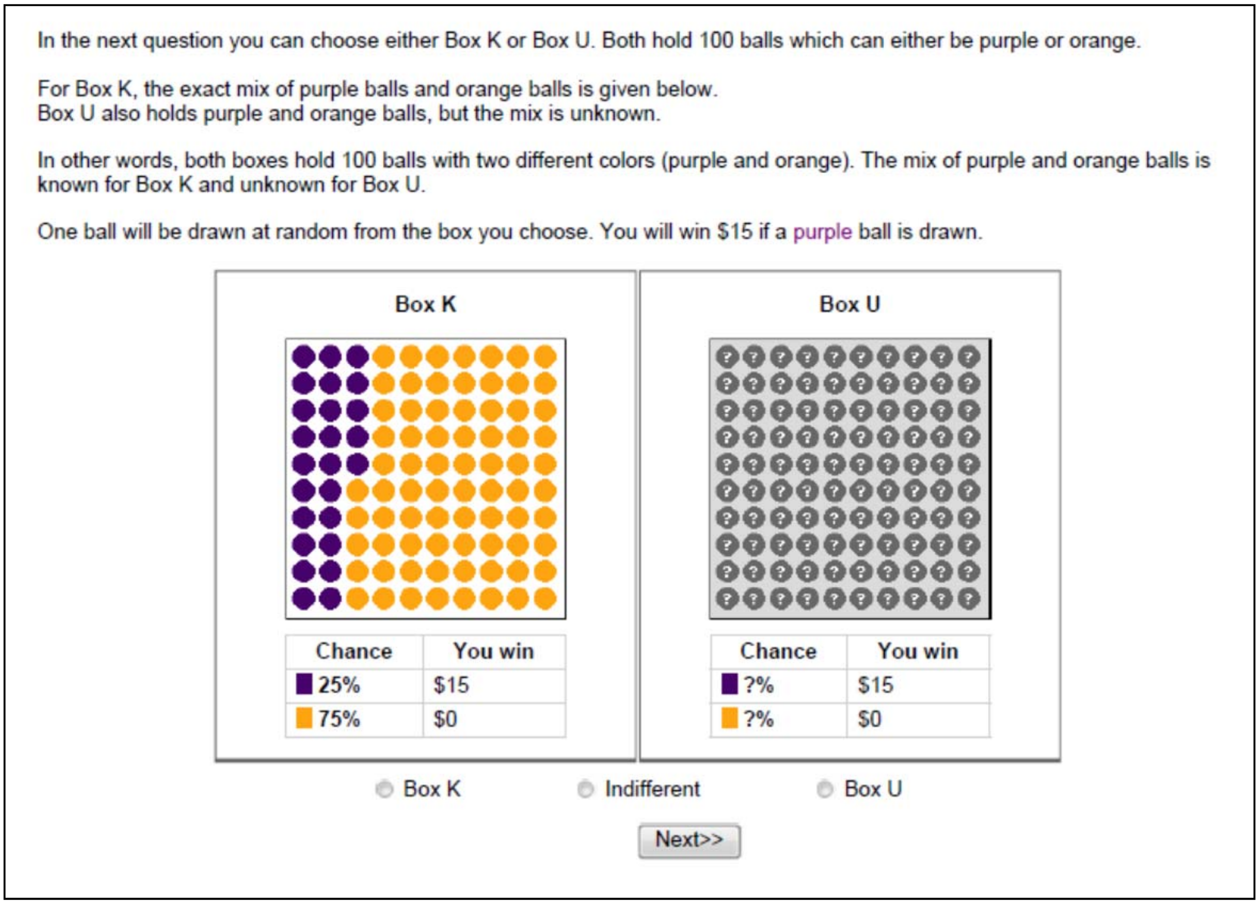
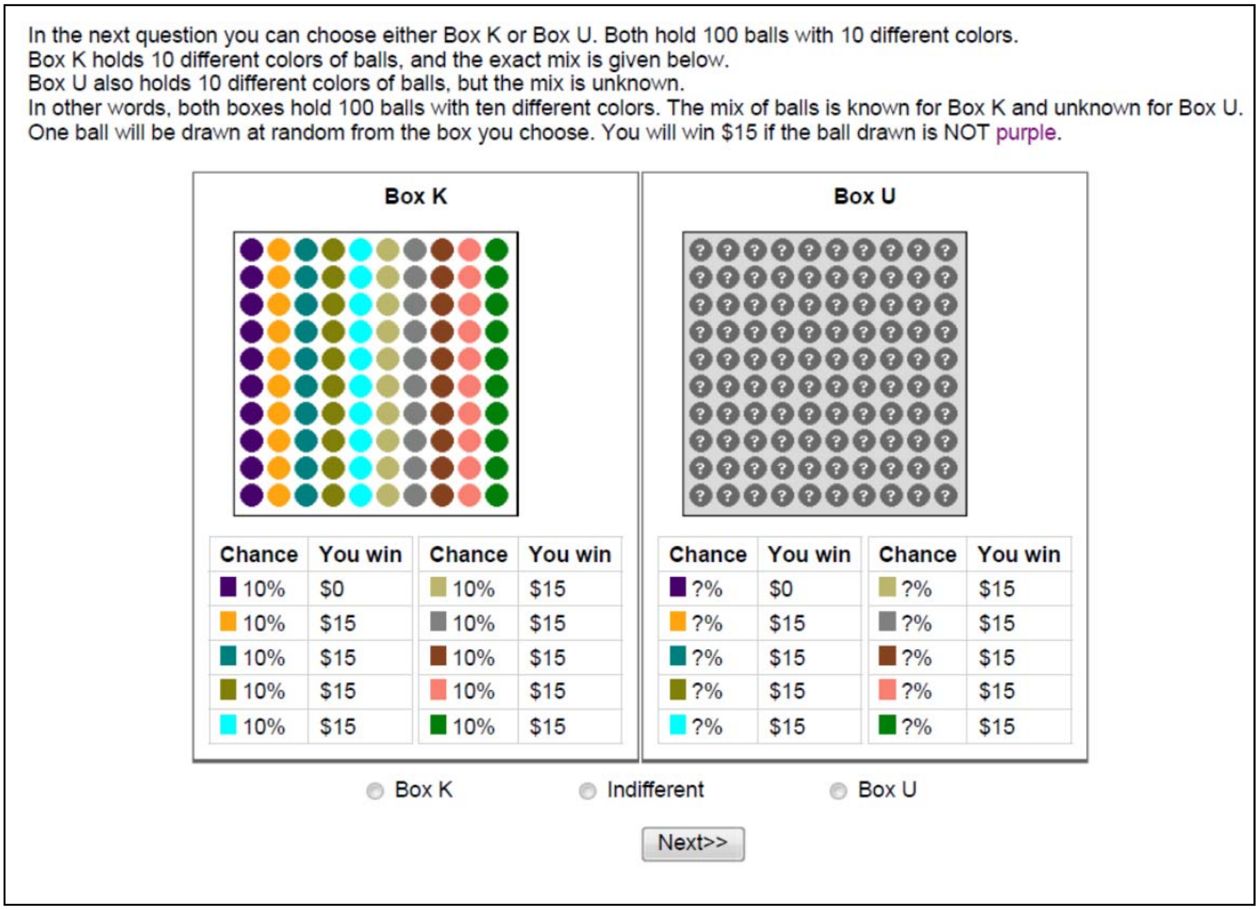


Figure A1-3: Screen Shot: First Round of 3rd Ambiguity Question (90%)



Appendix B: Ambiguity Attitudes Measured in the ALP

This appendix describes the measures of ambiguity aversion used for our Ellsberg experiments, as well as more general measures of ambiguity attitudes. Let q^i represent the respondent's matching probability for ambiguity question *i* for gains, where *i* (=10, 50, or 90) represents the initial chance of winning for the box with known composition. 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). We summarize ambiguity attitudes in two ways. First, we simply rescale the matching probabilities solicited with the four ambiguity questions.

Question with 10 colors, 10% prob.: $AA^{10} = 10\% - q^{10}$ (A1)

Question with 2 colors, 50% prob.: $AA^{50} = 50\% - q^{50}$ (A2)

Question with 10 colors, 90% prob.: $AA^{90} = 90\% - q^{90}$ (A3)

All three measures above are indices of ambiguity aversion. Positive values of measures AA^{10}, AA^{50} and AA^{90} indicate underweighting of ambiguous gains, indicating that the respondent is more pessimistic about the ambiguous box than the corresponding unambiguous box with known probability of winning *i* (*i* = 10%, 50% or 90%). 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.

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 aversions for likely events ($AA^{50} > 0$ and $AA^{90} > 0$), especially for highly likely events ($AA^{90} >> 0$). This pattern prevails because we think of ambiguity attitudes as consisting of two distinct components, following Tversky and Wakker (1995) and Abdellaoui et al. (2011). 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-likelihood insensitivity), which refers to individuals' tendency to overweight ambiguous events perceived as unlikely and underweight ambiguous events perceived as likely. Essentially, A-likelihood insensitivity is a tendency to treat all ambiguous events more as 50%-50% gambles.

A second way we summarize ambiguity attitudes captures the two distinct components of ambiguity attitudes, ambiguity aversion, and A-likelihood insensitivity:

Ambiguity aversion index $= (AA^{10} + 2AA^{50} + AA^{90})/4$ (A5)

A-likelihood insensitivity $= AA^{90} - AA^{10}$ (A6)

The Ambiguity aversion index measures the general tendency to dislike (underweight) ambiguous events. It is a weighted average of the three individual ambiguity aversion measures for gains (AA^{10}, AA^{50} and AA^{90}). We give extra weight given to AA^{50}, as it is less affected by A-likelihood insensitivity, and it represents the traditional Ellsberg setting with two ball colors.

The A-likelihood insensitivity Index measures likelihood insensitivity generated by ambiguous events, the tendency to treat all uncertain events as equally likely (50-50%). A-likelihood insensitivity predicts strong ambiguity seeking for unlikely events ($AA^{10} < 0$) and strong ambiguity aversion for high likelihood events ($AA^{90} > 0$). Hence, the higher the A-likelihood insensitivity measure ($= AA^{90} - AA^{10}$), the stronger the respondent's insensitivity to the likelihood of the ambiguous events. Note that negative values imply A-likelihood *sensitivity*: underweighting of unlikely events and overweighting of likely events.

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 subjective 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 and colleagues 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. Following Chew and Sagi (2008) and Abdellaoui et al. (2011) then we 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.

Figure 3 provides examples of the relation between subjective probabilities and decision weights, using the source function approach just described. 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. Panel A shows a source function consistent with expected utility (no probability weighting). Panel B shows a source function where the decision maker underweights all ambiguous events, reflecting ambiguity aversion (pessimism). Panel C shows a likelihood insensitive source function, with overweighting of unlikely events and underweighting of likely events. Panel D shows the most common finding, a source function that is both ambiguity averse and likelihood insensitive. This combination results in an ambiguity seeking attitude for low likelihood ambiguous events and ambiguity aversion elsewhere.

Our A-likelihood insensitivity measure can also be interpreted as a measure of the flatness of the weighting function for ambiguous events (Panel C of Figure 3), while the ambiguity aversion index is a measure of underweighting (Panel B of Figure 3). Abdellaoui et al. (2011) use an alternative approach to measure these two components of ambiguity attitudes, based on a regression of elicited decision weights on subjective probabilities. Their ambiguity aversion and A-likelihood insensitivity measures are nearly perfectly corrected with ours. Our measures have the advantage that they do not require a regression, and they are easier to explain.

Empirically, probability weighting does not only occur for ambiguous events, but also for events with known objective probabilities (see, e.g., Tversky and Kahneman, 1992). For example, consider the unambiguous box with 50 purple and 50 orange balls, with known chance of winning p=50%. A respondent 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, imply underweighting. Dimmock, Kouwenberg, and Wakker (2012) show that the matching probability q^i measures the *additional* probability weighting a respondent applies for an ambiguous event, on top of any probability weighting that already occurs for events with known probabilities, without the need to measure the respondent's utility function.[25]

[25] See Dimmock, Kouwenberg, and Wakker (2012) for a proof.

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.