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An Experimental Investigation of Updating under Ambiguity

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Abstract

We formulate new hypotheses that take advantage of information updating in order to discriminate between the two major specifications of multi-prior ambiguity models: "kinked" and "smooth". In particular, across comparable decision settings, we examine the effects of adding or trimming out certain priors, updating the weight on particular beliefs, changing the payoff for a single potential state, and modifying the distribution within certain priors. Our results show that the kinked specification does well in consistently predicting choices from 68% of participants, and the smooth specification predicts well for just 10%. We find evidence that people may use a compound lottery as one of their priors, subjects are insensitive to information that the best prior is more likely, and people place lower values on ambiguous lotteries that are relatively more complex. Our experimental methods are likely to be useful in other contexts, as they allow for simple tests of decision-making under ambiguity without placing restrictions on the weights participants place on priors, or reliance on comparisons to decision-making under risk.

JEL Classifications: C91, D81, D83

Keywords: uncertainty; ambiguity; updating; multiple priors models; alpha-maxmin expected utility; recursive expected utility; lab experiment; self-protection; subjective expected utility

1. Introduction

With the subjective expected utility (SEU) model, Savage (1954) argues that, under uncertainty, a decision maker maximizes utility by attaching a subjective probability distribution (i.e., priors) to all potential states of the world. With several inventive experiments, Ellsberg (1961) shows that people hold a non-neutral attitude between risk (known probability) and uncertainty (unknown probability), and labels this phenomenon "ambiguity aversion". Ambiguity aversion models have been applied to a wide range of settings, including participation in financial markets (Easley and O'Hara 2009), medical treatment decisions (Berger, Bleichrodt, and Eeckhoudt 2013), the take-up of genetic tests (Hoy, Peter, and Richter 2013), and climate change policy (Millner, Dietz, and Heal 2013). Even though empirical and theoretical research has been informative, it remains an open question as to which theoretical model, if any, adequately characterizes behavior under ambiguity. The importance of this issue is exemplified by several theoretical analyses that find conclusions are sensitive to the assumed ambiguity aversion model (e.g., Chambers and Melkonyan 2017), and overall mixed results from experiments.

In this study, we design novel experimental tests that allow us to discriminate better between the two main classes of multi-prior ambiguity models, commonly referred to as "kinked" and "smooth". The new tests take advantage of the fact that the two classes of models make stark predictions on how preferences change in response to new information. Under the kink specification, people adjust utility based on the changes in best and worst priors, while smooth ambiguity assumes that people take every potential prior into consideration. To our knowledge, our study is the first to test ambiguity models based on information updating. Across decision tasks, we add or trim out certain priors, manipulate the weight placed on a particular prior, change the payoff of a single potential state, and modify the distribution within certain priors. Simple differences in valuations across related tasks are used to test theoretical predictions, giving rise to powerful tests while minimizing auxiliary theoretical and statistical assumptions.

Our study complements the handful of recent experiments that provide insight on the empirical validity of ambiguity theories. Halevy (2007) and Adellaoui et al. (2011) use an Ellsberg-type experiment to distinguish among several theories by comparing valuations across four lotteries characterized either by simple risk, ambiguity, or two-stage objective lotteries. Halevy (2007) finds that the choice patterns of about 70% of participants can be explained by one of two smooth model specifications. He further finds that most participants able to reduce compound lotteries are highly likely to be ambiguity neutral, which is a prediction consistent with the SEU model. With a more general design that varies the probabilities of the winning event, Adellaoui et al. (2011) instead find only weak evidence between ambiguity attitudes and compound risk attitudes.

Hey, Lotito, and Maffilletti (2010) and Hey and Pace (2014) use a Bingo Blower that contains many balls of three colors that are visible to participants but constantly moving. Across between-subject treatments, the number of balls increases (although their proportions did not), which the authors argue increases the level of ambiguity. Participants complete a large number of decision tasks, distinguished by the payouts associated with the ball colors. Findings from both studies suggest that simple models such as SEU and α-maxmin expected utility (α-MEU; a kinked specification) are better at predicting behavior than more sophisticated ones, such as Choquet expected utility (CEU). Ahn et. al. (2014) ask participants to make financial allocation decisions over risky and ambiguous assets, and analyze the data based on parametric representations of the SEU, α-MEU, and recursive expected utility (REU; a smooth specification) models. The authors find that they are unable to reject the SEU model for 60% of participants, while the behavior of others may be explained by models of ambiguity or pessimism/optimism.

Relative to prior work, our experimental design has several advantages. First, our design is flexible in that we can carefully vary the number of priors, the payoffs associated with states, the distribution of a single prior, and the weight over priors. In contrast, the Bingo Blower approach only allows one to change payoffs. Second, relative to Halevy (2007) and Ahn et al. (2014), our identification strategy does not rely on comparisons between ambiguous and unambiguous lotteries. The presence of risky lotteries is likely to introduce context and reference points, with the potential to alter preferences for ambiguous lotteries. Thus, our design is likely to enhance external validity. Third, as the contents of all of the urns in our experiment are hidden, there is no potential for participants to form reasonable, objective estimates over the probabilities of outcomes. Fourth, there is a direct connection between the underlying theories we are testing and experimental treatments, giving rise to simple comparisons of valuations across related tasks, and avoiding the need for sophisticated econometric methods. Last, similar to Halevy (2007), we elicit valuations for different lotteries using the Becker-DeGroot-Marschak (BDM) mechanism (Becker, et al., 1964). Relative to other elicitation approaches, such as binary choices, this mechanism collects more precise information about preferences. As this mechanism is unfamiliar to participants, we provide extensive training, as advocated by Plott and Zeiler (2005) and Cason and Plott (2014).

Our results suggest that the vast majority of our participants display behavior consistent with the kinked specification. To be clear, using differences in valuations across tasks within six comparison sets, we find that 68% of participants adhere to the directional predictions of the kinked specification based on four or more comparison sets, in contrast to just 10% for the smooth specification. We also find supportive, but not universal, evidence that preferences for ambiguity are independent of the payoffs for a specific state, which is one of the most important assumptions underlying kinked ambiguity theories. With our experimental design, we have also identified behaviors that cannot be easily reconciled by existing theories. First, we find subjects might use a compound lottery as a prior, while the previous theories treat all priors as single lotteries. Second, by framing a subset of mathematically equivalent lotteries in two different ways, we find that elicited preferences differ based on the complexity of the decision task. In particular, participants tend to place higher values on simpler lotteries. Finally, our data analysis reveals that those with lower college GPAs are more likely to deviate from the prediction of the kinked specification, and further that those with higher GPAs are more likely to value mathematically equivalent lotteries equally. This suggests that the ability of a theory to predict behavior in settings characterized by ambiguity may be tied to critical thinking and learning skills. We further find statistical correlations that imply that those who are emotionally less stable, based on a Big-5 personality instrument, are more likely to adhere to predictions from the smooth ambiguity specification.

2. Experiment Design

Table 1 presents the 14 lottery tasks in the experiment, representing six comparison sets. Tasks identified by the same number belong to the same comparison set. In each task, participants place bids to play a particular lottery, which here refers to the opportunity to randomly draw one ball from an urn, and receive an amount of money based on the color of the ball drawn. Values associated with lotteries are elicited using the BDM mechanism, which under mild assumptions is incentive compatible in the sense that bidding one's true value for the lottery is a dominant strategy (Azrieli, Chambers, and Healy 2018).

An experiment session proceeds as follows. The experiment is conducted using paper and pencil. Participants are provided with written instructions, an example of which is provided in Appendix B. The moderator reads the instructions aloud and answers any questions about the procedures. Prior to the lottery tasks, subjects complete a double multiple price list (DMPL) (Gneezy, Imas, and List 2015), which elicits risk and ambiguity preferences. This is followed by extensive training on the BDM mechanism. Participants then complete 14 lottery tasks.

After all tasks are completed, earnings are determined for the DMPL and lottery tasks. It is common knowledge that after all lottery tasks are completed, just one of the tasks is binding in the sense that it will be played for real. For transparency, all relevant processes are determined by participant volunteers: selection of the binding task; the random BDM price; the draw of a card to determine what urn is in effect (when necessary); and the selection of a ball from the urn. Random processes associated with earnings for the DMPL are similarly determined by volunteer actions. The session ends with a questionnaire.

2.1 Lottery value elicitation

The BDM procedure for eliciting valuations (i.e. reservation prices) for lotteries works as follows. Participants place a bid for the right to play the lottery. Then, a price is randomly determined. If the bid is higher than the randomly determined price, the participant successfully makes a purchase (plays the lottery) and pays the random price; otherwise, no transaction takes place. During the experiment, there is no constraint on bidding – participants can bid any amount. To avoid anchoring associated with the upper bound of the price distribution (see Cason and Plott 2014), participants are informed that the price distribution is a uniform distribution from $0.00 to a “maximum price”. We state that the maximum price can be as high as the payoff associated with the highest-valued ball. As rational valuations for any of the lotteries are between the minimum and (expected) maximum possible price, the BDM mechanism remains incentive compatible.

2.2 BDM Training Procedures

As the BDM is not a familiar elicitation procedure to most, we provide participants with extensive training, following the recommendations of Plott and Zeiler (2005) and Cason and Plott (2014). In particular, our instructions closely follow those of Butler and Vossler (2018). The training is divided into three steps. In the first, participants are provided with instructions that clearly describe the purchase procedure, provide examples, and include language to disassociate bidding in this context with bidding in auctions. In the second step, subjects are asked to work through a set of practice examples and one additional question that elicits whether people can identify the dominate strategy. To motivate thoughtful responses, participants are paid for correct answers. After all answers are checked, the moderator discusses each answer and highlights how misconceptions (deviations from the dominant strategy) can decrease earnings.

In the last step, participants work through two training rounds. In the first, they bid on the opportunity to draw a ball from an urn containing three black balls (each worth $2 if drawn), which represents a simple version of the ambiguous lottery tasks. In the second, they bid on an urn that contains one black ball (worth $2 if drawn), one red ball ($3) and one white ball ($4). In each round, although only one bid is placed, the BDM procedure is played out multiple times, using a narrow price distribution that is unknown prior to bidding. This procedure thus motivates learning by giving rise to scenarios where over or underbidding leads to losses or foregone earnings. The instructions for the lottery tasks further emphasize the dominant strategy; i.e., the instructions state, "It will be in your best interest to place a bid equal to the highest price you are willing to pay".

Thus, even if the training procedures did not clarify the incentives of the BDM mechanism, simply believing that this advice is true may be sufficient to motivate truthful demand revelation. Importantly, as the elicitation mechanism does not change across tasks, it is reasonable to interpret differences in bids across tasks as a meaningful metric from which to test ambiguity theories.

2.3 Lottery tasks

Each task involves urn(s) containing at most three colors of balls: black, red and white. Across all tasks, the black ball is tied to the low prize, the red ball represents the medium prize, and the white ball is associated with the highest payoff. Most of our urns contain only three balls. We choose this structure because the number of priors increases rapidly as balls are added when there are three possible states. In the Halvey (2007) two-color setting, the author attempted to limit the maximum number of priors to be 11 to reduce task complexity. In our design, for the most complex tasks, the maximum number of priors is ten.

For each valuation task, subjects are presented with both written and graphical depictions of the urn(s). The picture contains most of the valuable information, including the total number of balls, potential colors and some other information. The tasks are grouped into two parts based on procedural differences. Part I includes the first two comparison sets (six tasks), and each task therein involves one possible urn. Part II includes sets 3 to 6 (eight tasks), and each task therein involves several possible urns. To implement this, a card is first drawn from a deck to determine what urn a ball will be drawn from. The number of cards is known, but only limited information is provided in terms of the likely values on the cards (i.e., the probability of selecting a particular urn). Within each part, related tasks are encountered in pairs. Each task is individually labelled, and appears on a separate page of the instruction packet. To control for order effects, the order of the two parts is randomized across sessions. Moreover, the order of the task pairs, as well as which task within a pair is first seen, is randomized across participants within a session.

The four tasks in the first comparison set allow us to identify the value of self-protection when the payoff of a state is altered. In particular, we implement self-protection by eliminating the possibility that the lowest-value (black) ball is drawn. We describe this process as follows:

> IF this urn contains one or more black balls, these balls will be replaced with red or white balls before a ball is drawn.

To be clear, we do not ask participants to value self-protection directly, and instead infer this value based on the difference in bids across tasks. We prefer this approach, as it allows us to keep the endowment (i.e., owning nothing) and framing consistent across all tasks in the experiment. To alter the payoff of a state, we vary the value of the highest-value (white ball) across tasks. To help insure *ceteris paribus* comparisons, participants are told that the same urn will be used for all four tasks.

The second comparison set allows us to test the effects of adding a prior. Task 2A only has two priors (all black or all white balls), whereas Task 2B has three (all black, all red, or all white balls). Tasks in set 3 and 4 identify the effect of changing the distribution within priors, and tasks in set 5 and 6 identify the effect of changing the weight on a specific prior. To make *ceteris paribus* comparisons across tasks within each of these sets, participants are told that the same deck of cards will be used within each set; i.e., the chances that a particular urn is selected does not change across paired tasks.

The lotteries in set 3 are identical to those in set 4, and the lotteries in set 5 are identical to those in 6. The main difference is how the identical lotteries are framed. In particular, for tasks in set 3 and 5, participants are told:

> IF a black ball is selected from the urn, you would repeat the procedure – draw a different card, and then draw a ball from the selected urn – until a red or white ball is chosen.

In contrast, the lotteries in sets 4 and 6 eliminate any mention of black balls. Therefore, we hypothesize that any difference in valuations across identical (but differently framed) lotteries may be attributable to decision complexity.

Our experimental tasks represent a new approach for implementing decisions involving ambiguity. Here, we briefly contrast this with the popular second-order probability method. With the second-order probability method, by changing the number of priors, researchers can easily modify the ambiguity level. In addition, employing a uniform distribution allows researchers to assume subjects place equal weight on each prior, which greatly simplifies the theoretical analysis. However, a shortcoming of this method is that it results in subjects valuing a compound lottery instead of a situation truly characterized by ambiguity.

In our experiment, instead of using a uniform distribution, participants are told, e.g., "there are four different urns, numbered 1, 2, 3 and 4. You would first draw a card from a stack of TWELVE cards to select what urn is used." This modification allows researchers to introduce unknown probabilities, and the ambiguity level can be altered by providing (incomplete) information on the distribution of card values. To make subsequent theoretical analysis tractable, we hold fixed the unknown probabilities within a comparison pair (i.e. participants are told that the same deck of cards would be used for either task). We then maintain the assumption that subjects place the same weights on the different priors within the task pair.

2.4 Survey

The experiment ends with a two-page questionnaire that elicits demographic information such as age and gender. Participants self-report their level of understanding regarding experiment procedures, and how well they were compensated using 5-point Likert scale questions. In addition, we include the 10-item Big-Five personality instrument of Gosling, Rentfrow, and Swann (2003). Previous research suggests that there is considerable heterogeneity in ambiguity preferences, with respect to both the level of ambiguity aversion and what theories explain behavior. By collecting information about personality traits, we hope to provide insight on whether personality may explain some of this heterogeneity.

2.5 Participants

The experiment was conducted at a designated experimental laboratory at a large public university. One-hundred and seventeen undergraduate students, recruited from a variety of majors, participated in the experiment during July 2017 and January 2018. There are data from four sessions, each lasting approximately 90 minutes. Earnings for the experiment are determined by a \$10 lump sum for completing all tasks and the questionnaire, the payout from the DMPL, earnings from the BDM training procedures, and the randomly selected lottery task. Earnings were paid in private at the end of the experimental session. Participants earned between \$15 and \$32.75, with a mean of \$21.91.

3. Theoretical Predictions and Testable Hypotheses

This section focuses on the theoretical predictions provided by the kinked and smooth specifications.[1] The kinked specification can be derived from a variety of models, including MEU, CEU, contraction expected utility, and α-MEU (see Ahn et al. 2014). The smooth ambiguity model is developed by Klibanoff, Marinacci, and Mukerji (2005), which is alternatively labeled as REU

[1] It is possible that behavior will be inconsistent with any multiple priors model. Later in the paper we consider whether results can instead be explained by SEU, for which we find limited support.

in Halevy (2007) and Ahn et al. (2014). Following Ahn et al. (2014), we chose α-MEU as the representative model for the kinked specification. Below we provide a theoretical framework and derive testable hypotheses from the experiment.

3.1 Kinked specification

Ghirardato, Maccheroni, and Marinacci (2004) derived α-MEU by relaxing the uncertainty aversion assumption of the standard MEU model (Gilboa and Schmeidler 1989). As shown in Ahn et al. (2014), α-MEU can be derived from different classes of preferences, and in each setting the value of α depends on the set of priors. Applying the theory to our experiment decision tasks, let $s \in \{B, W, R\}$ denote the possible ball colors in an urn (i.e., "states"), let p_s denote the probability of each color, and let x_s denote the payoff associated with the color. In the case that the p_s are known, the expected utility from a lottery involving a single urn can be represented as

(1) $v = \sum_{s\in\{B,W,R\}} p_s u(x_s)$.

In a setting characterized by ambiguity, an agent will not know the objective distribution of colors. Instead, she assigns subjective probabilities to the payoffs. In a multiple priors model, the decision maker does not simply assign point estimates of the prior probabilities. Instead, she assigns a subjective weight over prior probabilities. Denote ρ as a subjective probability distribution (a prior) over payoffs in the subject's mind and Δ as the set of all possible priors. The utility of a person exhibiting α-MEU preferences becomes:

(2) $V = \alpha \min_{\rho\epsilon\Delta} v(\rho) + [1-\alpha] \max_{\rho\epsilon\Delta} v(\rho)$,

where $0 \le \alpha \le 1$, represents the level of ambiguity aversion. When $\alpha = 1$, the subject is extremely ambiguity averse, while $\alpha = 0$ indicates the subject is ambiguity loving. As suggested by (2), α-MEU assumes that an agent's utility is a weighted average of the expected utilities associated with the worst and best priors.

3.2 Smooth specification

The REU model assumes that people place a subjective weight on *every* prior. Define w_ρ as the subjective weight placed on a prior. Then, the expected utility for a person with smooth ambiguity with discrete priors can be expressed as

(3) $$V = \sum_{\rho \epsilon \Delta} w_\rho \varphi[v(\rho)],$$

where, under ambiguity aversion, $\varphi(.)$ is a concave function over the expected utility of a single prior. As pointed out by Halevy (2007), the concavity of $\varphi(.)$ is equivalent to an aversion to the potential mean spreads.

The smooth ambiguity model is motivated by a single model, and places less structure on preferences relative to alternative models. For example, compared with ROCL model by Segal (1988, 1990), REU allows a subjective probability weight (instead of an objective weight) on different priors, together with different preferences over the first and second stage of a lottery. One potential issue with REU is, when a flexible functional form is assumed for $\varphi(.)$, ambiguity preferences are difficult to distinguish from the changes in the weights on different priors. Thus, in prior work researchers either induce an equal weight on different priors (Halevy 2007) or instead make functional form assumptions to separately distinguish ambiguity aversion from weights on priors (Ahn et al. 2014). As stated previously, we do not impose uniform weights on priors. Instead, we frame related decision tasks in a way that holds fixed the weights within a set of tasks. This allows us to test hypotheses while maintaining ambiguity.

3.3 Testable Hypotheses

We formulate hypotheses based on four situations: changing the payoff for a specific state; adding a new prior; modifying the distribution within some given priors, and updating the weight on a specific prior. In all cases, by exploiting differences in valuations due to information updating, the theories lead to distinct predictions. In the case of updating the weight on a specific prior, it is not clear how best to derive predictions from the α-MEU model as this setting has not been previously considered. So we consider two cases, one where α is assumed not to vary across related tasks, and a second where the value of α varies when an agent believes the best (or the worst) outcome is more likely to occur. Last, embedded in our design are pairs of mathematically equivalent tasks that vary only in terms of framing, and we consider a fifth set of hypotheses based on decision complexity. Unless otherwise indicated, in the derivations below we assume that subjects are ambiguity averse, and the value of α is held fixed when making predictions based on a related set of tasks.

3.3.1 The value of self-protection when the payoff of a state is altered

The difference in valuations for tasks 1A and 1A′ connotes the value of self-protection. That is, the tasks are identical with the exception that, if the urn contains one or more (low paying) black balls, in 1A′ any black ball will be replaced with either a red or a white ball. Tasks 1B and 1B′ parallel 1A and 1A′, with the exception that the value of the (high paying) white ball is increased from \$15 to \$30.

As suggested by equation (2) and (3), the two models differ in how people value an ambiguous event. α-MEU assumes the agent's utility function can be expressed as a weighted average of the expected utility from the worst and best prior. This specification implies that when subjects have at least three priors with a strict preference ordering, any changes to the best prior should not influence the utility gain from trimming out the worst one. The intuition here is that with the additive functional form, changing the best prior cancels out when calculating the utility gain from self-protection. On the other hand, the value of self-protection can be easily influenced by a change in the prize level under REU, since it assumes people update their subjective weights after trimming out certain beliefs. The differences across specifications gives rise to the following hypothesis. Theory derivations for this and the other hypotheses are provided in Appendix A.

Hypothesis 1: For an agent exhibiting α-MEU preferences, $V_{1A'} - V_{1A} = V_{1B'} - V_{1B}$. For an agent exhibiting REU preferences, $V_{1A'} - V_{1A} < V_{1B'} - V_{1B}$.

3.3.2 Adding a new prior

To distinguish between α-MEU and REU, Halevy (2007) studied whether a lower potential variance in expected payoff would increase subject valuations. Following the same logic, we design tasks 2A and 2B in such a way that the only difference is that 2B has an additional prior: 3 red balls. However, to maintain ambiguity, we did not place any restriction on the weight of each prior. As mentioned in Halevy (2007), one of the testable differences is the additional concave functional form proposed in the smooth specification. We assume subjects update based on the re-weightings of Bayes' rule by Hanany and Klibanoff (2009). Based on the discussion by Halevy (2007), our second hypothesis could also be derived from second-order preferences, which means subjects prefer the urn with a potential lower variance when the expected mean is the same (Halevy and Feltkamp 2005), or an issue preference, which means people might prefer one issue (risk) to the other (ambiguity) (Ergin and Gul 2009).

Hypothesis 2: For an agent exhibiting α-MEU preferences, $V_{2A} = V_{2B}$. For an agent exhibiting REU preferences, $V_{2A} < V_{2B}$.

3.3.3 Changing the distribution within priors

All multi-prior ambiguity models have two components. The first one is a prior that maps potential outcomes with a probability distribution; the second one is the weights on the priors, which reflect the relative possibility for the occurrence of each prior. This structure provides an explicit theoretical representation; however, it can become complicated when one attempts to define the set of priors in a decision setting. Suppose a person faces 1A and for simplicity, she has three priors: all black, all red, and all white. Applying α-MEU, we can express her utility as

$$V = \alpha[u(5)] + (1 - \alpha)[u(15)].$$

Now suppose she believes with certainty that the chance the urn contains all red balls or all black balls is the same. In this case there are two ways to express her utility. First, since the probabilities of the best and the worst priors are still unknown, we can express the utility as before. However, if she takes advantage of the new information and uses a compound lottery as one prior, then her utility becomes

$$V' = \alpha[u(5)] + (1 - \alpha)[u((15 + 10)/2)].$$

In our experiment, the only difference between 3A and 3B is as follows. In 3A, Urn 2 involves a two-thirds chance of drawing a white ball and a one-third chance of red ball, while Urn 3 involves a one-third chance of a white ball and two-thirds chance of red ball. For 3B, both Urn 2 and Urn 3 give an equal chance of drawing a red or white ball. Agents are told that the chance of taking a draw from Urn 2 or Urn 3 is the same, and that both occur with probability greater than zero. As a result, 3A is a convex combination between priors relative to 3B.

If an agent follows the α-MEU model and only uses a single lottery as prior, she prefers 3A since the best prior has a higher expected payoff. For a person with α-MEU preferences, who uses a compound lottery as prior, she should be indifferent between lotteries 3A and 3B. In contrast, if the decision maker follows the REU model, she prefers the one with a lower mean spread, i.e., she should derive more utility from lottery 3B. The same hypotheses hold when comparing 4A and 4B. Indeed, when we trim out the black balls in tasks 3A and 3B, and recalculate the outcome distribution in each potential prior, these are precisely the same lotteries as 4A and 4B, respectively.

Hypothesis 3: For an agent exhibiting REU preferences, (a) $V_{3A} < V_{3B}$ and (b) $V_{4A} < V_{4B}$. For an agent exhibiting α-MEU preferences, who uses a single lottery as a prior, (a) $V_{3A} > V_{3B}$ and (b) $V_{4A} > V_{4B}$. For an agent exhibiting α-MEU preferences, who uses a compound lottery as a prior, (a) $V_{3A} = V_{3B}$ and (b) $V_{4A} = V_{4B}$.

3.3.4 Changing the weight on a specific prior

We now focus on a situation where two lotteries are equivalent except for the fact that the best prior is more likely to happen in one of them. The lotteries 5A (6A) and 5B (6B) have the same best and worst priors: drawing a white ball for sure and drawing a red ball for sure. In 6A and 6B, the lotteries are the same except that, in constructing the latter, two of the red balls in Urn 2 are moved to Urn 3 in exchange for two white balls. A sophisticated bidder should notice that the best prior is more likely to occur in 6A since the only possible outcome of a draw from Urn 3 or Urn 4 would be a white ball. Hence, what we label as an agent with "sophisticated α-MEU" preferences prefers 6A to 6B. We label an agent who does not update across the two lotteries as holding "naïve α-MEU" preferences. At the same time, the REU model predicts that agents should prefer 6B to 6A since the former task has a lower variance. The same hypotheses hold when comparing 5A and 5B. Indeed, when we trim out the black balls in tasks 5A and 5B, and recalculate the outcome distribution in each potential prior, these are precisely the same lotteries as 6A and 6B, respectively.

Hypothesis 4: For an agent exhibiting naïve α-MEU preferences, (a) $V_{5A} = V_{5B}$ and (b) $V_{6A} = V_{6B}$. For an agent exhibiting sophisticated α-MEU preferences, (a) $V_{5A} > V_{5B}$ and (b) $V_{6A} > V_{6B}$. For an agent exhibiting REU preferences, (a) $V_{5A} < V_{5B}$ and (b) $V_{6A} < V_{6B}$.

3.3.5 Preferences and decision complexity

One common assumption is that preferences are stable across decision settings. However, this assumption has been challenged by behavioral economists (e.g., Smith 2010). As lotteries 3A (5A) and 3B (5B) are equivalent to 4A (6A) and 4B (6B), respectively, aside from framing, our design provides the opportunity to examine whether people have the same preferences over identical lotteries.

Hypothesis 5: Decision complexity has no effect on valuations. In particular, (a) $V_{3A} = V_{4A}$, (b) $V_{3B} = V_{4B}$, (c) $V_{5A} = V_{6A}$, and (d) $V_{5B} = V_{6B}$.

4. Results

Table 2 provides summary statistics related to the participants, and Table 3 provides statistics associated with each of the lottery task valuations. Table 4 presents hypothesis test results, and Figures 1 and 2 provide histograms of participant-level differences related to the various hypotheses, using bin widths of 25¢. As relayed from Table 2, the average participant is approximately 21 years old, 42% of our sample is female, and 40% have either a part-time or a full-time job. According to decisions in the DMPL, about 71% of our subjects may be classified as risk-averse, while 88% of our subjects may be classified as ambiguity-averse.[2] The correlation coefficient between risk and ambiguity attitudes is 0.15, which is close to the results of Dimmock et al. (2015a, 2015b).

As one indication of comprehension of experimental procedures, 83% of participants correctly identified the dominant strategy of the BDM in the context of a numerical example. As a second indication, we compare bids from task 1A to 1B, and bids from task 1A′ to 1B′. These tasks are identical except that the payoff associated with the white ball is increased from \$15 to \$30. Therefore, if any weight is placed on the best prior, valuations in the second of each pair of tasks should be higher. Valuations for task 1B and 1B′ are \$2.72 (Std. Err. = 0.36) and \$3.33 (0.41) higher than 1A and 1A′, respectively. Less than 2% of decisions correspond with higher valuations for the objectively less favorable lotteries. Last, 86% of respondents rated their understanding of instructions as either a 4 or 5 on a 5-point Likert scale, where 5 indicates "I understood very well".

[2] Unfortunately, the ambiguity MPL used in two sessions contained errors, and we are unable to characterize ambiguity in these sessions. Missing values prevents us from using this ambiguity measure as a control variable in the regression analysis.

4.1 Hypothesis tests: kinked versus smooth specifications

Panel (a) of Table 4 provides test statistics associated with the four hypotheses derived to distinguish between the kinked and smooth ambiguity models. We present both paired t-tests and nonparametric Wilcoxon signed-ranks tests. Given how the hypotheses are formulated, the smooth model predicts that differences in bids should be negative in every case. The kinked specification is supported by differences of zero, and in some cases by a positive difference. To provide some basic information on heterogeneity, Figure 1 displays histograms of the individual-level differences associated with each hypothesis test. Moreover, the last three columns of Table 4 present the percentage of respondents with negative, zero, and positive differences as they relate to the null hypotheses.

As can be gleaned from Figure 1, the most frequent outcome associated with each comparison is a difference of zero. In fact, considering all comparisons, 53% of the differences are (exactly) zero. This evidence supports the notion that the kinked specification has good predictive power. Some observations close to zero may be attributable to decision errors. If we consider deviations of +/- 50¢, this figure of *approximately* zero differences increases to 64%.

Hypothesis 1 exploits the difference in functional form between two ambiguity models. 1A and 1B are identical to 1A′ and 1B′, respectively, with the exception that latter set of tasks induces self-protection by trimming out the black balls. As stated before, here we treat the difference between the bid on 1A (1B) and 1A′ (1B′) as the value for self-protection and test whether it varies with the payoff associated with highest-value outcome (i.e. a white ball). Using paired t-tests we weakly reject (p=0.08) that the value for self-protection is the same regardless of the value of the white ball. The Wilcoxon test fails to reject equality with p = 0.26. The somewhat contrasting results can be explained by Figure 1(a). Although the frequency of positive and negative deviations is roughly the same, there are a few large and negative differences (i.e., one at -\$15 and one at -\$20), thus triggering a slight difference in the mean. It is possible that the negative and significant difference in means is partially due to decision error. If we restrict the sample to those who stated they understood the instructions well, Hypothesis 1 is no longer rejected (t = -1.52, p = 0.16).

Hypothesis 2 exploits differences that arise when a new prior is added. There are many more negative differences than positive ones, giving rise to a statistical difference in mean bids between 2A and 2B, and a difference in the median bids. The aggregate results thus support the smooth specification. At the participant level, an approximately equal number of pairwise choices can be explained by the kinked (44%) and smooth (43%) specifications.

For Hypothesis 3, our tests rely on changing the distribution within particular priors. The two pairwise comparisons reveal that the decisions of very few participants (less than 20%) can be explained by the smooth specification. At the aggregate level, there are no statistical differences when comparing 4A and 4B, but a positive and significant difference when comparing 3A and 3B. The high frequency of zero differences (59% and 62%) may support the conjecture that people use a compound lottery as a prior. Most of the multi-prior ambiguity models, including α-MEU and REU, are based on Ansombe and Aumann's (1963) joint objective-subjective approach, where utility is derived from a distribution of subjective weights over objective lotteries. Even though this structure does not force the objective lotteries to be one-stage, the existence of a compound lottery would challenge the mapping between the subjective weight and associated objective priors, as the set of priors would be unclear. Our finding also provides an example that runs counter to Segal (1988, 1990), who showed that under the assumption of time neutrality and compound independence, ambiguity aversion could be modeled as a failure of the reduction of compound lotteries. That most participants reveal indifference between 3A and 3B, and likewise between 4A and 4B, provides suggestive evidence of the successful reduction of compound lotteries.

The last hypothesis, which exploits differences due to changing the weight on a single prior, provides mixed support for either the kinked or the smooth specifications. At the participant level, the majority of outcomes adhere to the predictions of the kinked specification. However, there are a fair percentage of subjects (40%) that reveal a preference for 5B over 5A, leading to the null hypothesis to be rejected and providing aggregate support of the smooth specification. The smooth specification, however, is a poor predictor of the observed differences between 6A and 6B. With very few positive differences, this lends support of the naïve α-MEU model in contrast to the sophisticated α-MEU model.

Examining within-subject behavior, 79 of 117 participants (68%) adhere to the directional predictions of the kinked specification in at least four of the six comparisons. Just 12 participants (10%) revealed negative differences in at least four of the comparison sets. The remaining 22% of people cannot be easily classified. Of these, ten participants (9%) exhibit preferences consistent with the kinked specification in three cases and the smooth specification in three cases.

4.2 Hypothesis tests: task complexity

Panel (b) of Table 4 provides test statistics associated with four pairwise comparisons corresponding to the null hypothesis that task complexity does not matter. Figure 2 contains histograms for each comparison using participant-level data. If we assume that the kinked specification approximately characterizes behavior, then the important maintained assumption in these comparisons is that the value of α is fixed. If we instead rely on the smooth specification, we need the maintained assumption that the weights are held fixed. Overall, the results suggest a revealed preference for the relatively simple lotteries. These differences are significant in the aggregate for three of the four pairwise comparisons. The most striking difference occurs when comparing 5A to 6A, where nearly half of participants reveal a preference of 6A over 5A. Moreover, the average person with this directional preference values the simpler task 6A by $2.18, which is a 23% increase relative to 5A. One possible explanation for the results is that respondents are more ambiguity averse (e.g., α increases) in more complex environments.

4.3 Regression models

Table 5 presents linear regressions, where the dependent variable is the difference in bids as they correspond with the earlier hypothesis tests. These differences are stacked to create a panel data set; i.e., the first outcome for a subject is the difference associated with H1, the second outcome is the difference associated with H2, etc. Included as control variables are the Big-5 personality measures, gender, a measure of risk from the risk MPL, GPA, and an indicator for participants who are majoring in a STEM field. As those in a STEM field should have a higher aptitude for quantitative analysis, we hypothesize that this may explain heterogeneity in the data. Also included are controls for order effects, including whether Part I tasks were encountered first in the session, whether the #A task preceded the #B task in a comparison set in Part I, and whether the #A task preceded the #B task in a Part II comparison set. Finally, we include a full set of hypothesis indicators. All control variables are demeaned, which means that the coefficients on the hypothesis indicators are interpretable as measures of the mean differences associated with the various hypotheses. Standard errors are clustered by participant.

Model 1 and Model 2 present results based on the set of theory model comparisons (i.e., H1-H4) and complexity comparisons (H5), respectively. The coefficients on the hypothesis indicators largely confirm the earlier results from paired t-tests: mean differences are statistically different from zero, at the 5% level, for H2, H3a, H4a, H5b, and H5c. Thus, this serves as a robustness check on our earlier results. Based on Model 1, the bid difference is decreasing in risk aversion, and is lower for those in a STEM major. Based on Model 2, mean differences due to complexity are increasing with GPA. Overall, the control variables do very little to explain the variation in the data.

Table 6 presents the results from multinomial probit models. The dependent variable, similar to that of the prior regressions, is based on bid differences. Here, we create a categorical dependent variable with three categories: negative deviation, zero deviation, and positive deviation. The zero deviation category serves as the reference category. The control variables are the same as in the linear regressions.

Model 3 suggests that the probability of deviating from the zero difference prediction, in either direction, decreases with GPA and emotional stability. Deviating in the positive direction decreases with risk aversion and increases with extraversion. For Hypothesis 3 and 4, positive deviations may also be consistent with the kinked specification. As a robustness check, we estimated a binary probit model, where the dependent variable is whether the deviation is consistent with the kinked specification. The results tell a similar story: those with higher GPAs and a higher emotional stability are more likely to make decisions that adhere to the qualitative predictions of the kinked specification. Turning to Model 4, those with a higher GPA are less likely to alter valuations for mathematically identical lotteries based on task complexity. Those who are more extraverted are more likely to place a higher valuation on the less complex task, and those who are emotionally stable are less likely to bid in this manner.

5 Discussion

In this paper, we formulate new hypotheses that take advantage of information updating to distinguish between two major specifications of ambiguity models: "kinked" and "smooth". To test these hypotheses, we introduce a novel experimental design that allows one precise control over important attributes of multi-prior ambiguity models. In particular, identification is achieved by varying the number of priors, the payoffs associated with states, the distribution of particular priors, or the weight over priors. Our identification strategies do not rely on comparisons between ambiguous and risky lotteries, nor sophisticated econometric methods.

Our results show that most participants display behavior consistent with the kinked specification, and only 10% of participants provide evidence supporting smooth ambiguity models. Observed patterns in the data provide fodder for future theory development. We provide some evidence that participants may have priors in the form of a compound lottery. Most existing theoretical models only treat priors as simple lotteries. Our evidence also shows that, assuming participants follow the kinked specification, the degree of ambiguity aversion is independent of changing the value of one specific state, and is unaffected by changing the credibility (weight) of the best prior. Last, by framing mathematically equivalent, ambiguous lotteries in two different ways, we find evidence that valuations change due to complexity; in particular, participants tend to place higher values on more simply framed lotteries.

Ghirardato, Maccheroni, and Marinacci (2004) show that ambiguity attitudes depend on the relationship between states and outcomes. However, there is little discussion about how the mapping is structured and which factors influence the level of ambiguity. Our experimental evidence suggests that, consistent with the kinked theory prediction, people's ambiguity attitudes will not change when the expected value of the lottery, together with the worst and best prior, stays constant. Our results further support the notion that the ambiguity level is independent of the outcome of the states. This is not necessarily a prediction of the kinked specification, but consistent with our evidence. To the extent that the ambiguity level is approximately constant across related settings, researchers can elicit ambiguity attitudes in one setting and apply it to analyze another.

Our results generally support the notion that the relatively simple ambiguity models are more likely to predict behavior, which is consistent with some prior experimental work. The identification strategy we use to test our second hypothesis is similar to Halevy (2007), although in our case we do not place any restrictions on subjective weights. Our results are fairly similar in that, in this comparison, there is some support that subjects may have second-order beliefs. However, results from other hypothesis tests suggests that the smooth specification is not a robust predictor.

Some prior experimental evidence favors SEU theory, and so it is natural to ask whether this model predicts well the patterns in our data. For our first and second hypotheses, the SEU prediction coincides with that of the smooth specification, whereas the prediction for the third and fourth is a null effect. If we applied the same, simple rule for characterizing whether behavior is consistent with a particular theory at the individual level, we would classify 50 of 119 subjects (42%) as following SEU. The vast majority of these participants (41 of 50) can also be classified as following the kinked specification. Recalling that we can classify 68% with the kinked specification, we can conclude that – in our experiment – the kinked specification does better than both the smooth ambiguity and SEU models in predicting behavior.

There are nevertheless patterns in the data that are not easily explained by the theories we consider. One alternative explanation we explore here is motivated by observations from participant decision sheets. Decisions in our experiment were made with paper and pencil, and there is written evidence that some participants may have based valuations on the simple counting of the number of balls associated with each color. In our econometric analysis, we did uncover a negative correlation between GPA and deviations from the kinked specification prediction, which is suggestive evidence that some participants may be using simple heuristics to guide decisions. Tied to Hypothesis 3a, a simple count of the balls (noting that black balls are non-binding), yields 6 red and 3 white balls for lottery 3A, versus 5 red balls and 2 white balls for 3B. If one assumes each of these balls has an equal chance of selection, people should value 3A over 3B. This is what we find based on average valuations, and moreover 31% of individuals valued 3A over 3B. Using a similar heuristic suggests that, tied to Hypothesis 4a, people would value 5B over 5A. We again do find average valuations in this direction and 40% of individuals value 5B over 5A. We note that in other tests of Hypotheses 3 and 4, the ratio of red to white balls is exactly the same. Interestingly, the aggregate results reveal no statistical difference in mean valuations. Moreover, unlike for H3a and H4a, for H3b and H4b the number of non-zero deviations is smaller, and there are similar fractions of negative versus positive deviations. Turning to tests of decision complexity, applying the heuristic predicts that $V_{3A} = V_{4A}$, $V_{3B} < V_{4B}$, $V_{5A} < V_{6A}$, and $V_{5B} = V_{6B}$. Interestingly, these predictions match the aggregate results well, and helps to explain why we find a high number of negative deviations at the participant-level for H5b and H5d relative to H5a and H5c. Whether such simple heuristics can explain patterns in the data from related experiments remains an open question.

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Table 1. Description of lottery tasks

Set	Task	Payoffs ($B/$R/$W)	Description
1	1A	5/10/15	One urn, containing three balls. The possible ball colors are black, red and white.
1	1A′	trimmed/10/15	Same as 1A, except that IF this urn contains one or more black balls, these balls are replaced with red or white balls before a ball is drawn.
1	1B	5/10/30	Same as 1A, except payoff of white ball increased to 30.
1	1B′	trimmed/10/30	Same as 1A′, except payoff of white ball increased to 30.
2	2A	5/–/15	One urn, containing three balls. Either all are black or all are white.
2	2B	5/10/15	Same as 2A, except that it is now also possible that all balls are red.
3	3A	trimmed/10/15	Four urns, each containing three balls. The possible ball colors are black, red and white. Urn 1: all are black. Urn 2: all are red. Urn 3: two red and one white. Urn 4: one red and two white. An urn is selected by drawing a card from a stack of 12 cards, numbered 1 to 4. All that is known is that there is an equal chance of selecting Urn 3 or Urn 4. IF a black ball is selected from the urn, the urn selection procedure is repeated until a red or white ball is drawn.
3	3B	trimmed/10/15	Same as 3A, except that Urn 3 and Urn 4 now contain one ball of each color.
4	4A	–/10/15	Three urns, each containing six balls. The possible ball colors are red and white. Urn 1: all are red. Urn 2: four white and two red. Urn 3: four red and two white. An urn is selected by drawing a card from a stack of 12 cards, numbered 1 to 3. All that is known is that there is an equal chance of selecting Urn 2 or Urn 3.
4	4B	–/10/15	Same as 4A, except Urn 2 and Urn 3 now each contain three red and three white balls.
5	5A	trimmed/10/15	Five urns, each containing three balls. The possible ball colors are black, red and white. Urn 1: all are black. Urn 2: all are red. Urn 3: two red and one white. Urn 4: two black and one white. Urn 5: all are white. An urn is selected by drawing a card from a stack of 12 cards, numbered 1 to 5. All that is known is that there is an equal chance of selecting Urn 3 or Urn 4. IF a black ball is selected from the urn, the urn selection procedure is repeated until a red or white ball is drawn.
5	5B	trimmed/10/15	Same as 5A, except that Urn 3 and Urn 4 now each contain one red and two white balls.
6	6A	–/10/15	Four earns, each containing six balls. The possible ball colors are black, red and white. Urn 1: all are red. Urn 2: four white and two red. Urn 3: all are white. Urn 4: all are white. An urn is selected by drawing a card from a stack of 12 cards, numbered 1 to 4. All that is known is that there is an equal chance of selecting Urn 2 or Urn 3.
6	6B	–/10/15	Same as 6A, except that Urn 2 and Urn 3 now each contain two red and four white balls.

Table 2. Variables and descriptive statistics

Variable name	Description	Mean	Std. Dev.
Female	=1 if identified gender is female	0.42	0.49
Employed	=1 if participant has a part time or full time job	0.40	0.49
Age	age, in years	20.71	1.74
GPA	cumulative GPA; midpoint of selected range	3.37	0.43
STEM	=1 if majoring in a STEM field	0.42	0.49
Extraversion	measure of personality trait “extraversion”, 1 to 7	4.54	1.51
Agreeableness	measure of personality trait “agreeableness”, 1 to 7	4.75	1.27
Conscientiousness	measure of personality trait “conscientiousness”, 1 to 7	5.49	0.96
Emotional Stability	measure of personality trait “emotional stability”, 1 to 7	4.90	1.35
Openness	measure of personality trait “openness to experience”, 1 to 7	5.31	1.17
Risk	number of Lottery A (safe) choices selected in risk MPL	6.26	1.50
Risk Averse	=1 if number of Lottery A (safe) choices >5 in risk MPL	0.71	0.45
Ambiguity Averse	=1 if number of Urn A choices >5 in ambiguity MPL	0.89	0.31
Comprehension	stated understanding of the experiment; Likert-scale with 1 “very poorly” and 5 “very well”	4.33	0.75
Compensation	stated satisfaction about experiment compensation; Likert-scale with 1 “very poorly” and 5 “very well”	4.46	0.70
Earnings	earnings from experiment session, in $	21.91	4.58

Table 3. Lottery valuations, by task (in $)

Task	Mean	Std. Dev.	Min	Max
1A	7.70	2.79	4.00	15.00
1A′	10.65	2.01	5.00	15.00
1B	10.41	5.76	4.99	30.00
1B′	13.98	5.44	5.00	30.00
2A	7.52	3.33	1.37	20.00
2B	8.30	3.29	2.25	25.00
3A	10.26	2.09	4.19	19.99
3B	9.91	1.86	4.00	15.00
4A	10.47	1.90	2.21	15.00
4B	10.34	2.01	3.75	15.00
5A	10.30	2.32	2.00	15.00
5B	11.05	2.33	3.00	15.00
6A	11.26	2.15	5.25	15.00
6B	11.09	2.38	4.25	15.00

Table 4. Hypothesis test results, based on lottery valuations

Null hypothesis	Paired *t*-test	Wilcoxon signed-rank test	Negative difference	Zero difference	Positive difference
(a) Tests of kinked versus smooth specifications					
H1: $V_{1A'} - V_{1A} = V_{1B'} - V_{1B}$	-1.79 (0.08)	-1.12 (0.26)	32%	42%	26%
H2: $V_{2A} = V_{2B}$	-3.63 (<0.01)	-4.12 (<0.01)	43%	44%	14%
H3a: $V_{3A} = V_{3B}$	2.08 (0.04)	3.30 (0.01)	10%	59%	31%
H3b: $V_{4A} = V_{4B}$	1.24 (0.21)	0.95 (0.34)	17%	62%	21%
H4a: $V_{5A} = V_{5B}$	-3.91 (<0.01)	-4.29 (<0.01)	40%	48%	12%
H4b: $V_{6A} = V_{6B}$	1.74 (0.09)	1.34 (0.18)	15%	63%	21%
(b) Tests of task complexity					
H5a: $V_{3A} = V_{4A}$	-1.40 (0.16)	-1.77 (0.08)	26%	57%	16%
H5b: $V_{3B} = V_{4B}$	-2.64 (<0.01)	-2.42 (0.02)	34%	48%	18%
H5c: $V_{5A} = V_{6A}$	-5.79 (<0.01)	-5.98 (<0.01)	49%	44%	8%
H5d: $V_{5B} = V_{6B}$	-0.25 (0.80)	0.16 (0.87)	21%	56%	23%

Notes: *p*-values in parentheses. The last three columns indicate the percentage of participants with negative, zero, or positive differences when evaluating the null hypothesis; e.g., for H2, 43% of respondents placed higher bids for lottery 2B, and 14% of participants placed bids higher bids for 2A.

Table 5. Linear regression models, bid differences

Variable	Model 1: Theory Specification	Model 2: Task Complexity
Female	0.102 (0.195)	-0.141 (0.226)
Risk	-0.128** (0.052)	-0.032 (0.054)
GPA	-0.141 (0.217)	0.933** (0.330)
STEM	-0.455** (0.208)	-0.007 (0.207)
Extraversion	0.054 (0.065)	0.047 (0.062)
Agreeableness	-0.082 (0.079)	0.022 (0.079)
Conscientiousness	-0.010 (0.099)	0.007 (0.096)
Emotional Stability	-0.020 (0.057)	-0.129 (0.089)
Openness	0.083 (0.074)	0.028 (0.110)
H1	-0.586 (0.356)	
H2	-0.797** (0.223)	
H3a	0.382** (0.176)	
H3b	0.088 (0.107)	
H4a	-0.746** (0.202)	
H4b	0.165 (0.108)	
H5a		-0.135 (0.150)
H5b		-0.428** (0.162)
H5c		-0.954** (0.162)
H5d		-0.043 (0.173)
Controls for task order?	Yes	Yes
R^2	0.079	0.166
F-stat	3.83**	3.66**
Number of observations	666	444

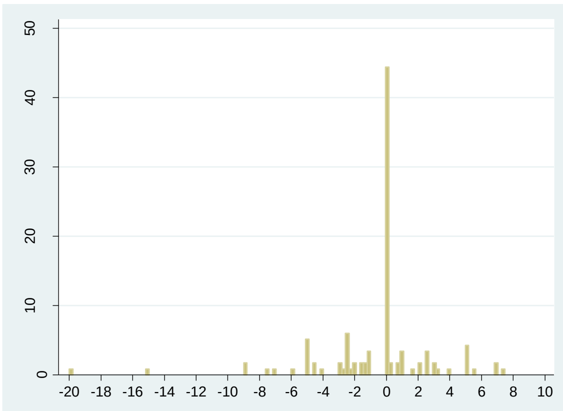
Notes: cluster-robust standard errors in parentheses. * and * indicate estimate is statistically significant at the 10% and 5% significance levels, respectively.

Table 6. Multinomial probit models, bid difference categories

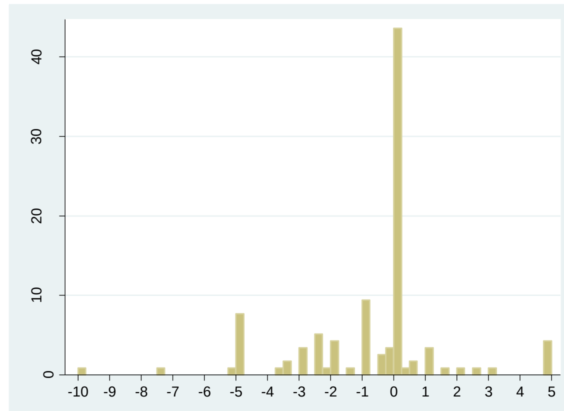
Variable	Model 3: Theory Specification		Model 4: Task Complexity	
	Negative difference	Positive difference	Negative difference	Positive difference
Female	-0.030	0.069	-0.251	-0.305
	(0.236)	(0.253)	(0.302)	(0.320)
Risk	-0.109	-0.220**	-0.137	-0.144
	(0.069)	(0.077)	(0.089)	(0.101)
GPA	-0.644**	-0.961**	-0.132**	-0.937**
	(0.289)	(0.305)	(0.352)	(0.367)
STEM	0.263	0.058	-0.113	0.236
	(0.218)	(0.218)	(0.262)	(0.274)
Extraversion	0.077	0.159**	0.056	0.202**
	(0.068)	(0.077)	(0.098)	(0.091)
Agreeableness	-0.058	-0.113	-0.123	-0.181
	(0.092)	(0.090)	(0.104)	(0.115)
Conscientiousness	0.033	-0.026	0.008	0.104
	(0.130)	(0.122)	(0.156)	(0.164)
Emotional Stability	-0.204**	-0.219**	-0.053	-0.244**
	(0.085)	(0.086)	(0.113)	(0.102)
Openness	-0.015	0.011	0.170	0.162
	(0.099)	(0.098)	(0.118)	(0.116)
Hypothesis indicators?	Yes		Yes	
Controls for task order?	Yes		Yes	
Log-likelihood	-604.276		-383.463	
Wald-stat	130.65**		112.17**	
Number of observations	666		444	

Notes: cluster-robust standard errors in parentheses. * and * indicate estimate is statistically significant at the 10% and 5% significance levels, respectively. Reference category is Zero difference.

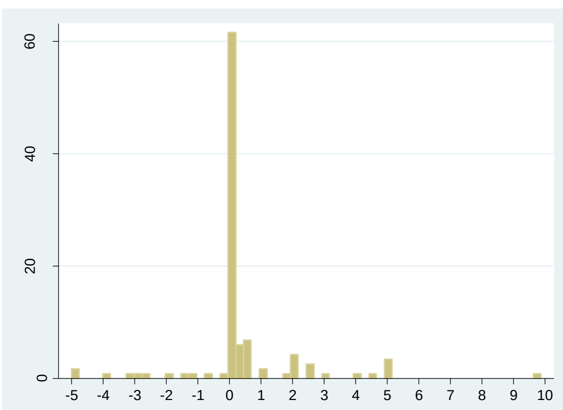
Figure 1. Individual-level results, kinked versus smooth specifications (Hypotheses 1 to 4)



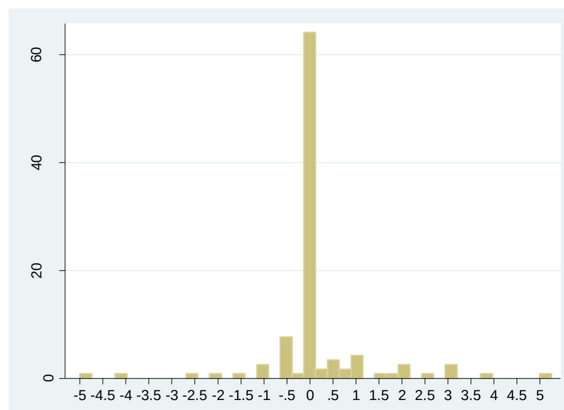
(a) H1, $V_{1A'} - V_{1A} - (V_{1B'} - V_{1B})$



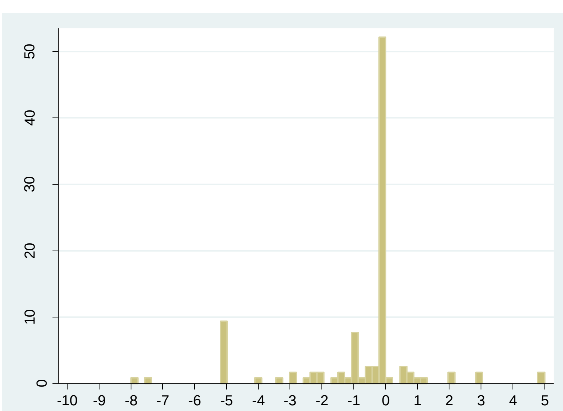
(b) H2, $V_{2A} - V_{2B}$



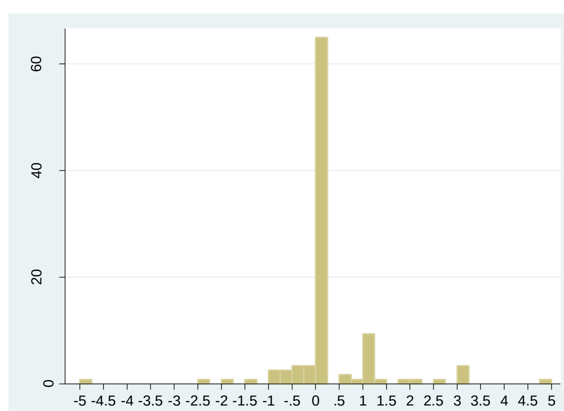
(c) H3a, $V_{3A} - V_{3B}$



(d) H3b, $V_{4A} - V_{4B}$

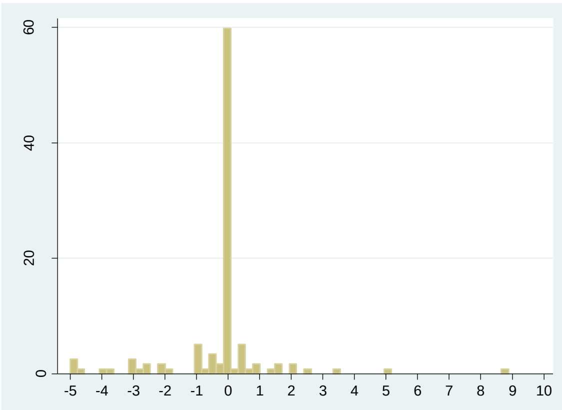


(e) H4a, $V_{5A} - V_{5B}$

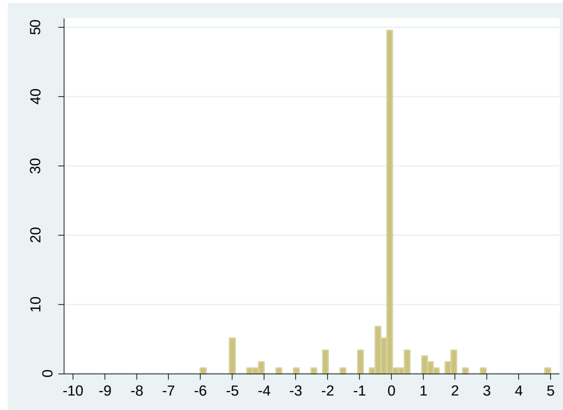


(f) H4b, $V_{6A} - V_{6B}$

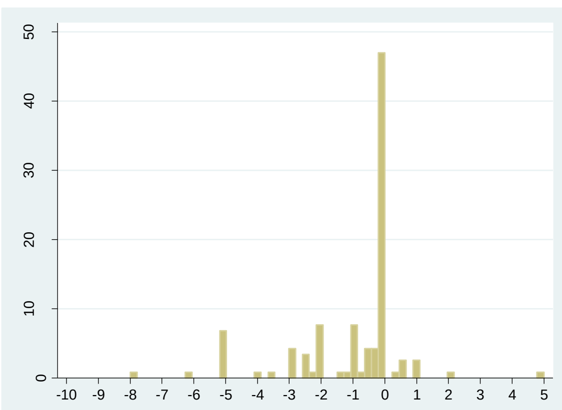
Figure 2. Individual-level results, task complexity (Hypothesis 5)



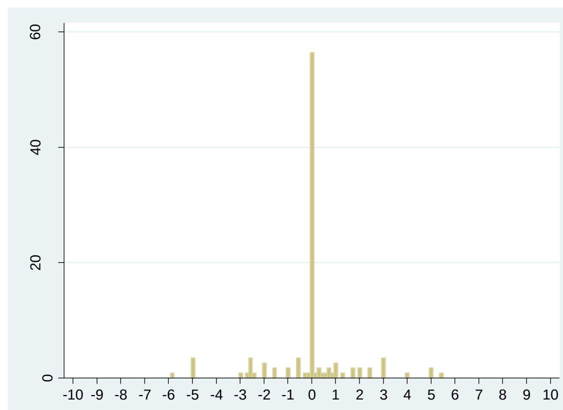
(a) H5a, $V_{3A} - V_{4A}$



(b) H5b, $V_{3B} - V_{4B}$



(c) H5c, $V_{5A} - V_{6A}$



(d) H5d, $V_{5\mathrm{B}} - V_{6B}$

Appendix A. Theory Derivations

Support for Hypothesis 1:

We first start with the α-MEU model. For task 1A, a player's utility can be described as

$$V_{1A} = \alpha u(5) + (1-\alpha)u(15),$$

as the best (worst) prior is drawing a white (black) ball for sure. After trimming out the black ball, utility is:

$$V_{1A}{}' = \alpha u(10) + (1-\alpha)u(15),$$

as the worst prior becomes getting a red ball for sure. The value of self-protection in this case is:

$$V_{1A}^{P} = V_{1A'} - V_{1A} = \alpha[u(10) - u(5)],$$

which is independent of the utility of the best prior. The value of self-protection based on tasks 1B and 1B$'$ is:

$$V_{1B}^{P} = V_{1B'} - V_{1B} = V_{1A}^{P} = \alpha[u(10) - u(5)].$$

Thus, changing the payoff from the white ball has no effect on the value of self-protection.

On the other hand, using the re-weighting Bayesian rule, the value for lottery 1A and 1A$'$ are, respectively,

$$V_{1A,REU} = w_1\varphi[u(5)] + w_2\varphi[u(10)] + w_3\varphi[u(15)] \text{ and}$$

$$V_{1A\prime,REU} = \frac{w_2}{1-w_1}\varphi[u(10)] + \frac{w_3}{1-w_1}\varphi[u(15)].$$

The value of self-protection is then

$$V_{1A,REU}^{P} = V_{1A,REU} - V_{1A',REU} = \frac{w_2 w_1}{1-w_1}\varphi[u(10)] + \frac{w_3 w_1}{1-w_1}\varphi[u(15)] - w_1\varphi[u(5)].$$

The value of self-protection based on comparing 1B and 1B$'$ is

$$V_{1B,REU}^{P} = \frac{w_2 w_1}{1-w_1}\varphi[u(10)] + \frac{w_3 w_1}{1-w_1}\varphi[u(30)] - w_1\varphi[u(5)],$$

and the difference in the values of self-protection is positive, i.e.,

$$V_{1B,REU}^{P} - V_{1A,REU}^{P} = \frac{w_3 w_1}{1-w_1}\{\varphi[u(30)] - \varphi[u(15)]\} > 0,$$

given both φ and u are monotonically increasing. This result implies that regardless the ambiguity averse level, for a subject with REU, the value self-protection is higher when the value of highest prize increases.

Support for Hypothesis 2:

Since the best and worst priors have not changed, the α-MEU model predicts the same valuations for both lotteries, assuming α is held fixed. For REU, an agent's utility for lottery 2A is

$$V_{2A} = w_1\varphi[u(5)] + w_3\varphi[u(15)],$$

where w_1 is the weight on the prior of all black balls and w_3 is the weight on the prior of all white balls. With Bayesian updating on the weights, when adding a third prior, w_2 (all red balls), we have

$$V_{2B} = w_1(1-w_2)\varphi[u(5)] + w_2\varphi[u(10)] + w_3(1-w_2)\varphi[u(15)].$$

Given the concavity of $\varphi(.)$, it follows that

$$2\varphi[u(10)] > \varphi[u(5)] + \varphi[u(15)].$$

If $w_1 = w_3, w_1 + w_3 = 1$ then we have

$$V_{2A} - V_{2B} = w_2\{(w_1\varphi[u(5)] + w_3\varphi[u(15)]) - \varphi[u(10)]\} < 0.$$

If $w_1 > w_3$, it follows that

$$V_{2A} - V_{2B} = w_2\{(w_1\varphi[u(5)] + w_3\varphi[u(15)]) - \varphi[u(10)]\}$$

$$< w_2\{(0.5\varphi[u(5)] + 0.5\varphi[u(15)]) - \varphi[u(10)]\} < 0$$

We do not consider the case where $w_1 < w_3$, as putting a higher weight on the best prior potentially contradicts the assumption that agents are ambiguity averse.

Support for Hypothesis 3:

For α-MEU with a compound lottery as a prior, we have

$$V_{3A}^{r} = \alpha u(10) + (1-\alpha)\left[0.5\left(\frac{2}{3}u(10) + \frac{1}{3}u(15)\right) + 0.5\left(\frac{1}{3}u(10) + \frac{2}{3}u(15)\right)\right], \text{ and}$$

$$V_{3B}^{r} = \alpha u(10) + (1-\alpha)\left[\frac{1}{2}u(10) + \frac{1}{2}u(15)\right].$$

It follows that $V_{3A}^{r} = V_{3B}^{r}$. For α-MEU with a single lottery as a prior, we have

$$V_{3A}^{u} = \alpha u(10) + (1-\alpha)\left[\frac{1}{3}u(10) + \frac{2}{3}u(15)\right],$$

$$V_{3B}^{u} = \alpha u(10) + (1-\alpha)\left[\frac{1}{2}u(10) + \frac{1}{2}u(15)\right], \text{ and}$$

$$V_{3A}^{r} > V_{3B}^{r}.$$

Under REU we have:

$$V_{3A} = w_1\varphi[u(10)] + w_2\varphi[\frac{2}{3}u(10) + \frac{1}{3}u(15)] + w_3\varphi[\frac{1}{3}u(10) + \frac{2}{3}u(15)], \text{ and}$$

$$V_{3B} = w_1\varphi[u(10)] + 2w_3\varphi\left[\frac{1}{2}u(10) + \frac{1}{2}u(15)\right].$$

It follows that $V_{3A} < V_{3B}$ as $w_2 = w_3$ and $\varphi(.)$ is a concave function.

Support for Hypothesis 4:

For sophisticated α-MEU it follows that

$$V_{5\mathrm{A}}^{s} = \alpha' u(10) + (1-\alpha')u(15), \text{ and}$$

$$V_{5\mathrm{B}}^{s} = \alpha u(10) + (1-\alpha)u(15).$$

As a "sophisticated" bidder will have $\alpha' < \alpha$, since the prior with only white balls is more likely to happen for task 5A, it follows that $V_{5\mathrm{A}}^{s} > V_{5\mathrm{B}}^{s}$.

For naïve α-MEU preferences we have

$$V_{5\mathrm{A}}^{n} = V_{5\mathrm{B}}^{n} = \alpha u(10) + (1-\alpha)u(15).$$

For the REU model,

$$V_{5\mathrm{A}} = w_1\varphi[u(10)] + w_2\varphi[\tfrac{2}{3}u(10) + \tfrac{1}{3}u(15)] + (w_3 + w_4)\varphi[u(15)], \text{ and}$$

$$V_{5\mathrm{B}} = w_1\varphi[u(10)] + 2w_2\varphi\left[\frac{1}{3}u(10) + \frac{2}{3}u(15)\right] + w_4\varphi[u(15)].$$

It follows that $V_{5\mathrm{A}} < V_{5\mathrm{B}}$ since $w_2 = w_3$ and $\varphi(.)$ is a concave function.

Appendix B. Experiment Instructions

(Note: Instructions are unaltered, with the exception of changing the task labels to reflect those used in the manuscript)

Thank you for participating in today's study. If you have a question at any time, please raise your hand. We ask that you do not communicate with other study participants, unless instructed to do so. Your decisions will not be associated with your name or other identifying information. Your name will not be linked in any way to the results of the study.

The session is divided into three experiments. You will have the opportunity to earn money in each experiment based on your decisions. You will also receive $10 for completing all three experiments, along with a post-experiment questionnaire. You will be paid your earnings privately, and in cash, at the end of the experiment session. **We will proceed through the written materials together. Please do not make any decisions until instructed.**

Instructions for Experiment 1

Please refer to the Decision Sheet for Experiment 1 as we read the instructions.

We would like you to make a decision for each of 10 scenarios. Each scenario involves a choice between receiving $2 for sure (Option A) or playing a lottery that pays $3.85 or $0.10 with the stated chances (Option B).

You will notice that the only differences across scenarios are the chances of receiving the high or low prize for the lottery.

At the end of the session, ONE of the 10 scenarios will be selected at random and you will be paid according to your decision for this selected scenario ONLY. Each scenario has an equal chance of being selected.

Please consider your choice for each scenario carefully. Since you do not know which scenario will be played out, it is in your best interest to treat each scenario as if it will be the one used to determine your earnings.

Before making decisions, are there any questions?

Decision Sheet for Experiment 1

This is your Decision Sheet. Please indicate which option you prefer by circling the letter in the "choice" column.

No.	Option A	Option B	Choice
1	receive $2 for sure	10% chance of $3.85 90% chance of $0.10	A B
2	receive $2 for sure	20% chance of $3.85 80% chance of $0.10	A B
3	receive $2 for sure	30% chance of $3.85 70% chance of $0.10	A B
4	receive $2 for sure	40% chance of $3.85 60% chance of $0.10	A B
5	receive $2 for sure	50% chance of $3.85 50% chance of $0.10	A B
6	receive $2 for sure	60% chance of $3.85 40% chance of $0.10	A B
7	receive $2 for sure	70% chance of $3.85 30% chance of $0.10	A B
8	receive $2 for sure	80% chance of $3.85 20% chance of $0.10	A B
9	receive $2 for sure	90% chance of $3.85 10% chance of $0.10	A B
10	receive $2 for sure	100% chance of $3.85 0% chance of $0.10	A B

At the end of the session, after a scenario is played out, please fill-in the information below:

The selected scenario: _______.

The option you selected for this scenario: _______.

Your earnings from the selected scenario: _________.

Please also record your earnings on the record sheet

Instructions for Experiment 2

Please refer to the Decision Sheet for Experiment 2 as we read the instructions.

The Decision Sheet contains 20 separate Decisions numbering 1 through 20. Each of these Decisions is a choice between drawing a ball from "Urn A" or "Urn B". You will select a color, White or Black, and this will be your **Success Color**. Your earnings will be determined by whether the ball drawn from the Urn matches your Success Color.

In each of the 20 decisions, Urn A has 50 White balls and 50 Black balls, and pays 4 dollars if the ball drawn from Urn A matches your Success Color, and 0 if it does not match. Since each color has a 50% chance of being drawn, this means that drawing from Urn A pays 2 dollars with a chance of 50%, and pays 0 with a chance of 50%.

Urn B, on the other hand, has an unknown number of white and Black balls (with a total of 100 balls). It pays a positive amount if the ball drawn from Urn B matches your Success Color, and 0 if it does not match. Since the chance of each color being drawn is unknown, the chance of Urn B paying a positive amount is unknown as well.

You will notice that the only differences across scenarios is the amount paid when a ball matching your Success Color is drawn from Urn B.

At the end of the session, ONE of the 20 scenarios will be selected at random and you will be paid according to your decision for this selected scenario ONLY. Each scenario has an equal chance of being selected.

Please consider your choice for each scenario carefully. Since you do not know which scenario will be played out, it is in your best interest to treat each scenario as if it will be the one used to determine your earnings.

Before making decisions, are there any questions?

Decision Sheet for Experiment 2

My Success Color is (please circle one): **White** **Black**

.

	Urn A	Urn B	
No.	50 White balls, 50 Black balls	? White balls, ? Black balls	Choice
1	$4 if Success Color, 0 if not	$3.28 if Success Color,0 if not	A B
2	$4 if Success Color, 0 if not	$3.44 if Success Color,0 if not	A B
3	$4 if Success Color, 0 if not	$3.60 if Success Color,0 if not	A B
4	$4 if Success Color, 0 if not	$3.76 if Success Color,0 if not	A B
5	$4 if Success Color, 0 if not	$3.92 if Success Color,0 if not	A B
6	$4 if Success Color, 0 if not	$4.08 if Success Color,0 if not	A B
7	$4 if Success Color, 0 if not	$4.24 if Success Color,0 if not	A B
8	$4 if Success Color, 0 if not	$4.40 if Success Color,0 if not	A B
9	$4 if Success Color, 0 if not	$4.56 if Success Color,0 if not	A B
10	$4 if Success Color, 0 if not	$4.72 if Success Color,0 if not	A B
11	$4 if Success Color, 0 if not	$4.88 if Success Color,0 if not	A B
12	$4 if Success Color, 0 if not	$5.04 if Success Color,0 if not	A B
13	$4 if Success Color, 0 if not	$5.20 if Success Color,0 if not	A B
14	$4 if Success Color, 0 if not	$5.36 if Success Color,0 if not	A B
15	$4 if Success Color, 0 if not	$5.52 if Success Color,0 if not	A B
16	$4 if Success Color, 0 if not	$5.68 if Success Color,0 if not	A B
17	$4 if Success Color, 0 if not	$5.84 if Success Color,0 if not	A B
18	$4 if Success Color, 0 if not	$6.00 if Success Color,0 if not	A B
19	$4 if Success Color, 0 if not	$6.16 if Success Color,0 if not	A B
20	$4 if Success Color, 0 if not	$6.32 if Success Color,0 if not	A B

At the end of the session, after a scenario is played out, please fill-in the information below:

The selected scenario: _______.

The urn you selected for this scenario: _______.

Your earnings from the selected scenario: _________.

Please also record your earnings on the record sheet

Instructions for Experiment 3

This experiment involves many decision "rounds". In each, the moderator will offer an item for sale. Your task will be to place a bid to buy the item for sale. As the purchase procedure will be new to you, we will first go through training rounds.

We will use the following purchase procedure in all rounds:

1. You will place a bid on the item. You will not know the price prior to bidding.
2. The price of the item will be randomly drawn. A volunteer will be asked to roll dice to determine this price. The random price will be the same for all participants.
3. **If your bid is equal to or higher than the random price, you buy the item and pay the random price (<u>not</u> your bid!). If your bid is lower than the random price, you do not buy the item.**

Here are some possible scenarios based on the purchase procedure:

— You bid \$2. The random price is drawn to be \$1.50. Since your bid is equal to or higher than the random price, you buy the item at a price of \$1.50.

— You bid \$5. The random price is drawn to be \$5. Since your bid is equal to or higher than the random price, you buy the item at a price of \$5.

— You bid \$3. The random price is drawn to be \$3.50. Since your bid is lower than the random price, you do not buy the item.

It is important to point out some aspects of the procedure. First, different from auctions, you are <u>not</u> bidding against other players. The bids of other players do <u>not</u> impact whether you buy an item. If, for example, everyone bids an amount higher than the random price, each person will pay the random price and each person will receive the item. Second, different from some auctions, if you buy something, the price is <u>not</u> equal to your bid. Instead, you pay the randomly selected price.

Third, your bid sets the highest price for which you agree to buy the good. For example, if you bid \$6.25, this means that you agree to buy the item as long as the price is something less than or equal to \$6.25. Your bid of \$6.25 guarantees that you do <u>not</u> buy the item at prices above \$6.25.

Before bidding you should ask yourself "what is the highest price I am willing to pay for the item?" It is in your best interest to place a bid equal to this highest price.

“What If” Scenarios

To help you understand the procedures, we ask that you consider a number of “what if” scenarios. Here is the good news: you will be paid 25 cents for each scenario you answer correctly. There is a bonus question, and you will be paid 50 cents for a correct answer to this.

The item for sale in these scenarios is a $5 bill. Remember: If your bid is equal to or higher than the random price, you buy the item and pay the random price (not your bid!). If your bid is lower than the random price, you do not buy.

1. Suppose you **bid $2.50**. Then, a volunteer draws a **random price** of **$4.00**.
   Based on the procedure we described would you purchase the $5 bill? Yes No
   If you answered “Yes”, what price would you pay? $ ______________

2. Suppose you **bid $3.12**. Then, a volunteer draws a **random price** of **$6.37**.
   Based on the procedure we described would you purchase the $5 bill? Yes No
   If you answered “Yes”, what price would you pay? $ ______________

3. Suppose you **bid $5.00**. Then, a volunteer draws a **random price** of **$4.25**.
   Based on the procedure we described would you purchase the $5 bill? Yes No
   If you answered “Yes”, what price would you pay? $ ______________

4. Suppose you **bid $5.00**. Then, a volunteer draws a **random price** of **$6.56**.
   Based on the procedure we described would you purchase the $5 bill? Yes No
   If you answered “Yes”, what price would you pay? $ ______________

5. Suppose you **bid $7.16**. Then, a volunteer draws a **random price** of **$4.12**.
   Based on the procedure we described would you purchase the $5 bill? Yes No
   If you answered “Yes”, what price would you pay? $ ______________

6. Suppose you **bid $8.00**. Then, a volunteer draws a **random price** of **$6.50**.
   Based on the procedure we described would you purchase the $5 bill? Yes No
   If you answered “Yes”, what price would you pay? $ ______________

Bonus question. Given the purchase procedure, how much should you bid for the $5 bill? Keep in mind that it is in your best interest to place a bid equal to the highest price you are willing to pay.

You should bid: $ __________ . __________

Please raise your hand when you are ready to have your calculations checked.

Training Round 1

In this training round you will have the opportunity to earn money.

Your task in this round is to place a bid to buy a ticket to draw ONE ball from an urn containing three balls. If you successfully buy a ticket, you will receive an amount of money based on the color of the ONE ball drawn. All three balls are black. Drawing a black ball pays $2.

After everyone has placed a bid, a volunteer will roll dice to determine the random price. Although you will not know the price range before you bid, know that three dice will be rolled. The first will determine the dollars and the other two will determine the cents.

If your bid is equal to or higher than the random price, you will receive the amount of money for the ball drawn and pay the random price. If you make a purchase at a price that is higher than the value of the ball drawn you will in fact have negative earnings (lose money).

If your bid is less than the random price, you will not buy a ticket. You will not pay the random price. You will earn $0.

For training purposes, we will play out the procedures several times. However, you will only bid once. **You will not be able to change your bid after the random prices are determined**.

Your bid (in dollars and cents): $ _________ . _________

Trial 1

Random price: $_________ . _________

Is your bid equal to or higher than the random price? (check the box below)

☐ **Yes**. You bought a ticket.

Your earnings are equal to: $___________ – _____________ = $ _________ . _________

(value of ball) (random price)

☐ **No**. You did not buy a ticket. Your earnings for this trial are $0.

Record your earnings on your Record Sheet.

Training Round 1—Continued

Trial 2
Random price: $_________ . _________

Is your bid equal to or higher than the random price? (check the box below)
☐ **Yes**. You bought a ticket.
Your earnings are equal to: $___________ – _____________ = $ _________ . _________
(value of ball) (random price)

☐ **No**. You did not buy a ticket. Your earnings for this trial are $0.
Record your earnings on your Record Sheet.

Trial 3
Random price: $_________ . _________

Is your bid equal to or higher than the random price? (check the box below)
☐ **Yes**. You bought a ticket.
Your earnings are equal to: $___________ – _____________ = $ _________ . _________
(value of ball) (random price)

☐ **No**. You did not buy a ticket. Your earnings for this trial are $0.
Record your earnings on your Record Sheet.

Trial 4
Random price: $_________ . _________

Is your bid equal to or higher than the random price? (check the box below)
☐ **Yes**. You bought a ticket.
Your earnings are equal to: $___________ – _____________ = $ _________ . _________
(value of ball) (random price)

☐ **No**. You did not buy a ticket. Your earnings for this trial are $0.
Record your earnings on your Record Sheet.

Training Round 2

In this training round you will have the opportunity to earn money.

Your task in this round is to place a bid to buy a ticket to draw ONE ball from an urn containing three balls: one black ball, one red ball and one white ball. If you successfully buy a ticket, you will receive an amount of money based on the color of the ONE ball drawn. The black ball pays 2 dollars, the red ball pays 3 dollars and the white ball pays 4 dollars if drawn.

After everyone has indicated their bid, a volunteer will roll dice to determine the random price. Although you will not know the price range before you bid, know that three dice will be rolled. The first will determine the dollars and the other two will determine the cents.

If your bid is equal to or higher than the random price, you will receive the amount of money for the ball drawn and pay the random price. If you make a purchase at a price that is higher than the value of the ball drawn you will in fact have negative earnings (lose money).

If your bid is less than the random price, you will not buy a ticket. You will not pay the random price. You will earn $0.

We will play out the procedures several times. However, you will only bid once. **You will not be able to change your bid after the random prices are determined**.

Your bid (in dollars and cents): $ _________ . _________

Trial 1

Random price: $_________ . _________

Is your bid equal to or higher than the random price? (check the box below)

☐ **Yes**. You bought a ticket.

Your earnings are equal to: $___________ – _____________ = $ _________ . _________
(value of ball) (random price)

☐ **No**. You did not buy a ticket. Your earnings for this trial are $0.

Record your earnings on your Record Sheet.

Training Round 2—Continued

Trial 2
Random price: $_________ . _________

Is your bid equal to or higher than the random price? (check the box below)

☐ **Yes**. You bought a ticket.
Your earnings are equal to: $___________ – _____________ = $ _________ . _________
(value of ball) (random price)

☐ **No**. You did not buy a ticket. Your earnings for this trial are $0.
Record your earnings on your Record Sheet.

Trial 3
Random price: $_________ . _________

Is your bid equal to or higher than the random price? (check the box below)

☐ **Yes**. You bought a ticket.
Your earnings are equal to: $___________ – _____________ = $ _________ . _________
(value of ball) (random price)

☐ **No**. You did not buy a ticket. Your earnings for this trial are $0.
Record your earnings on your Record Sheet.

Trial 4
Random price: $_________ . _________

Is your bid equal to or higher than the random price? (check the box below)

☐ **Yes**. You bought a ticket.
Your earnings are equal to: $___________ – _____________ = $ _________ . _________
(value of ball) (random price)

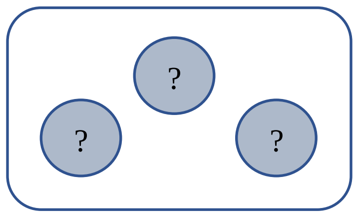
☐ **No**. You did not buy a ticket. Your earnings for this trial are $0.
Record your earnings on your Record Sheet.

Experiment 3 Decision Rounds – Part A

The decision rounds in Experiment 3 are divided into two parts – Part A and Part B. There are six decision rounds in this part.

Your task in each round is to place a bid to buy a ticket to draw ONE ball from an urn. You will be told the possible colors of the balls in the urn, and the payoffs for each color.

In this part, may not know exactly how many balls of a particular color there are. As an example, you might know there are three balls in the urn, and that the possible ball colors are black, red and white. This could mean that all three balls are the same color, or that there are two of one color and one of a second color, or one of each color. Any combination is possible.



The purchase procedure is the same as before. Your bid will be compared to a random price. You will purchase the ticket only if your bid is equal to or higher than the random price. The random price will be a randomly drawn number between $0.00 and a maximum price. The maximum price will an amount equal to or lower than the payoff associated with the highest-valued ball in the urn. For example, if the highest-valued ball is $15, the maximum possible price may be as high as $15. Any price within this range is equally likely to be chosen.

As before, <u>it is in your best interest to place a bid equal to the highest price you are willing to pay for the ticket</u>. By doing so, you will only purchase the ticket at prices you are willing to pay. You will not purchase the ticket at prices you are not willing to pay.

If you instead bid lower than the highest price you are willing to pay, you risk not purchasing the ticket at prices favorable to you. If you instead bid more than the highest price you are willing to pay, you risk purchasing the ticket at prices that are not favorable to you.

Only one decision round, which may be from Part A or Part B, will be implemented for real. After all decision rounds are completed, we will have a volunteer roll dice to determine which round this is. Since you will not know which round will be selected prior to making any decisions, <u>it is in your best interest to take each decision seriously as if it will determine an actual purchase</u>.

After this paid round is selected, a volunteer will roll dice to determine the random price. Another volunteer will draw a ball. Before we proceed to the decision rounds, are there any questions?

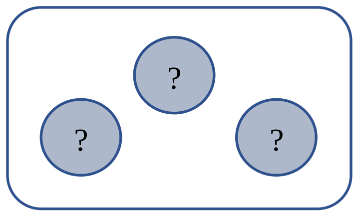
In the next FOUR rounds, the <u>same</u> urn will be used. The urn contains three balls of unknown colors.

Please, proceed to the next decision round.

Please read the description carefully. It will be in your best interest to place a bid equal to the highest price you are willing to pay. If you buy a ticket, you will receive the payoff associated with the color of the ONE ball drawn from the urn, and pay the random price.

Description:

There is one urn containing three balls. The possible ball colors are black, red and white.



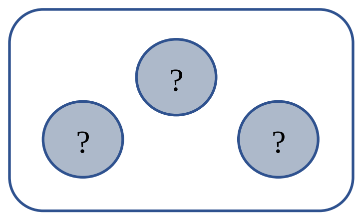
Payoff if drawn	Black - $5	Red - $10	White - $15
Total number of balls in an urn		3	

Your bid (in dollars and cents): $_________ . _________

Please read the description carefully. It will be in your best interest to place a bid equal to the highest price you are willing to pay. If you buy a ticket, you will receive the payoff associated with the color of the ONE ball drawn from the urn, and pay the random price.

Description:

There is one urn containing three balls. The possible ball colors are black, red and white.



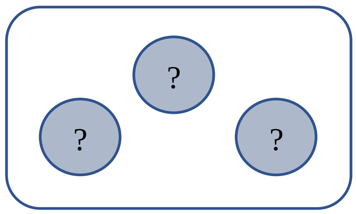
Payoff if drawn	Black - $5	Red - $10	White - $30
Total number of balls in an urn		3	

Your bid (in dollars and cents): $__________ . __________

Please read the description carefully. It will be in your best interest to place a bid equal to the highest price you are willing to pay. If you buy a ticket, you will receive the payoff associated with the color of the ONE ball drawn from the urn, and pay the random price.

Description:

There is one urn containing three balls. The possible ball colors are black, red and white. IF this urn contains one or more black balls, these balls will be replaced with red or white balls before a ball is drawn.



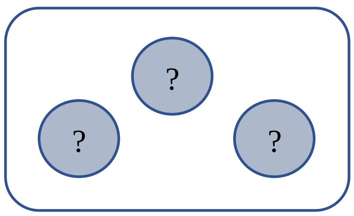
Payoff if drawn	Red - $10	White - $15
Total number of balls in an urn	3	

Your bid (in dollars and cents): $_________ . _________

Please read the description carefully. It will be in your best interest to place a bid equal to the highest price you are willing to pay. If you buy a ticket, you will receive the payoff associated with the color of the ONE ball drawn from the urn, and pay the random price.

Description:

There is one urn containing three balls. The possible ball colors are black, red and white. IF this urn contains one or more black balls, these balls will be replaced with red or white balls before a ball is drawn.



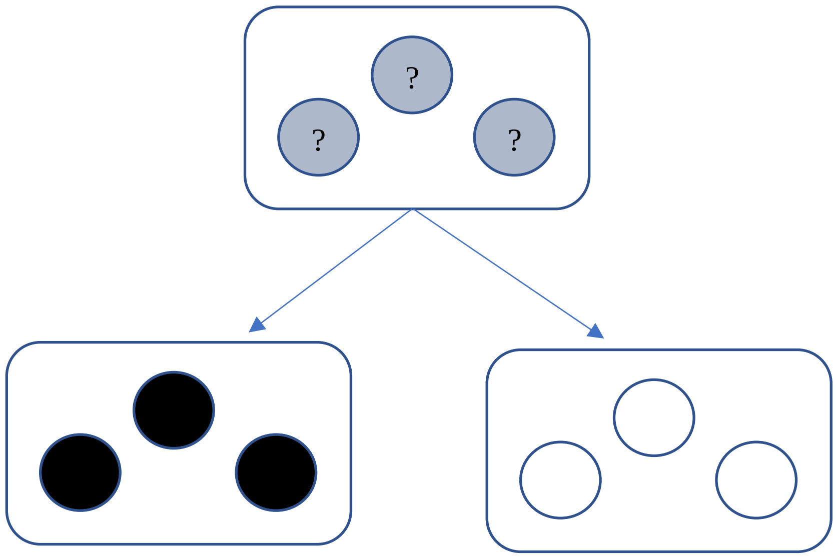
Payoff if drawn	Red - $10	White - $30
Total number of balls in an urn	3	

Your bid (in dollars and cents): $_________ . _________

Please read the description carefully. It will be in your best interest to place a bid equal to the highest price you are willing to pay. If you buy a ticket, you will receive the payoff associated with the color of the ONE ball drawn from the urn, and pay the random price.

Description:

There is one urn containing three balls. Either all balls in the urn are black or all balls in the urn are white. There are no other possibilities.



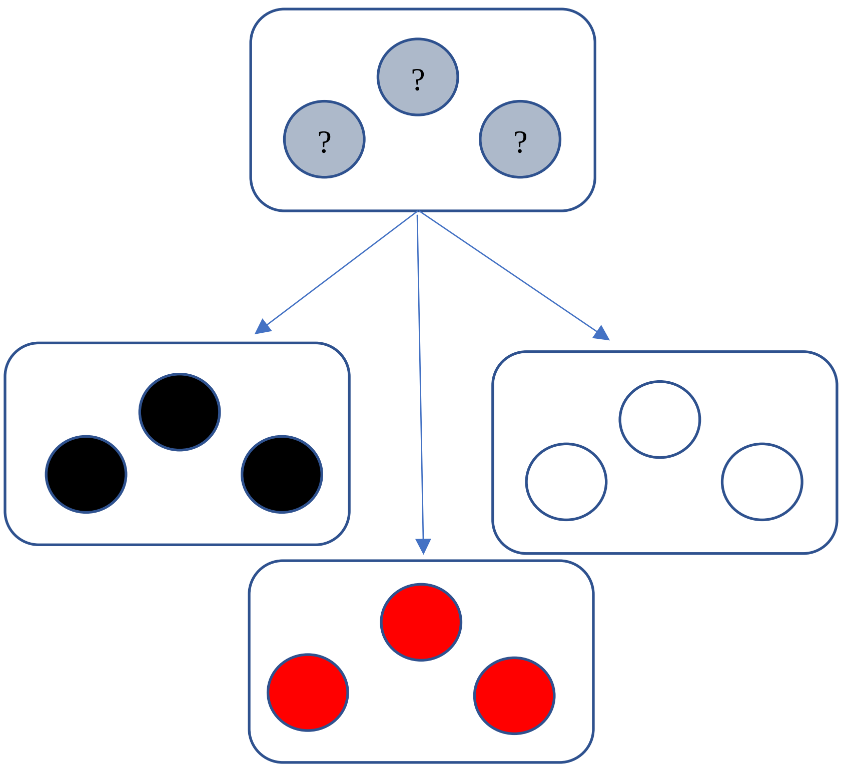
Payoff if drawn	Black - $5	White - $15
Total number of balls in an urn	3	

Your bid (in dollars and cents): $_________ . _________

Please read the description carefully. It will be in your best interest to place a bid equal to the highest price you are willing to pay. If you buy a ticket, you will receive the payoff associated with the color of the ONE ball drawn from the urn, and pay the random price.

Description:

There is one urn containing three balls. Either all balls in the urn are black, all balls in the urn are red or all balls in the urn are white. There are no other possibilities.



Payoff if drawn	Black - $5	Red - $10	White - $15
Total number of balls in an urn		3	

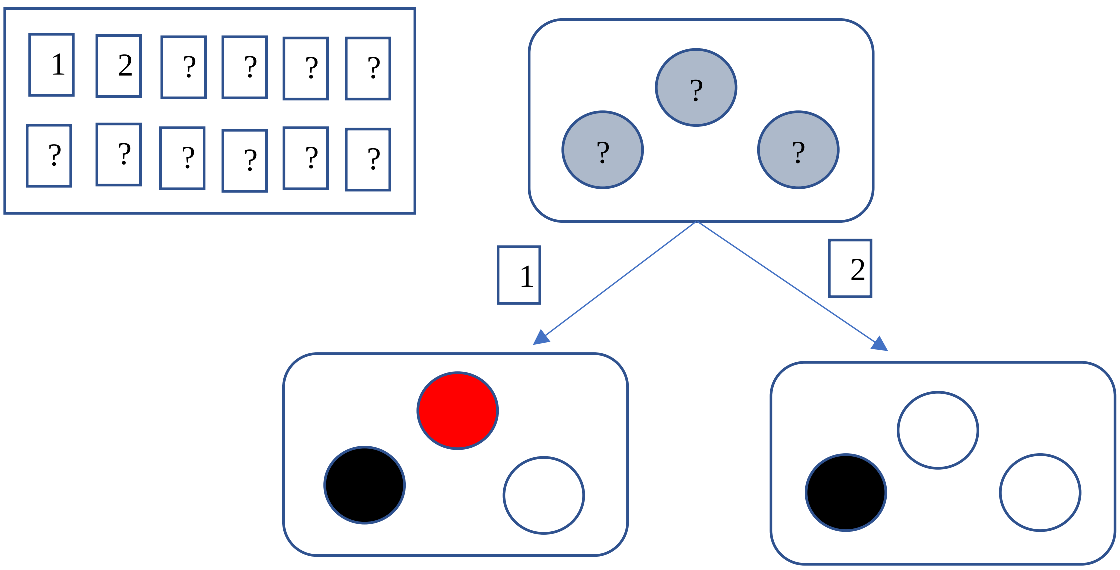
Your bid (in dollars and cents): $_________ . _________

Experiment 3 Decision Rounds – Part B

The decision rounds in Experiment 3 are divided into two parts – Part A and Part B. There are eight decision rounds in this part.

Your task in each round is to place a bid to buy a ticket to draw ONE ball from an urn. You will be told the possible colors of the balls in the urn, and the payoffs for each color.

In this part, a ball may be drawn from one of several possible urns. If you buy a ticket to draw a ball from an urn, you will first draw a card to determine what urn is in play, and then draw a ball from the selected urn. To illustrate how this works, we will go through an example.



In this example, there are two different urns, numbered 1 and 2. Urn 1 contains one black ball, one red ball and one white ball. Urn 2 contains one black ball and two white balls. If you purchased a ticket in this situation, you would first draw a card from a stack of TWELVE cards. You know for sure that one of the cards is for Urn 1 and one is for Urn 2. You do not know the number on the other cards – they can all be 1s or all be 2s or any combination of 1s and 2s. The number on the card drawn identifies the urn in play, and then a ball is selected from this urn. As before, each ball will be worth a particular amount of money based on its color.

The purchase procedure is the same as before. Your bid will be compared to a random price. You will purchase the ticket only if your bid is equal to or higher than the random price. The random price will be a randomly drawn number between $0.00 and a maximum price. The maximum price will an amount equal to or lower than the payoff associated with the highest-valued ball in the urn. For example, if the highest-valued ball is $15, the maximum possible price may be as high as $15. Any price within this range is equally likely to be chosen.

As before, it is in your best interest to place a bid equal to the highest price you are willing to pay for the ticket. By doing so, you will only purchase the ticket at prices you are willing to pay. You will not purchase the ticket at prices you are not willing to pay.

If you instead bid lower than the highest price you are willing to pay, you risk not purchasing the ticket at prices favorable to you. If you instead bid more than the highest price you are willing to pay, you risk purchasing the ticket at prices that are not favorable to you.

Only one decision round, which may be from Part A or Part B, will be implemented for real. After all decision rounds are completed, we will have a volunteer roll dice to determine which round this is. Since you will not know which round will be selected prior to making any decisions, it is in your best interest to take each decision seriously as if it will determine an actual purchase.

After this paid round is selected, a volunteer will roll dice to determine the random price. Another volunteer will select a ball from the urn.

Before we proceed to the decision rounds, are there any questions?

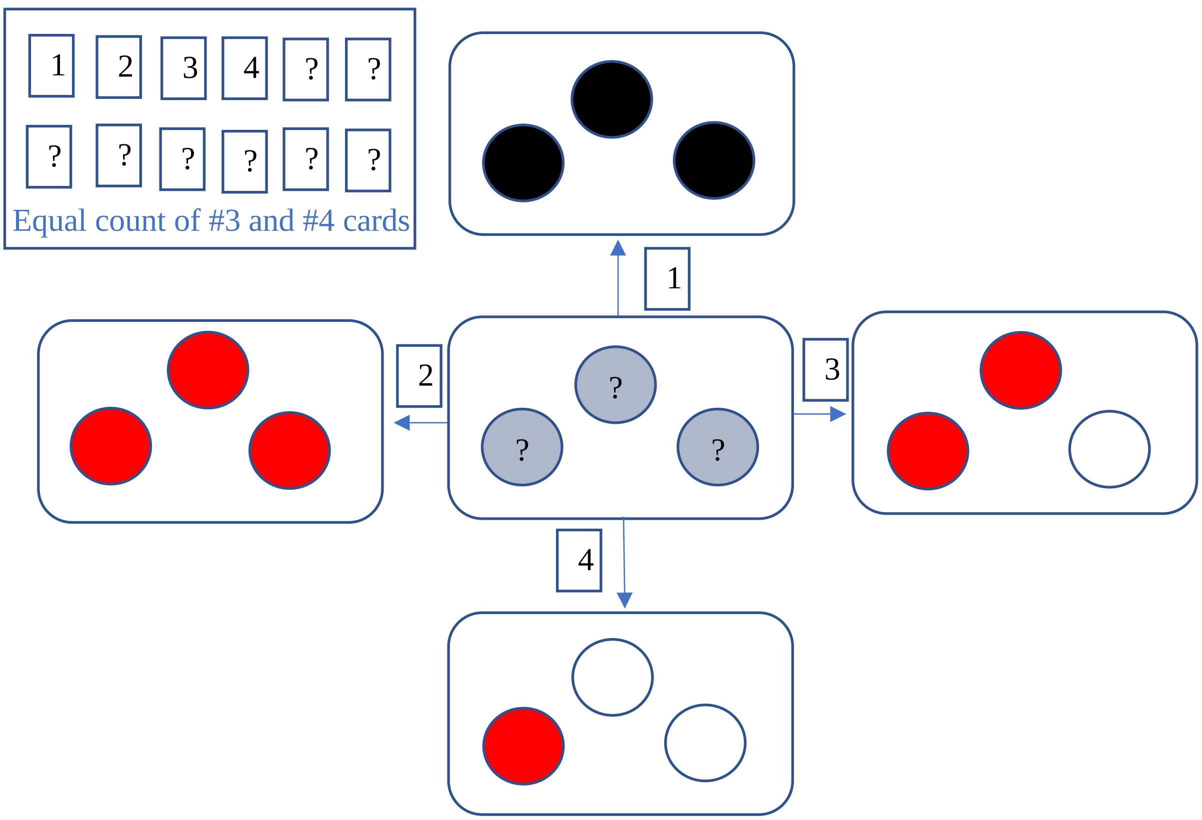
In the next two rounds, the <u>same</u> stack of cards will be used to determine the number of the urn selected.

Please, proceed to the next decision round.

Please read the description carefully. It will be in your best interest to place a bid equal to the highest price you are willing to pay. If you buy a ticket, you will receive the payoff associated with the color of the ONE ball drawn from the selected urn, and pay the random price.

Description:

There are four different urns, numbered 1, 2, 3 and 4. The ball colors in each are illustrated in the figure below. If you purchase a ticket, you would first draw a card from a stack of TWELVE cards to select what urn is used. There are an equal number of #3 and #4 cards. IF a black ball is selected from the urn, you would repeat the procedure – draw a different card, and then draw a ball from the selected urn – until a red or white ball is chosen.



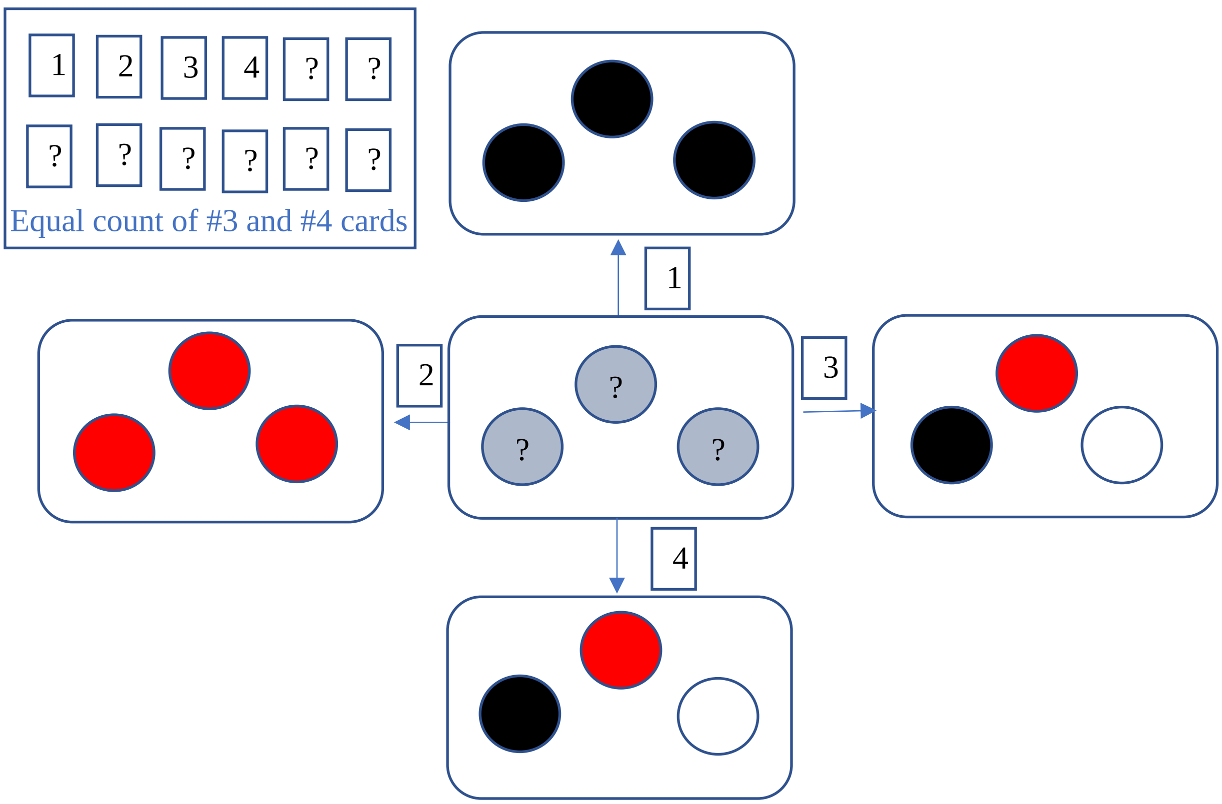
Payoff if drawn	Red - $10	White - $15
Total number of balls in an urn	3	
Total number of cards	12	

Your bid (in dollars and cents): $_________ . _________

Please read the description carefully. It will be in your best interest to place a bid equal to the highest price you are willing to pay. If you buy a ticket, you will receive the payoff associated with the color of the ONE ball drawn from the selected urn, and pay the random price.

Description:

There are four different urns, numbered 1, 2, 3 and 4. The ball colors in each are illustrated in the figure below. If you purchase a ticket, you would first draw a card from a stack of TWELVE cards to select what urn is used. There are an equal number of #3 and #4 cards. IF a black ball is selected from the urn, you would repeat the procedure – draw a different card, and then draw a ball from the selected urn – until a red or white ball is chosen.



Payoff if drawn	Red - $10	White - $15
Total number of balls in an urn	3	
Total number of cards	12	

Your bid (in dollars and cents): $_________ . _________

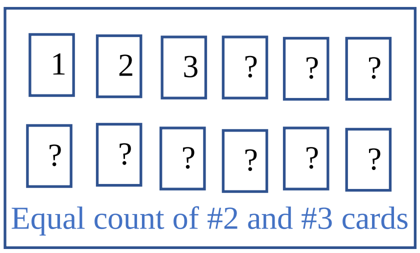
In the next two rounds, the <u>same</u> stack of cards will be used to determine the number of the urn selected.

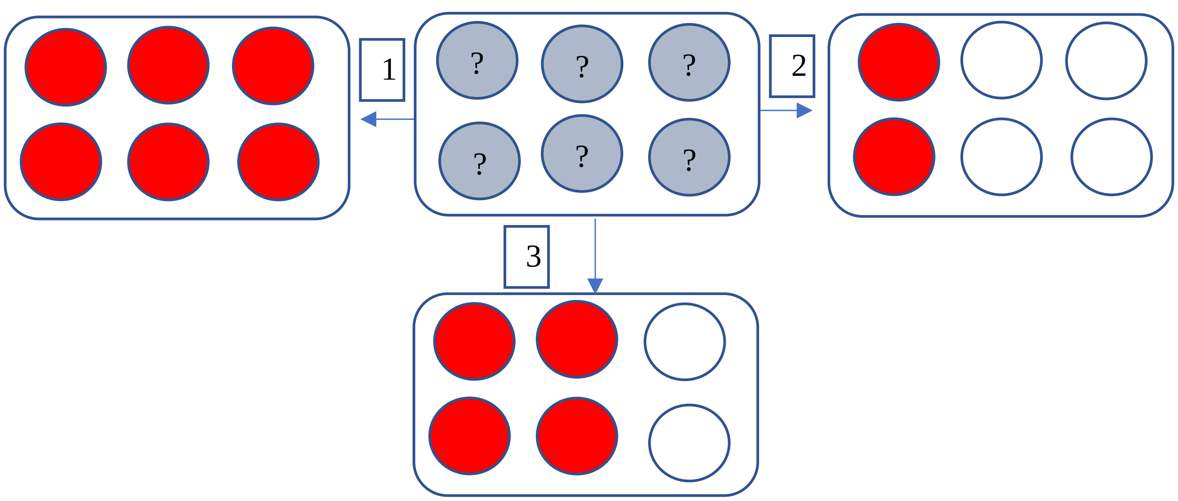
Please, proceed to the next decision round.

Please read the description carefully. It will be in your best interest to place a bid equal to the highest price you are willing to pay. If you buy a ticket, you will receive the payoff associated with the color of the ONE ball drawn from the selected urn, and pay the random price.

Description:

There are three different urns, numbered 1, 2 and 3. The ball colors in each are illustrated in the figure below. If you purchase a ticket, you would first draw a card from a stack of TWELVE cards to select what urn is used. There are an equal number of #2 and #3 cards.





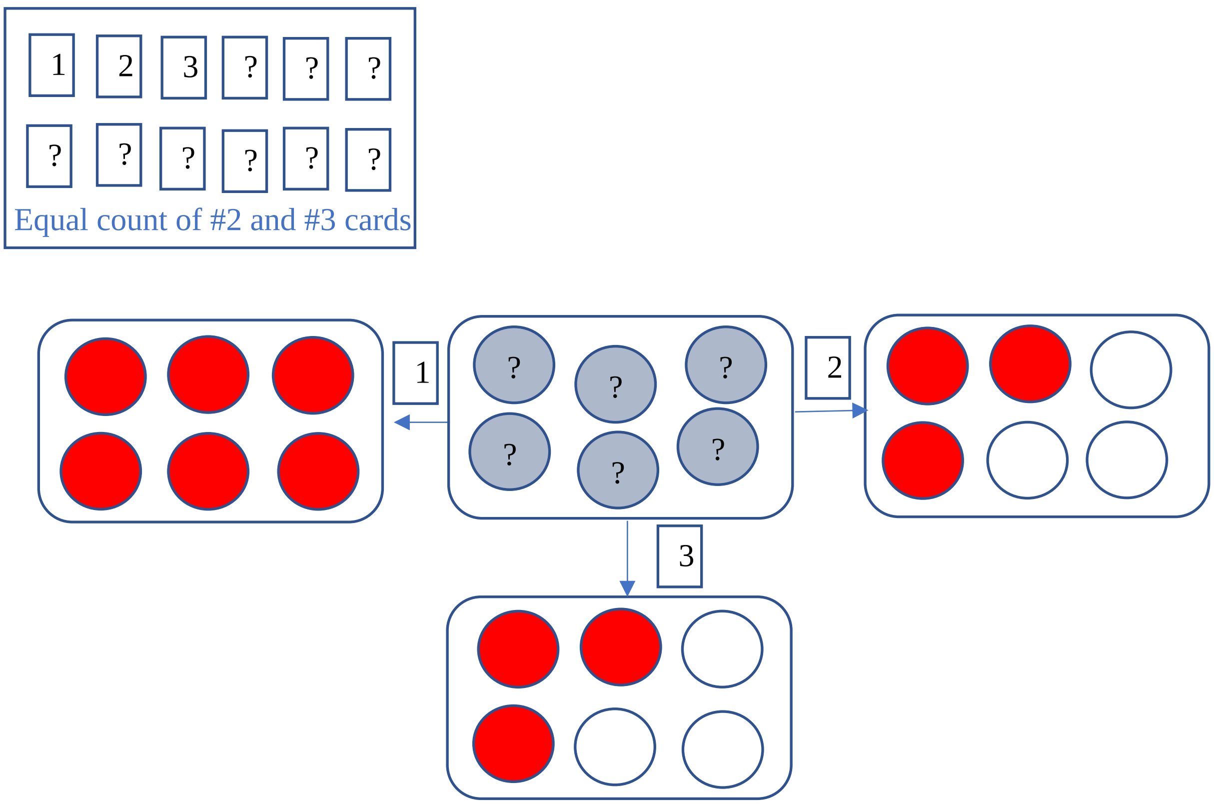
Payoff if drawn	Red - $10	White - $15
Total number of balls in an urn	6	
Total number of cards	12	

Your bid (in dollars and cents): $_________ . _________

Please read the description carefully. It will be in your best interest to place a bid equal to the highest price you are willing to pay. If you buy a ticket, you will receive the payoff associated with the color of the ONE ball drawn from the selected urn, and pay the random price.

Description:

There are three different urns, numbered 1, 2 and 3. The ball colors in each are illustrated in the figure below. If you purchase a ticket, you would first draw a card from a stack of TWELVE cards to select what urn is used. There are an equal number of #2 and #3 cards.



Payoff if drawn	Red - $10	White - $15
Total number of balls in an urn	6	
Total number of cards	12	

Your bid (in dollars and cents): $__________ . __________

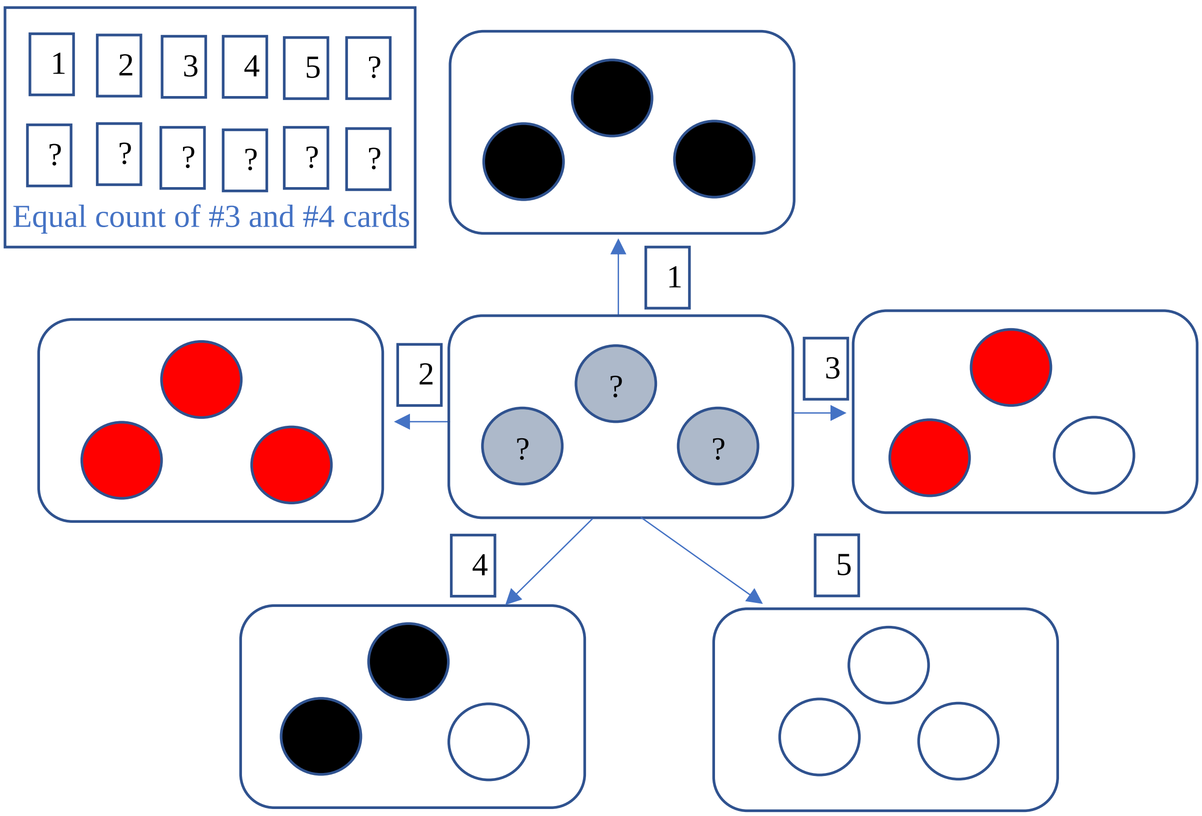
In the next two rounds, the <u>same</u> stack of cards will be used to determine the number of the urn selected.

Please, proceed to the next decision round.

Please read the description carefully. It will be in your best interest to place a bid equal to the highest price you are willing to pay. If you buy a ticket, you will receive the payoff associated with the color of the ONE ball drawn from the selected urn, and pay the random price.

Description:

There are five different urns, numbered 1, 2, 3, 4 and 5. The ball colors in each are illustrated in the figure below. If you purchase a ticket, you would first draw a card from a stack of TWELVE cards to select what urn is used. There are an equal number of #3 and #4 cards. IF a black ball is selected from the urn, you would repeat the procedure – draw a different card, and then draw a ball from the selected urn – until a red or white ball is chosen.



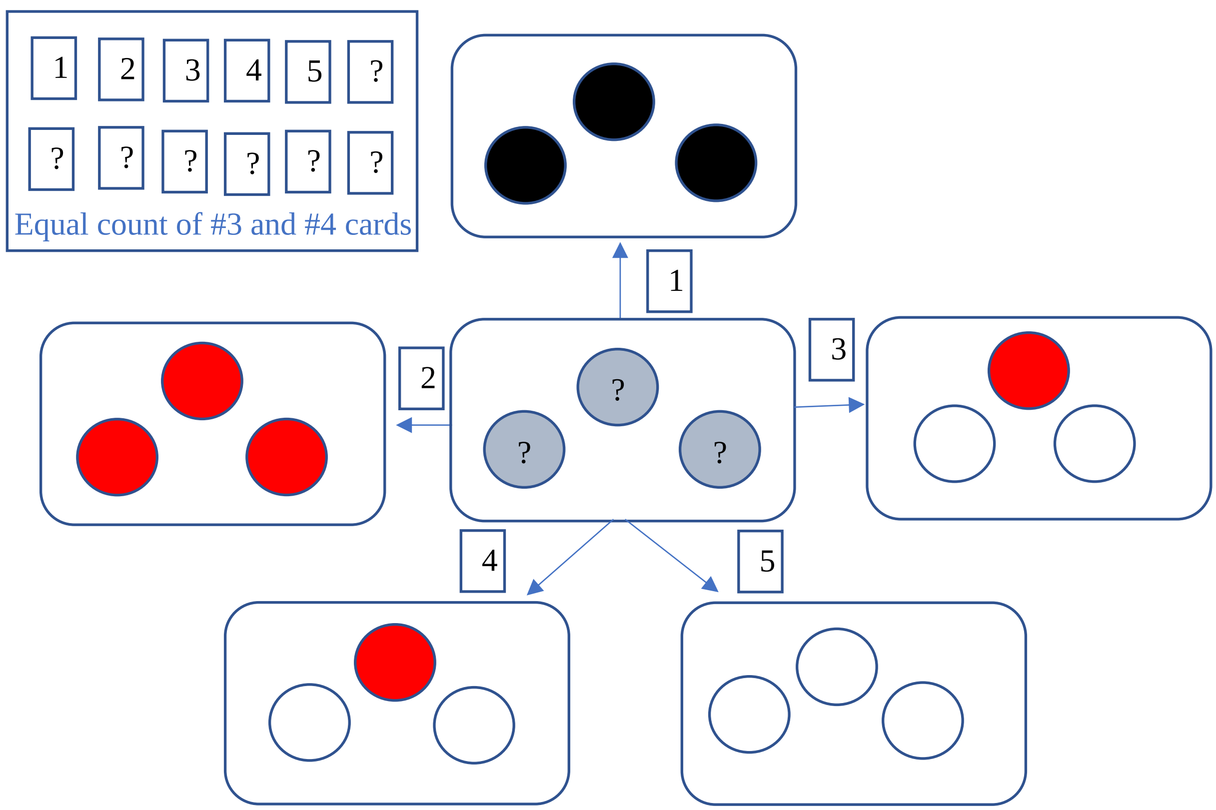
Payoff if drawn	Red - $10	White - $15
Total number of balls in an urn	3	
Total number of cards	12	

Your bid (in dollars and cents): $__________ . __________

Please read the description carefully. It will be in your best interest to place a bid equal to the highest price you are willing to pay. If you buy a ticket, you will receive the payoff associated with the color of the ONE ball drawn from the selected urn, and pay the random price.

Description:

There are five different urns, numbered 1, 2, 3, 4 and 5. The ball colors in each are illustrated in the figure below. If you purchase a ticket, you would first draw a card from a stack of TWELVE cards to select what urn is used. There are an equal number of #3 and #4 cards. IF a black ball is selected from the urn, you would repeat the procedure – draw a different card, and then draw a ball from the selected urn – until a red or white ball is chosen.



Payoff if drawn	Red - $10	White - $15
Total number of balls in an urn	3	
Total number of cards	12	

Your bid (in dollars and cents): $_________ . _________

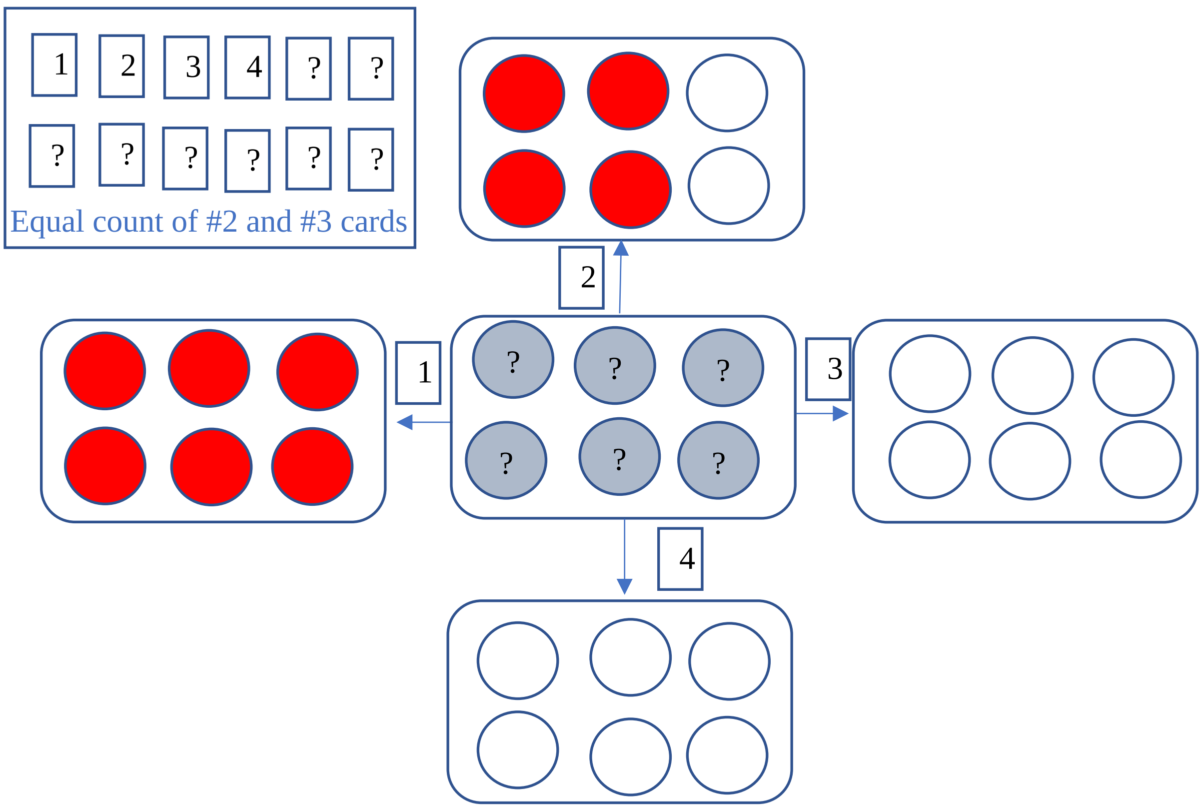
In the next two rounds, the <u>same</u> stack of cards will be used to determine the number of the urn selected.

Please, proceed to the next decision round.

Please read the description carefully. It will be in your best interest to place a bid equal to the highest price you are willing to pay. If you buy a ticket, you will receive the payoff associated with the color of the ONE ball drawn from the selected urn, and pay the random price.

Description:

There are four different urns, numbered 1, 2, 3 and 4. The ball colors in each are illustrated in the figure below. If you purchase a ticket, you would first draw a card from a stack of TWELVE cards to select what urn is used. There are an equal number of #2 and #3 cards.



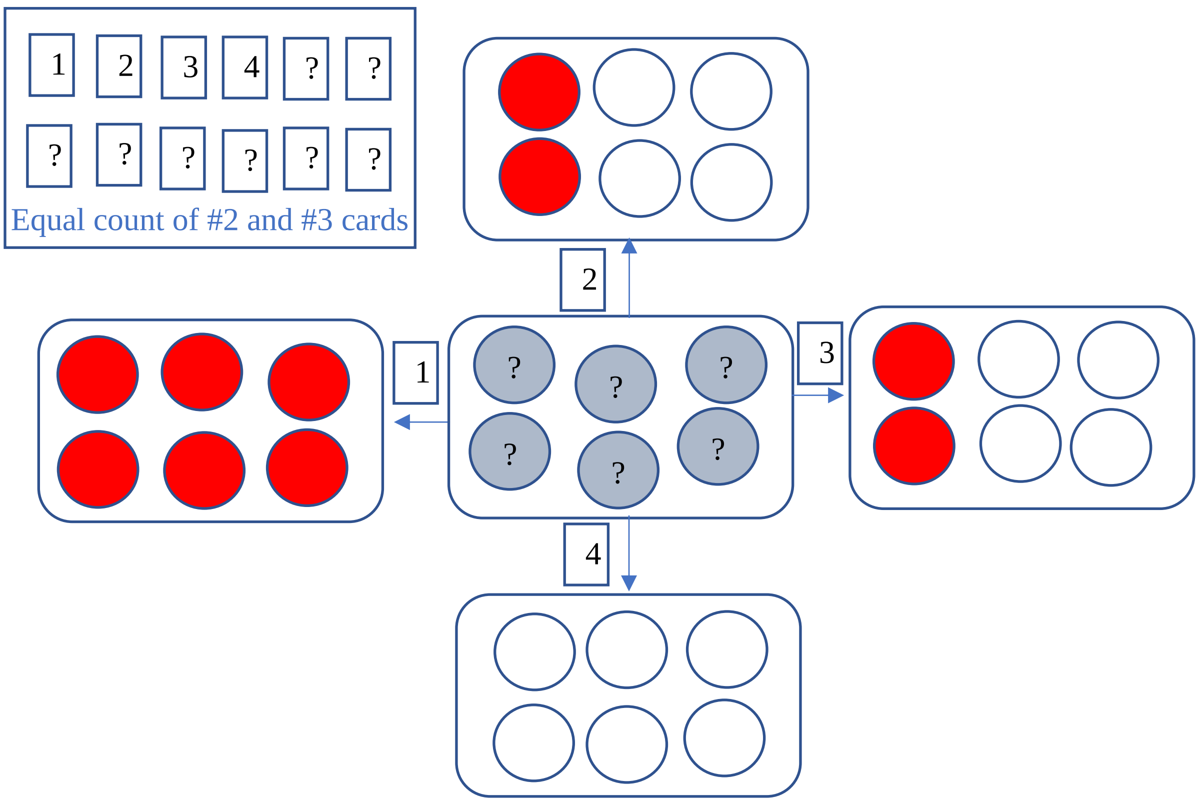
Payoff if drawn	Red - $10	White - $15
Total number of balls in an urn	6	
Total number of cards	12	

Your bid (in dollars and cents): $_________ . _________

Please read the description carefully. It will be in your best interest to place a bid equal to the highest price you are willing to pay. If you buy a ticket, you will receive the payoff associated with the color of the ONE ball drawn from the selected urn, and pay the random price.

Description:

There are four different urns, numbered 1, 2, 3 and 4. The ball colors in each are illustrated in the figure below. If you purchase a ticket, you would first draw a card from a stack of TWELVE cards to select what urn is used. There are an equal number of #2 and #3 cards.



Payoff if drawn	Red - $10	White - $15
Total number of balls in an urn	6	
Total number of cards	12	

Your bid (in dollars and cents): $_________ . _________

Earnings Record Sheet

Payment for completing all experiments and the questionnaire	$10.00
Earnings from Experiment 1	
Earnings from Experiment 2	
Practice calculations	
Training round 1 – trial 1	
Training round 1 – trial 2	
Training round 1 – trial 3	
Training round 1 – trial 4	
Training round 2 – trial 1	
Training round 2 – trial 2	
Training round 2 – trial 3	
Training round 2 – trial 4	
Paid Decision Round **Is your bid equal to or higher than the random price?** ☐ **Yes**. You bought a ticket. Your earnings are equal to: $____________ – ______________ (value of ball) (random price) ☐ **No**. You did not buy a ticket. Your earnings are $0.	

Total earnings (add up <u>all</u> amounts above): $_________._________

Round up your total earnings to the **next highest quarter**, and record this amount here and on your receipt form:

$_________._________

Questionnaire

We would now like for you to complete a short survey. Please note that all answers are strictly confidential and will be used for statistical purposes only.

1. Have you previously participated in an economics experiment?

(*circle one*) YES NO

2.Did you understand the instructions for the experiment today? Please rate your understanding on a scale from 1 to 5. (Circle one number.)

I understood very poorly				I understood very well
1	2	3	4	5

3.Did you feel that you were well-compensated for your participation in this experiment? Please rate your satisfaction with the compensation on a scale from 1 to 5. (Circle one number.)

I was compensated very poorly				I was compensated very well
1	2	3	4	5

4. What is your age? ___________

5. What is your gender? (circle one) Male Female

6. What is your major? (*be specific*)

____

7. What is your classification for the spring 2017 semester? (*circle one*)

Freshman Sophomore Junior Senior

Master's Student Law Student Doctoral Student

Other _____________

8. What is your student status for the current semester? (*circle one*)

Full-time student   Part-time student (taking fewer than 12 hours/sem)

Not a student   Other (please specify)

9. How many economic courses have you taken at the university level? (include this semester)

____

10. How would you best describe your current employment situation? (*circle one*)

Full-time employment outside of the university

Part-time employment outside of the university

Student only

Work at the university/research assistantship

11.In what range is your GPA? (*circle one*)

0 to 2.0 / 2.1 to 2.5 / 2.6 to 3.0 / 3.1 to 3.5 / 3.6 to 4.0

Here are a number of personality traits that may or may not apply to you. Please write a number next to each statement to indicate the extent to which *you agree or disagree with that statement*. You should rate the extent to which the pair of traits applies to you, even if one characteristic applies more strongly than the other.

Disagree strongly	Disagree moderately	Disagree a little	Neither agree or disagree	Agree a little	Agree moderately	Agree strongly
1	2	3	4	5	6	7

I see myself as:
1. _____ Extraverted, enthusiastic.
2. _____ Critical, quarrelsome.
3. _____ Dependable, self-disciplined.
4. _____ Anxious, easily upset.
5. _____ Open to new experiences, complex.
6. _____ Reserved, quiet.
7. _____ Sympathetic, warm.
8. _____ Disorganized, careless.
9. _____ Calm, emotionally stable.
10. _____ Conventional, uncreative.

Please use the space below to write any comments you may have about the experiment.