A Certainty Effect for Preference Reversals Under Risk: Experiment and Theory[*]

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Abstract

Under the expected utility paradigm, two behavioral anomalies stand out. First, individuals tolerate risk when the odds are unfavorable but become more averse to risk as the odds approach certainty. Second, individuals exhibit context-dependent reversals in their attitudes towards risk. Understanding how these anomalies interact is critical for adjudicating among competing behavioral theories, but most empirical research examines them in isolation. To address this gap, we conduct a lab-in-the-field experiment with high stakes and expert subjects. We find that reversals persist at higher stakes and among experts, and we observe a certainty effect for preference reversals. Although our novel findings cannot be explained by leading theories from economics and psychology, they can be explained by a model that combines stochastic reference dependence from economics and context-dependent sensitivity from psychology.

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1 Introduction

Two choice anomalies serve as the litmus test for theories of decision-making under risk: (1) the effect that proximity to certainty exerts over risk attitudes and (2) context-dependent preference reversals. Although leading behavioral theories predict a relationship between these two anomalies, most empirical research examines them in isolation. This mismatch between theory and empirics limits our ability to adjudicate among competing theories.

The *effect of proximity to certainty* on risk preferences is well established. Notable examples include Allais' paradoxes Allais (1953), the overweighting of unlikely events (Preston and Baratta, 1948; Edwards, 1953; Tversky and Kahneman, 1979), and the simultaneous willingness to gamble and insure (Friedman and Savage, 1948; Markowitz, 1952).Traditional theoretical explanations for certainty effects include disappointment aversion, probability weighting, and reference dependence.

Preference reversals are also well established and, in the domain of risk, researchers have identified a robust pattern. When individuals compare lotteries, they are more risk-averse than when they price each lottery in isolation (Lichtenstein and Slovic, 1971). The same pattern emerges when individuals assign a sure amount to a lottery (pricing) as opposed to when they select a lottery that is equivalent to a sure amount (comparing) (Hershey et al., 1982; Hershey and Schoemaker, 1985; Schoemaker, 1990). To explain these context-dependent preference reversals, behavioral scholars have proposed stimulus-response compatibility and stochastic reference dependence (Slovic et al., 1990; Loomes and Sugden, 1982).

Although theory suggests the two anomalies are related to each other (Schmidt et al., 2008; Bordalo et al., 2012), most empirical research evaluates them independently. Moreover, to our knowledge, no empirical studies evaluate risk attitude reversals near certainty. This omission is a problem given that Allais' original insight was that choices near certainty are more likely to violate rational choice theories (Allais, 1953).

Here, we explore the effect that certainty exerts over preference reversals and address external validity concerns from prior experiments. To non-parametrically measure risk attitudes, we use the risk premium, which is the difference between a lottery's expected value and its subjective value ($EV(L) - c(L)$). To elicit risk premia, we use two types of choice lists. For pricing lists, we fix a two-outcome lottery ($p, \$150; 1-p, \$0$) and elicit a subject's value using a choice list with an increasing sure amount (c). In other words, we fix $EV(L)$ and elicit $c(L)$. For comparing lists, we fix a certain amount $c(L)$ and elicit the equivalent in preference lottery L. We fix $c(L)$ to be equal to the pricing lottery's expected value and elicit a subject's willingness to switch to a lottery with increasing chances of \$150. These types of binary choice lists are commonly referred to as eliciting "certainty equivalents" in the pricing lists and eliciting "probability equivalents" in the comparing lists.

Our experimental design builds on Andreoni and Sprenger (2011) and Sprenger (2015) but has three distinguishing features. First, we use a wider range of probabilities for the comparing choice lists. This wider range allows us to determine the effect of certainty on reversals. Second, we use a mixed design for the elicitation of equivalent risk premia; i.e., we have both between-subject and within-subject data. The within-subject data allow us to measure the magnitude of individual welfare losses from reversals. Third, we recruit both students and experts in risky decision-making (commercial agricultural producers), and we increase the stakes five-fold: from a maximum outcome of \$30 to \$150. Including experts and higher stakes addresses external validity critiques of the low stakes and student subjects of laboratory experiments.

For our pre-registered, lab-in-the-field experiment, we recruited 398 commercial agricultural producers from across the United States. Our median producer is 60 years old and earns an annual income of \$267,158, suggesting they manage risks well. We also recruited 115 university students to determine whether our new experimental design replicates the results of prior studies that used students. The risk attitudes of students also serve as a benchmark for the behaviors of our expert decision-makers. Our initial conjecture was that experts and more meaningful stakes would lower the preponderance of reversals. Thus, we recruited a larger sample of producers to account for the possibility of smaller effect sizes.[1]

Our core empirical finding is that the median subject exhibits preference reversals, and these reversals exhibit a certainty effect. Like the prior literature on preference reversals, we find that subjects are more risk-tolerant when pricing lotteries than when comparing them under unfavorable odds. However, unlike the prior literature, we find another reversal near certainty. Near certainty, the act of pricing induces more risk aversion than the act of comparing. Prior studies could not detect this reversal because their designs lacked comparisons near certainty.

Moreover, this heretofore undetected preference reversal cannot be rationalized by existing models. There are two leading explanations for preference reversals, one from economics and one from psychology: Köszegi and Rabin's (KR) stochastic reference dependence model (Kőszegi and Rabin, 2006, 2007) and stimulus-response compatibility theory (Tversky et al., 1988; Slovic et al., 1990; Tversky et al., 1990). Sprenger (2015) showed that the KR model, with the aid of an exogenous referent, is the only stochastic reference-dependent model that can explain why subjects are more risk-tolerant when pricing lotteries than when comparing them under unfavorable odds. This model predicts an endowment effect for risk in which decision makers prefer the option they consider to be the default. In a comparing choice list, the endowment is the sure amount. In a pricing choice list, the endowment is the lottery. In contrast, stimulus-response compatibility theory posits that preference reversals arise from context-dependent sensitivity to changes in the outcomes. In the pricing list, preferences are more responsive to the changes in the outcomes, whereas, in the comparing list, they are less responsive. This observed increase in risk

[1] See our pre-analysis plan Feldman and Ferraro (2021) and how it was implemented in Appendix C.

tolerance while pricing can be captured using a more risk-tolerant, Bernoullian utility function (i.e., a convex function that exhibits increasing sensitivity). Although both theories can rationalize some of the behaviors in our experiment, we show (Section 2) that they cannot account for the preference reversal near certainty because they both predict that comparing can only increase aversion to risks.

To rationalize the behavioral patterns observed in prior experiments and in our new experiment, we propose a generalization of stochastic reference dependence that incorporates context-dependent sensitivity through loss-gain utility.

We show that a KR model with context-dependent sensitivity for the loss-gain reference-dependent utility predicts a certainty effect for reversals. The KR model splits the utility of an outcome (x) with a given referent (r) into two parts: the intrinsic consumption utility for the outcome $m(x)$ and the loss-gain reference-dependent utility $\mu(m(x) - m(r))$. We show that increasing sensitivity for the loss-gain reference-dependent utility function $\mu(\cdot)$ can generate the inverse-S-shaped probability weighting pattern observed in the pricing choice list. The combination of increasing sensitivity for the pricing lists and decreasing sensitivity for comparing lists for loss-gain utility generates the additional reversal near certainty.

Therefore, our model incorporates an endowment effect for risk from KR and context-dependent sensitivity from compatibility theory. Note, that we are not adding degrees of freedom to the model. These two model attributes are defined by the elicitation lists and hence our model is disciplined by the way choices are presented to subjects. In experiments, the endowment effect is the effect of the fixed alternative in the choice lists, while the context-dependent sensitivity is the effect of the changing alternative.

Our new model also provides an alternative behavioral explanation for the so-called overweighting of low probability events, which has been observed in myriad experiments and which prior studies have attributed to probability weighting (Quiggin, 1982; Tversky and Kahneman, 1979, 1992; Yaari, 1987). In our model, individuals do not misperceive their odds, as they do in probability weighting explanations, but rather they anticipate utility from an unexpected outcome to be higher than utility from an equal but expected outcome.

Our rival explanation for the overweighting of low probability events in prior experiments also explains why lottery incentives are not used as widely as probability weighting theory would imply they ought to be used, and why the field evidence about the superiority of lottery incentives over fixed incentives is, at best, mixed (Filiz-Ozbay et al., 2015; Halpern et al., 2011). In any setting where n probability-weighting agents are to be remunerated for their efforts, paying them a fixed amount, say w, is strictly dominated by a 5% chance of nw. Both payment mechanisms have equal (expected) costs, but a probability-weighting agent who perceives chances to be better than they are would prefer the random lottery mechanism. Yet our experimental results and theoretical model suggest that decision context effects are likely to have a non-negligible effect on the attractiveness of random incentive mechanisms.

Our model also emphasizes a compromise between the psychological and the economic interpretation of preferences. Economists have predominantly argued that preferences are a stable trait, captured by $m(\cdot)$. In contrast, psychologists assert that preferences are constructed by the elicitation procedure, captured by the context-dependent sensitivity of $\mu(\cdot)$. Our model highlights how both perspectives can coexist. Unlike the prior literature, we do not add to the lengthy list of biases to explain new experimental results but rather combine well-documented biases.

In summary, our theory, like prospect theory, accommodates certainty effects and, like theories of stochastic reference dependence and context-dependent sensitivity, it accommodates preference reversals when subjects price lotteries rather than compare them. Unlike prior theories, however, our theory also accommodates the additional reversal that occurs close to the certainty of a good outcome. The theory also yields a tractable way to disentangle the stable trait in risk preference from the labile element introduced by different elicitation procedures. Finally, our model suggests that the interaction of endowment effects and context-dependent sensitivity may be a mechanism behind some of the perplexing inconsistencies in people's choices.

Our paper is organized in the following manner. Section 2 presents our theoretical framework and contrasts it to previously developed frameworks. Next, section 3 introduces our experimental design and sample. We then proceed to discuss our results in section 4. Finally, section 5 discusses implications and our concluding thoughts.

2 Theoretical Considerations

Prior to presenting our new theoretical model, we formalize the insights that our model builds upon. We first present the KR model's prediction for the pricing and comparing choice lists under the assumption of exogenous referents. Then, we formalize the theory of stimulus-response compatibility and present its predictions. Finally, we develop our new model that extends the KR model by adding context-dependent sensitivity, as suggested by compatibility theory.

2.1 KR Preferences

The KR model can be described as follows. First, assume an individual has latent utility over monetary outcomes x given by $m(x)$. The individual also derives additional utility from reference dependence loss-gain utility. For a fixed referent outcome r, their loss-gain utility is $\mu(m(x)-m(r))$. We assume further that $\mu(\cdot)$ is a piecewise continuous linear function (constant sensitivity) with a unique kink at zero. The extent of the kink is given by loss aversion–the change in the slope under a negative value. The usual functional form is then

$$\mu(y) = \begin{cases} \eta y & y \geq 0 \\ \lambda \eta y & y < 0 \end{cases},$$

where η is the weight attached to loss-gain utility and λ denotes the degree of loss aversion. Thus,

$$u(x|r) = m(x) + \mu(m(x) - m(r))$$

denotes the preferences for an outcome x and a reference point r. Note that the KR model assumes constant sensitivity to loss-gain utility, i.e. linear loss-gain utility, an assumption that we will relax in our extension of this model.

Second, given two probability measures, F (for outcomes) and G (for reference points), we have that the utility over these measures is given by

$$U(F|G) = \int\int u(x|r)dG(r)dF(x).$$

As long as $\mu(\cdot)$ is a piecewise linear function, $m(\cdot)$ is unique only up to positive affine transformations. This feature allows us to normalize latent utility to have a value of one for the maximum outcome and zero for the minimum outcome. For an in-depth discussion on other reference-dependence models, see O'Donoghue and Sprenger (2018).

In the next section 2.2, we characterize KR preferences for the pricing lists. We show they are indistinguishable from the preferences of an expected utility maximizer with preferences over monetary outcomes given by $m(\cdot)$. Afterward, in section 2.3, we characterize KR preferences for the comparing choice list. Then, contrasting both we show that loss-aversion leads to more risk-aversion in the comparing choice list than under the pricing choice list.[2] Our methods of proof are similar to those used in Sprenger (2015), but we do not rely on the assumption that $m(\cdot)$ be linear and we simplify the notation by normalizing latent utility.

2.2 KR Preferences when Pricing Binary Lotteries

We argue that KR preferences when pricing binary lotteries and constant sensitivity are indistinguishable from an expected utility agent with the equivalent latent preferences.

For a stochastic referent, with binary outcomes ($r_H > r_L$) with a fixed probability $\mathbb{P}(r_H) = q$, we can compute the value of a certain amount c as

$$qu(c|r_H) + (1-q)u(c|r_L). \tag{1}$$

We can also compute the value of the fixed binary lottery L as

$$q^2u(r_H|r_H) + (1-q)^2u(r_L|r_L) + q(1-q)u(r_H|r_L) + q(1-q)u(r_H|r_L). \tag{2}$$

In this manner, indifference between the certain amount and the fixed lottery is given by equalizing equation 1 to equation 2. After normalizing the maximum and minimum outcomes and a bit of algebra we get the following condition.

$$m(c) + q\mu\left(m(c) - 1\right) + (1-q)\mu\left(m(c)\right) = q^2 + q(1-q)(1 + \mu(1) + \mu(-1))\ .$$

[2]Formally, preferences for pricing are given by $m(\cdot)$, while preferences for the pricing choice list are given by $f(m(\cdot))$ with f a strictly increasing concave function.

Now, multiplying out the terms on the right-hand-side of this equivalence and using the piecewise-linearity of μ we get

$$m(c) + q\lambda m(c)\mu(1) - q\lambda\mu(1) + m(c)\mu(1) - qm(c)\mu(1)\ ,$$

and by factorizing $m(c)$ out, we get

$$m(c)[1 + q\lambda\mu(1) + \mu(1) - q\mu(1)] - q\lambda\mu(1).$$

Now, for the left-hand-side, if we multiply out the terms and rearrange, we get

$$q^2 + q + q\mu(1) - q\lambda\mu(1) - q^2 - q^2\mu(1) + q^2\lambda\mu(1),$$

and factorizing q out gives us

$$q(1 + q\lambda\mu(1) + \mu(1) - q\mu(1)) - q\lambda\mu(1).$$

Clearly, the multiplicative and additive terms in both sides of the equation are equal, and thus, we conclude with

$$m(c^*) = q\ , \tag{3}$$

which can be alternatively written as

$$c^* = m^{-1}\left(qm(r_H) + (1-q)m(r_L)\right).$$

Therefore, choices are indistinguishable from an expected utility maximizer with preferences over money given by the Bernoullian utility function $m(\cdot)$.

2.3 KR Preferences when Comparing Binary Lotteries

We argue that constant-sensitivity KR preferences exhibit more risk aversion when comparing binary lotteries. Let the switching lottery be $(p^*, x_H; (1-p^*), x_L) \sim c$. We show that the switching lottery determined by p^* under KR is larger than the switching lottery given by EU p^*_{EU}, with $u(\cdot) = m(\cdot)$. Notice, larger probabilities imply more risk aversion.

For a fixed certain referent, we can compute its value as

$$u(r|r) = m(r)\ . \tag{4}$$

On the other hand, the value of a lottery $(p, x_H; p, x_L)$ under the fixed certain referent is

$$pu(x_h|r) + (1-p)u(x_l|r) = p + p\mu\left(1 - m(r)\right) + (1-p)\mu\left(0 - m(r)\right)\ . \tag{5}$$

When equation 4=5, we get the value for the probability equivalent

$$p^* = \frac{m(r) - \mu(-m(r))}{\mu\left(1 - m(r)\right) - \mu\left(-m(r)\right)}. \tag{6}$$

Evaluating the probability equivalent under expected utility preferences ($p^*_{EU} = m(r)$) against the probability equivalent under general KR preferences (p^*), implies the following critical inequality, we have that $p^* > p^*_{EU}$ iff

$$\frac{1 - m(r)}{m(r)} \geq \frac{\mu\left(1 - m(r)\right)}{-\mu\left(-m(r)\right)}, \tag{7}$$

if under both preference specifications latent preferences are represented by $m(\cdot)$, we get

$$\frac{\mu\left(1 - m(r)\right)}{-\mu\left(-m(r)\right)} = \frac{1 - m(r)}{\lambda m(r)}, \tag{8}$$

$p^* > p^*_{EU(m)}$ iff $\lambda > 1$. That is, a loss-averse individual with KR preferences, under constant loss-gain utility and latent utility $m(\cdot)$, is more risk-averse than an agent with EU preferences given by the Bernoullian utility function $m(\cdot)$.

2.4 KR Preferences and Multiple Reversals

We have argued that KR preferences give different predictions for the pricing and comparing choice lists. For the pricing lists, both the KR and the expected utility models make identical predictions under equivalent preferences given by $m(\cdot)$. For the comparing lists, the model predicts individuals will be more risk-averse when they are loss-averse. The intuition for this result is that the negative outcome of the lottery is overweighted relative to its positive component.

Because this endowment effect can only affect risk attitudes in one direction, the constant-sensitivity KR model can only accommodate a single reversal. The model, as stated, is also incapable of generating certainty effects for pricing choice lists–i.e., the inverse-S pattern observed in many prior experiments (Tversky and Kahneman, 1992; Wu and Gonzalez, 1996; Abdellaoui, 2000; Andreoni et al., 2017).

In the next section, we provide a psychological model that formalizes Lichtenstein and Slovic's original intuition that individuals are more sensitive to outcomes when pricing than when comparing. We emphasize that this context-dependent explanation is based on the changing attribute–either chances or monetary amounts–and not the referent, as in the KR model.

2.5 Stimulus-Response Compatibility Theory

To formalize compatibility theory, we use the simple contingent weighting model from Tversky et al. (1990). The model captures changes in the sensitivity across contexts through the curvature of the Bernoullian utility function. More curvature implies less sensitivity to *changes* in the outcomes.

For the comparing choice lists ($\mathcal{C}$) we assume that preferences over outcomes are given by

$$u(L) = p\frac{x_h^{\alpha(\mathcal{C})}}{\alpha(\mathcal{C})};$$

while for the pricing choice lists, preferences are given by

$$v(L) = p\frac{x_h^{\alpha(\mathcal{P})}}{\alpha(\mathcal{P})}.$$

Like in Tversky et al. (1990), we also require that preferences over outcomes be more sensitive to the outcomes under the pricing choice lists ($\mathcal{P}$). Hence $\alpha(\mathcal{C}) < \alpha(\mathcal{P})$ which is equivalent to

$$\frac{-u''(x) * x}{u'(x)} > \frac{-v''(x) * x}{v'(x)}.$$

Because $u(\cdot)$ is a concave transformation of $v(\cdot)$ this model will accommodate only one reversal. Like the KR model above in section 2.2, this model is also incapable of generating certainty effects for pricing choice lists.

In the next section 2.6, we propose an extension to KR that can accommodate certainty effects. Our model has the attractive feature that latent intrinsic preferences represented by $m(\cdot)$ are fixed across choice environments. Consequently, any changes in behavior across contexts are driven entirely by the loss-gain utility.[3]

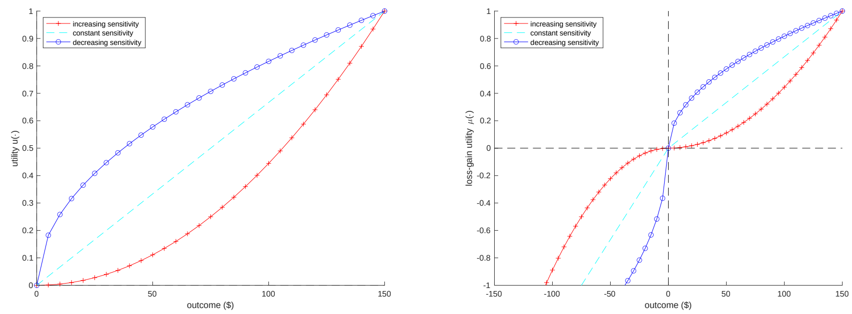
2.6 KR Preferences with Context-Dependent Sensitivity

Here, we develop our theory which adds context-dependent sensitivity to the KR model. Our theory will allow us to accommodate both old and new results. Our model has two features that distinguish it from traditional applications of the KR model.

The first novel feature is the exogenous reference distribution. Like Sprenger (2015) and unlike other applications, we use an exogenous referent to generate an endowment effect for risk. In traditional applications of the KR model, the referent is determined by rational expectations and equilibrium selection criteria. In contrast, the referent in our model is determined by the endowment–i.e., the fixed alternative. Note that a KR model with any endogenous referent predicts pricing and comparing will result in the same choices in both decision contexts, that is, procedural invariance. Violations of procedural invariance have been previously documented (Tversky et al., 1990; Sprenger, 2015). That is why endogenous referent models may not be a reasonable explanation for unfamiliar experimental environments; notwithstanding, they provide a reason for why experience may decrease context effects "in the wild". We expect referents may conform with rational expectations with additional experience.

The second novel feature of our model is that it allows for different sensitivities to types of choice lists. This change from standard KR applications is consistent with Lichtenstein and Slovic's initial insight, but, in our extension, individuals are more sensitive to outcomes only through their loss-gain utility.

[3]Recent work explores how to identify latent preferences independently in riskless contexts (Goette et al., 2019). In section 4.3, we provide an alternative for identifying both latent and labile preferences in risky settings using multiple contexts.



(a) Stimulus-Response Compatibility Theory

(b) Context-Dependent Sensitivity for Loss-Gain Utility

Figure 1: Modeling Context-Dependent Sensitivity to Changes int the Outcomes

The psychology behind context-dependence is that individuals will be more sensitive to the changing alternative. Clearly, pricing induces more sensitivity to changes in the outcomes than comparing. Probabilities change when comparing within a choice list while outcomes do not.

By integrating context-dependent sensitivity in to a KR model with an exogenous referent, we allow latent utility to be a fixed individual trait while procedural variance is captured by loss-gain utility. While economists often argue that preferences are stable, psychologists often argue that preferences are constructed by the elicitation procedure. Our model allows both perspectives to be true.

The KR model with context-dependent sensitivity is

$$\begin{aligned} u(x|r) &= m(x) + \mu(m(x) - m(r)) \\ V(F|G) &= \int\int u(x|r) dG(r) dF(x), \end{aligned} \tag{9}$$

with,

$$\mu(y) = \begin{cases} \eta y^{\alpha(ctx)} & y \geq 0 \\ \lambda \eta y^{\alpha(ctx)} & y < 0\ . \end{cases}$$

$G(r)$ is determined by the endowment (e.g., the fixed alternative in the choice list), and the coefficient for the curvature of the reference dependence function is given by the context (e.g., the increasing alternative in the choice list). Both the theory and the empirical data from preference reversals suggest $\alpha(pricing) > 1 \geq \alpha(comparing)$. That is, we expect increasing sensitivity to changes in the outcomes under the pricing lists and decreasing sensitivity under the comparing lists. Figure 1a provides a visual representation for modeling increasing sensitivity using Bernoullian utility functions in the standard case while Figure 1b represents the extension for loss-gain utility.

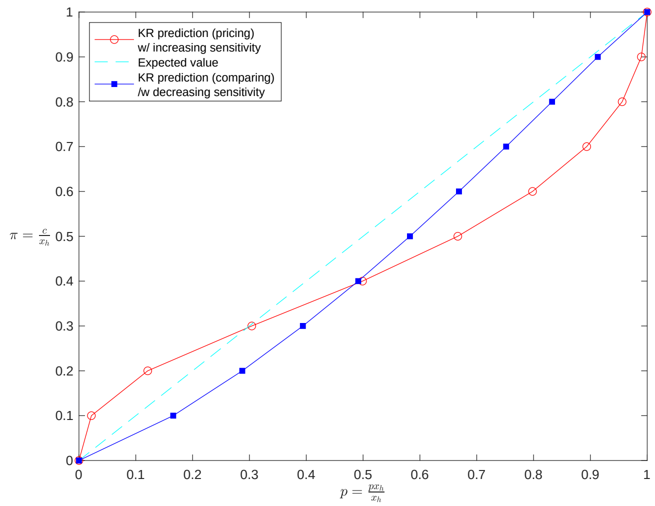


Figure 2: KR with Context-Dependent Sensitivity

Notes: The parameter values are $\lambda \approx 2$, $m(x) = x^{.95}$, $\eta = 1$, $\alpha(pricing) = 2$, $\alpha(comparing) = .8$, $x_L = \$0$, and $x_H = \$150$.

Our model is different from models that include probability weighting. Inverse S-shaped probability weighting is one of the leading behavioral explanations for certainty effects under the pricing choice lists. Standard applications of probability weighting predict that longshots are weighted more heavily since small chances are magnified. In contrast, our model predicts a certainty effect under pricing lists because individuals get higher utility from longshots than from an equivalent but more likely outcome.

Figure 2 provides illustrative predictions for our environment using standard parameter values. In the figure, we plot the two components of the risk premia. We plot the expected value on the x-axis and the sure amount on the y-axis. We standardize these values by dividing both values by the maximum lottery outcome. This standarization allows deviations above the 45-degree line to be interpreted as risk tolerance and deviations below the line as risk aversion. To readers familiar with prospect theory, the generated figure is also analogous to the probability weighting function under a linear Bernoullian utility or value function.

In summary, our model predicts two certainty effects. The first predicted effect is that individuals will be risk-tolerant when the probabilities are unfavorable and become risk-averse as they become favorable. That is, they prefer certainty when the odds are favorable. The second predicted effect is that reversals will have the opposite effect near certainty. That is, they prefer certainty less when the odds are favorable and when comparing.

3 Experimental Design

The primary motivation for our experimental design was to determine whether reversals exhibit a certainty effect. A secondary motivation was to assess the external validity of prior results. We now discuss our experimental design. To assess the external validity of prior results, we aimed to raise the stakes and change the subject pool of prior experiments from students to commercial agricultural producers, who make frequent decisions under uncertainty. To establish a benchmark for comparisons with prior studies and with the new subject pool, we conducted lab experiments with students using both low stakes of prior experiments and high stakes of our experiment with producers. For this reason, the student experiment had more choice lists than the producer experiment. Our results with students and low stakes qualitatively replicate prior results. An interested reader may verify this claim by comparing our Figure 3a to Sprenger (2015)'s Figure 2.

In the following section 3.1, we first describe the main design, fixed for both subject types. We then expand on their differences. In section 3.2, we describe the implementation of the design.

3.1 Design

Our experiment uses two types of choice lists: a "pricing-a-fixed-lottery" choice list and a "comparing-lotteries-to-a-fixed-sure-amount" choice list. For any choice list, subjects choose between two alternatives multiple times. The option on the left-hand side of the list is fixed while the option to the right increases. As subjects move down the list, the probabilities or the outcome increases. Table 2 shows two sample choice list types.

Table 1: Pricing and Comparing Choice Lists

	Option A			or	Option B	
	Chance of \$0	Chance of \$150			Certain Amount	
	50 in 100	50 in 100	☑	*or*	\$0.00	☐
1)	50 in 100	50 in 100	☐	*or*	\$7.50	☐
2)	50 in 100	50 in 100	☐	*or*	\$15.00	☐
3)	50 in 100	50 in 100	☐	*or*	\$22.50	☐
⋮						
18)	50 in 100	50 in 100	☐	*or*	\$135.00	☐
19)	50 in 100	50 in 100	☐	*or*	\$142.50	☐
	50 in 100	50 in 100	☐	*or*	\$150.00	☑

	Option A		or	Option B		
	Certain Amount			Chance of \$150	Chance of \$0	
	\$75.00	☑	*or*	0 in 100	100 in 100	☐
1)	\$75.00	☐	*or*	5 in 100	95 in 100	☐
2)	\$75.00	☐	*or*	10 in 100	90 in 100	☐
3)	\$75.00	☐	*or*	15 in 100	85 in 100	☐
⋮						
18)	\$75.00	☐	*or*	90 in 100	10 in 100	☐
19)	\$75.00	☐	*or*	95 in 100	5 in 100	☐
	\$75.00	☐	*or*	100 in 100	0 in 100	☑

3.1.1 Main Choice Lists

For the pricing lists, the fixed alternatives are in the set of lotteries defined by $(p_i, 150; 1 - p_i, 0)$ and

$$p_i \text{ in } \{5\%, 10\%, 25\%, 50\%, 75\%, 90\%, 95\%\}.$$

For the comparing lists, the set of sure amounts match the lotteries' expected values; in other words,

$$c_i \text{ in } \{\$7.50, \$15.00, \$37.50, \$75.00, \$112.50, \$135.00, \$142.50\}.$$

The changing alternative always increases by 5% increments or the corresponding expected value increases. The common baseline design has fourteen choice lists, and each choice list has nineteen binary choices.

Table 2: Choice Lists

Choice List	Fixed Alternatives	Increments	Maximum Outcome
Pricing	{5%, 10%, 25%, 50%, 75%, 90%, 95%} chance of maximum outcome	\$7.50	\$150.00
Comparing	{\$7.50, \$15.00, \$37.50, \$75.00, \$112.50, \$135.00, \$142.50}	5%	\$150.00

3.1.2 Skewness Choice Lists

Table 3: Skewness Pricing and Comparing Choice Lists

	Option A: Chance of \$401	Option A: Chance of \$58		or	Option B: Certain Amount	
	5 in 100	95 in 100	☑	*or*	\$0.00	☐
1)	5 in 100	95 in 100	☐	*or*	\$7.50	☐
2)	5 in 100	95 in 100	☐	*or*	\$15.00	☐
3)	5 in 100	95 in 100	☐	*or*	\$22.50	☐
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18)	5 in 100	95 in 100	☐	*or*	\$135.00	☐
19)	5 in 100	95 in 100	☐	*or*	\$142.50	☐

	Option A: Chance of \$401	Option A: Chance of \$58		or	Option B: Chance of \$150	Option B: Chance of \$0	
	5 in 100	95 in 100	☑	*or*	0 in 100	100 in 100	☐
1)	5 in 100	95 in 100	☐	*or*	5 in 100	95 in 100	☐
2)	5 in 100	95 in 100	☐	*or*	10 in 100	90 in 100	☐
3)	5 in 100	95 in 100	☐	*or*	15 in 100	85 in 100	☐
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.							
18)	5 in 100	95 in 100	☐	*or*	90 in 100	10 in 100	☐
19)	5 in 100	95 in 100	☐	*or*	95 in 100	5 in 100	☐

To explore the out-of-sample predictive validity of our model, we also use (positively) skewed lotteries. These skewed lotteries provide an intermediate block of choice lists between the main pricing and comparing lists. In section 4.4, the skewness choice lists are also leveraged to explore and isolate the effect of context-dependent sensitivity. We elicit preferences for positive skewness using three types of lotteries (1) significant positive skew (s^H), (2) moderate positive skew (s^M), and (3) no skew (s^0). We use a high-stakes version for producers and a low-stakes version for students. Table **??** has an example of skewed-lotteries pricing and comparing choice lists.[4]

For the high incentives version ($x^H = \$150$) the (skewed) binary lotteries are $L_{s^H} = (.05, 401; .95, 58)$, $L_{s^M} = (.25, 204; .75, 32)$[5], and $L_{s^0} = (.5, 150; .5, 0)$. For the low incentives version ($x^H = \$30$) the (skewed) binary lotteries are $L_{s^H} = (.05, 81; .95, 12)$, $L_{s^M} = (.25, 41; .75, 7)$[6], and $L_{s^0} = (.5, 30; .5, 0)$. The

[4] We use Ebert and Karehnke (2019) to construct binary lotteries that increase skewness without affecting the first two moments.

[5] Note, the exact moments of the lotteries are the following: $\mathbb{E}(L_{s^H}) = 75.15$, $\sigma(L_{s^H}) = 74.75$, $skew(L_{s^H}) = 4.13$, $\mathbb{E}(L_{s^M}) = 75$, $\sigma(L_{s^M}) = 74.48$, and $skew(L_{s^M}) = 1.15$. The moments were chosen so the probabilities are rounder numbers.

[6] Note, $\mathbb{E}(L_{s^H}) = 15.45$, $\sigma(L_{s^H}) = 15.04$, $skew(L_{s^H}) = 4.13$, $\mathbb{E}(L_{s^M}) = 15.50$, $\sigma(L_{s^M}) = 14.72$, and $skew(L_{s^M}) = 1.15$.

unskewed lottery is in our original set of lotteries. Thus, these lists only add four additional choice lists to the overall design.

3.1.3 Difference between Experimental Designs and Choice List Order

Producers complete 18 incentivized choice lists while students complete 32 lists. The additional 14 lists for students are identical to the main choice lists but with a maximum outcome of \$30, versus \$150 in the main design. The maximum outcome of \$30 is comparable to the prior literature. Table 4 describes one potential ordering for a student and a producer. Instructions and examples precede each type of choice list. The skewness lists also have two different sets of examples and instructions, one for the skewness pricing lists and another for the skewness comparing lists.

Table 4: Sample Choice List Orderings

	block 1 (main)	block 2 (skew)	block 3 (main)
Ag. Producers	7 Comparing Lists w/ Max Outcomes of \$150	2 Comparing Lists (L_{sH} and L_{sM}) + 2 Pricing Lists w/ expected value of \$75	7 Pricing Lists Max Outcomes of \$150
Students	14 Comparing Lists, 7 w/ Max Outcomes of \$30 and 7 w/ \$150	2 Comparing Lists (L_{sH} and L_{sM}) + 2 Pricing Lists w/ expected value of \$30	14 Pricing Lists, 7 w/ Max Outcomes of \$30 and 7 w/ \$150

Our overall design is a within-subjects where we randomize the first type of choice lists. Half of our subjects, randomly assigned, complete all pricing choice lists first, and then all comparing choice lists. Conversely, the other half complete all pricing lists first. Within a block of either pricing or comparing lists, we randomize the order of the main lists. The same is true within a skewness list block. The randomness in the initial type of choice list enables us to test the prior first-contact endowment hypothesis and to determine whether the concern over evolving expectations for the referent/endowment is warranted.

3.2 Implementation

The experimental design was implemented online in oTree (Chen et al., 2016). Participants comprised 398 agricultural producers (experts), recruited from the top-twenty agricultural producing states, and 115 undergraduate students, recruited from the University of Delaware. The total number of recruited participants is consistent with the target sample sizes from the power analyses in our pre-analysis plan. To recruit students, we used the Center for Experimental and Applied Economics online recruiting tool. We posted an ad via the tool and closed recruitment once our target was reached. To recruit producers, we purchased a list of 10,000 mailing addresses from a private firm (Farm MarketID) and mailed them each producer a personalized invitation letter and a reminder letter. The mailers, the participation payment, and recruitment protocols for producers were based on prior research by one of the coauthors (Weigel et al., 2020).

To complete the experiment, the median student took 37.85 minutes and the median producer took 51 minutes. The average experimental (variable) payoffs were \$54.47 for students and \$90.48 for producers. Additionally, students received \$15 and producers received \$50 for their participation. Students participated during the winter of 2020, and producers participated in the spring of 2021.

To pay subjects, one binary choice from one choice list was selected at random for payment, and subjects were fully informed of this procedure (See Appendix A). This procedure is standard in the literature and is incentive compatible under specific preferences. In particular, preferences that are not linear in the probabilities will create portfolio effects, where subjects do not make decisions as if they treat each binary choice as independent but rather as if they are diversifying their portfolio over the choice list elements weighted by the probability of each binary choice (Karni and Safra, 1987; Cox et al., 2015). Under portfolio effects preferences over binary lotteries are not observable. Because the (stochastic) endowment for every choice list is fixed, our proposed model becomes expected utility for every list and hence does not exhibit portfolio effects. To communicate the randomization device to participants, we used an animation of a prize wheel. The back end of the animation used a random number generator, and all choices were equally likely to be selected for payment.

Some economic models rule out "multiple switching behavior" in choice lists like the ones we use in our design. Letting subjects exhibit this behavior, however, may reveal stochastic preferences (Chew et al., 2015; **?**). We thus allowed subjects to express multiple switch points but took steps to minimize the chance that mistakes drive such switching. First, we presented preselected dominant options at the top and bottom of the list when a monotonic relationship existed. Second, on the first screen, we allowed subjects to select a unique switch point. On the first screen, subjects could choose to make all of their binary choices manually or, after having selected a unique switching point on the first screen, they could change any individual choice manually. We hoped that this feature would also reduce the tedium of the experimental tasks.

4 Results

Our results are organized into four sections. First, we discuss between-subject risk attitude reversals. We also contrast results between students and producers at different incentive levels and context orders. Second, we assess within-subject differences to understand the potential welfare losses induced by reversals. Third, we perform a calibration exercise to provide parameter estimates for our model. Finally, we assess the out-of-sample predictive validity of our model. That is, we assess how well our model predicts in the skewness choice lists when compared to constant sensitivity KR and expected utility. None of the models were calibrated using the skewness lists.

Our results are organized into four sections. First, we report on risk attitude reversals in the between-subjects analysis. We also contrast the behavioral patterns of students and producers at different incentive levels and context orders. Second, to understand the potential welfare losses induced by the reversals, we conduct a within-subjects analysis. Third, to provide parameter estimates for our model (equation 9), we perform a calibration exercise. Finally, we assess the out-of-sample predictive validity of our parameterized model in comparison to a parameterized constant sensitivity KR model and an expected utility model with no loss-gain utility ($\mu(y) = 0 \; \forall y$).

In our analysis, we use subjects who only switch once on every choice list. We exclude subjects who switch multiple times because interpreting their choices requires stronger assumptions. If we instead use all the subjects and their first switching point, the results are qualitatively similar, see Appendix B. Fewer than 8% of the subjects in our experiment engaged in multiple switching, which is much lower than has been reported in some prior studies. For example, Jacobson and Petrie (2009) report that more than half of their subjects were multiple switchers. Our median subject exhibited no multiple switching. Out of 398 producers, 307 switched once: 141/181 who experienced pricing first and 166/207 who experienced comparing first. Out of 115 students, 88 switched once: 38/55 who experienced pricing first and 50/60 who experienced comparing first. Given the interval nature of our observations, for almost all analysis we use average value implied by the interval. For a given switch row in a list, the interval for a subject's preferences is the previous row and the switch row. To show that our results are robust to using the entire interval rather than the average value, we employ an interval regression at the end of section 4.1.

4.1 Risk Attitude Reversals

Risk premia are measured using the following function

$$\text{Risk Premia } = \begin{cases} \mathbf{p} \times \$150 - c & \text{comparing choice list }, \\ p \times \$150 - \mathbf{c} & \text{pricing choice list }. \end{cases}$$

Bold letters denote the value elicited by the choice list, and non-bold letters denote the fixed attribute. We use risk premia to examine risk attitude reversals using two measures.

The first measure of risk attitude reversals is the sign of the risk premia differences between pricing and comparing choice lists. The sign provides a coarse measure of reversals, and subsequent analyses strengthen these results. Table 5 shows that most producers exhibit a higher risk premium for comparing choice lists when the odds are unfavorable. However, when the odds are favorable, subjects exhibit the opposite pattern. This pattern reversal implies a *certainty effect for preference reversals*.

p / c	More Risk Averse when Comparing $\#(RP_{\mathcal{C}} \geq RP_{\mathcal{P}})$	Less Risk Averse when Comparing $\#(RP_{\mathcal{C}} < RP_{\mathcal{P}})$
5% / \$7.50	294	13
10% / \$15.00	295	12
25% / \$37.50	298	9
50% / \$75.00	241	66
75 % /\$112.50	98	209
90% / \$135.50	81	226
95% / \$142.50	72	235

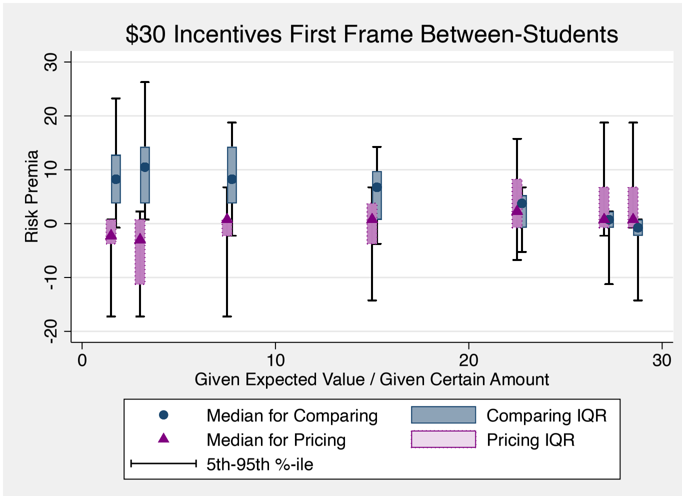
Table 5: Producers' Reversals by Value of the Fixed Alternative

Notes: Data is from 307 producers. RP=Risk premia, $\mathcal{C}$=comparing choice list, and $\mathcal{P}$=pricing choice list.

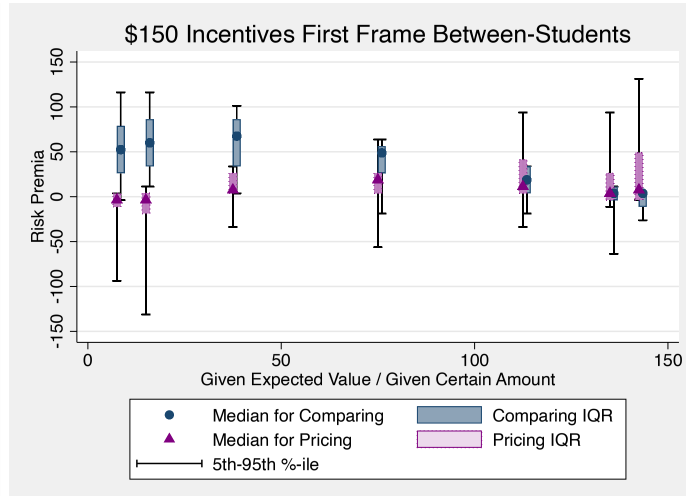
The second measure of risk attitude reversals is the distribution of risk premia across the pricing and comparison tasks (Figure 3). To facilitate comparisons across the two tasks in Figure 3, values on the x-axis are either sure amounts for comparing tasks or expected values for the pricing tasks. A positive risk premium implies the individual is risk-averse, and a negative risk premium implies the individual is risk-tolerant. As we inferred from the patterns in Table 5, we can infer the following from the patterns in Figure 3: subjects exhibit a higher risk premium for comparing tasks when the odds are unfavorable, but when the odds are favorable, they exhibit the opposite pattern. We note that Figure 3 is a simple way to represent deviations from risk neutrality; however, differences between the measures appear less substantial as the x-axis units across choice list types are not equal.

Figure 3 also allows us to assess the moderating effects on risk attitude reversals from a change in the subject pool, the stakes, or the order in which the tasks were presented. Recall that we use the student subject pool to assess the effects of stakes on risk attitude reversals.

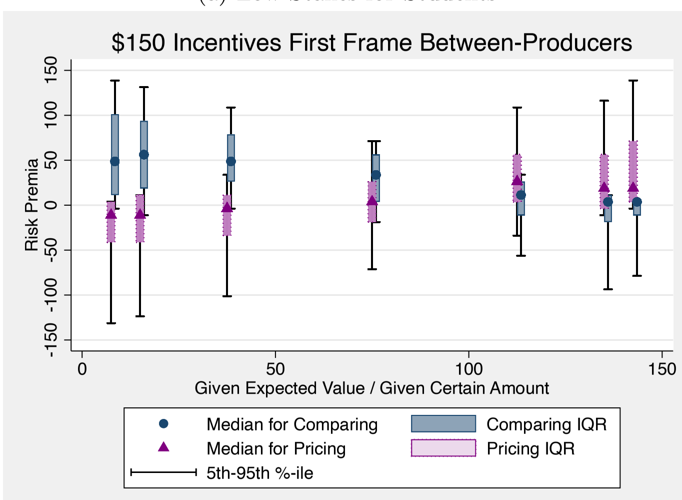
Subject Pool: By comparing panels (b) and (c), we observe that students and producers exhibit similar reversal patterns. Stakes: By comparing panels (a) and (b), we observe a substantial difference in the dollar values of risk premia differences (differences are larger with larger stakes) and a constant proportion of the highest outcome between the low and high stakes. Ordering: By comparing panels (c) and (d), we observe that subjects exhibit similar reversal patterns regardless of whether they already did one of the other task types or not.



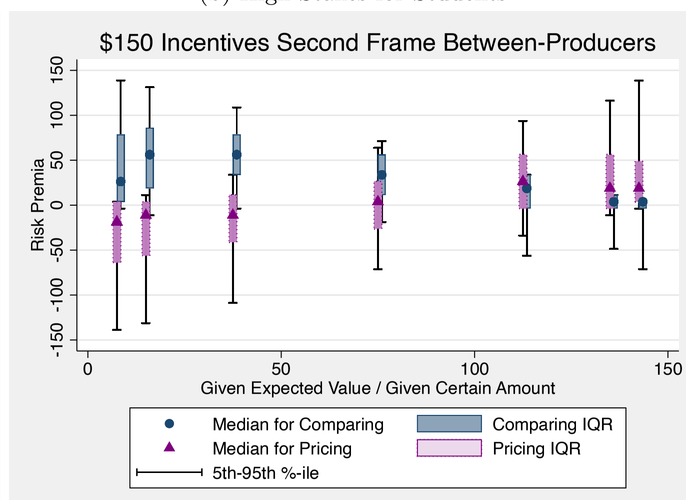
(a) Low Stakes for Students



(b) High Stakes for Students



(c) First Frame for Ag. Producers



(d) Second Frame for Ag. Producers

Figure 3: Comparisons by Stakes, Populations, and Context Ordering

Notes: Data is from 307 producers and 88 students who reported a unique switch point for every choice list. Results are qualitatively unchanged if we instead use all 398 producers and 115 students and their first switching point (see Appendix B).

To formalize the comparisons across subject pools and across ordering, Table 6 uses interval regression. The estimated context-dependent effect is larger for producers than for students, as implied by the larger coefficient when comparing as opposed to pricing (Comparing Choice List). The larger coefficient can be interpreted as producers exhibiting a larger endowment effect for risk. The estimated order effects from the first type of choice list (Pricing first dummy) are small and not statistically different from zero.

Table 6: Interval Regressions for Comparisons

Dependent Variable: Risk Premia Interval

	Farmers		Students	
	(1)	(2)	(1)	(2)
	$X_{max} = \$150$	$X_{max} = \$150$	$X_{max} = \$150$	$X_{max} = \$150$
Comparing	23.038	23.038	16.887	16.887
Choice List	[2.193]	[2.193]	[2.268]	[2.268]
$C_{comparing}$ or	.011	.011	-.063	-.063
$EV_{pricing}$	[.012]	[.012]	[.0180]	[.018]
Pricing first		-2.249		5.261
dummy		[2.361]		[3.411]
Constant	1.572	2.789	15.964	12.974
	[1.986]	[2.316]	[2.482]	[2.797]
Observations	4,298	4,298	1,232	1,232
Clusters	307	307	88	88
Log likelihood	-14,071.67	-14,070.495	-3,672.401	-3669.120

Notes: Data is from 307 producers and 88 students who reported a unique switch point for every choice list. Results are qualitatively unchanged if we instead use all 398 producers and 115 students and their first switching point (see Appendix B). Standard errors are reported in square brackets.

We conclude by pooling all of our producer data together and showing the certainty effect for risk graphically. Figure 4 presents the median choices for all our producers. As in the theoretical section, we normalize certainty equivalents on the y-axis and expected values on the x-axis dividing by the maximum outcome. Again, the normalization allows us to interpret deviations from the 45-degree line as specific risk attitudes and also visualize them as probability weighting functions. We stress Figure 4 should be compared to Figure 2.

We emphasize three main takeaways from Figure 4. First, we replicate the endowment effect for risk as the majority of median decisions when comparing lie below the median decisions when pricing. This implies producers are more risk when comparing. Second, we replicate the inverse-S pattern for producers. When pricing, producers are clearly more risk tolerant when the chances of a favorable outcome are low than when they are high. Third, producers exhibit less risk aversion when comparing near certainty. To our knowledge, this behavioral pattern had not been previously documented, and behavioral models that explain preference reversal would struggle to accommodate this pattern.

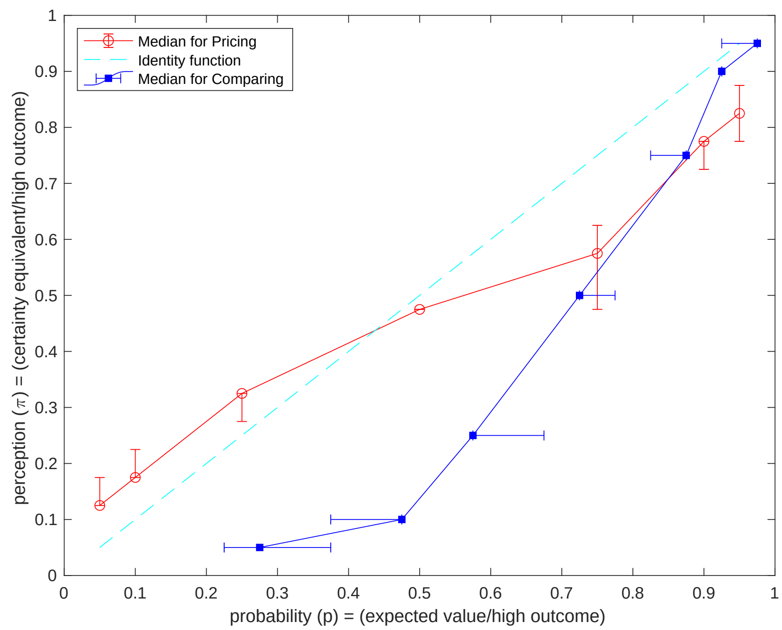


Figure 4: Normalized Median Choices by Choice List Type

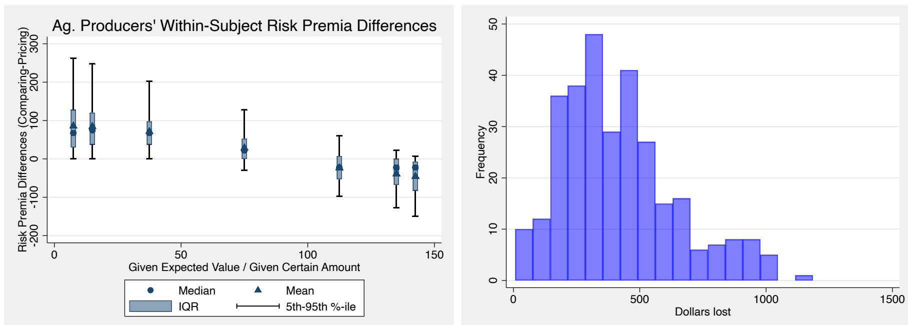
Notes: Data is from 307 producers and 88 students who reported a unique switch point for every choice list. Results are qualitatively unchanged if we instead use all 398 producers and 115 students and their first switching point (see Appendix B). Standard errors are reported in square brackets. Error bars represent 95% confidence intervals for median values.

4.2 Within-Subject Differences

In this section, we use the within-subject data to estimate the potential magnitude of the welfare losses due to risk attitude reversals. The welfare results rely on a money-pump or dutch-book type argument. That is, not only that subjects make these types of suboptimal choices, but they would *repeatedly* make them.

We present two types of suggestive welfare results. The first type requires subjects to only participate in one unfavorable trade. To determine whether participants would participate in multiple suboptimal trades would require paying for every choice, which can be financially and theoretically unsound (Azrieli et al., 2018; Cox et al., 2015). In our design, all choices are paid with positive probability, but only one choice is selected at random for payment. As a second type of welfare result, we use the total loss that results from participating in all the suboptimal trades that are consistent with a subject's preference reversals.

Figure 5a summarizes the (expected) welfare loss due to a single preference reversal for different odds. The median welfare loss is over a third of the maximum outcome for unfavorable odds. The median welfare loss is lower near favorable odds and is about a third of the maximum loss. Figure 5b summarizes the distribution of welfare losses due to all unfavorable trades being executed. The average total loss is \$416.75 (\$11.72 s.e.) from a total expected value of \$1050 for all fourteen choice lists.



(a) (Expected) Welfare Loss from One Preference Reversal

(b) (Expected) Welfare Loss from All Preference Reversals

Notes: Data is from 307 producers and 88 students who reported a unique switch point for every choice list. Results are qualitatively unchanged if we instead use all 398 producers and 115 students and their first switching point (see Appendix B).

4.3 Calibration

We now proceed to estimate a parametric version of the KR model with context-dependent sensitivity and contrast the estimated parameter values to those from parametric versions of the EU model and the KR model with constant sensitivity. For the calibration, we assume that $\eta = 1$ and latent preferences are given by $m(x) = \frac{x^\rho}{\rho}$, i.e., constant relative risk aversion (CRRA).

$$\begin{aligned} u(x|r) &= \frac{x^\rho}{\rho} + \mu(\frac{x^\rho}{\rho} - \frac{r^\rho}{\rho}) \\ V(F|G) &= \int\int u(x|r)dG(r)dF(x), \end{aligned} \tag{10}$$

with,

$$\mu(y) = \begin{cases} \frac{y^{\alpha(ctx)}}{\alpha(ctx)} & y \geq 0, \\ \lambda\frac{y^{\alpha(ctx)}}{\alpha_(ctx)} & y < 0\ . \end{cases}$$

Where ρ is the latent risk aversion parameter, λ is the (stochastic) loss aversion parameter, $\alpha(pricing)$ measures the context-dependent sensitivity of loss-gain utility under pricing, and $\alpha(comparing)$ is the analog under the comparing context.

To estimate parameters at the individual level, we use nonlinear least squares to compute our estimates to find the set of parameters that minimize the squared sum of prediction errors. We use the chance of the maximum outcome (p_H) as our independent variable and derive the estimating equations from the indifference conditions. Equation 6 gives the estimating equation for the comparing choice lists while solving for the positive root for equation 1 equal to equation 2 gives the estimating equation for the pricing choice list. Explicitly, we use the following calibrating equation:

$$p_H = \begin{cases} \dfrac{\frac{c^\rho}{\rho} + \frac{\lambda}{\alpha(\mathcal{C})}\left(\frac{c^\rho}{\rho} - \frac{x_L^\rho}{\rho}\right)^{\alpha(\mathcal{C})}}{\frac{x_H^\rho}{\rho} + \frac{1}{\alpha(\mathcal{C})}\left(\frac{x_H^\rho}{\rho} - \frac{c^\rho}{\rho}\right)^{\alpha(\mathcal{C})} + \frac{\lambda}{\alpha(\mathcal{C})}\left(\frac{c^\rho}{\rho} - \frac{x_L^\rho}{\rho}\right)^{\alpha(\mathcal{C})}} & \text{if comparing,} \\ \\ \frac{-B+\sqrt{B^2-4AC}}{2A} & \text{if pricing ,} \end{cases} \tag{11}$$

with

$$A = \frac{(\lambda - 1)}{\alpha(\mathcal{P})}\left(\frac{x_H^\rho}{\rho} - \frac{x_L^\rho}{\rho}\right)^{\alpha(\mathcal{P})},$$

$$B = \frac{x_H^\rho}{\rho} - \frac{x_L^\rho}{\rho} + \frac{(1-\lambda)}{\alpha(\mathcal{P})}\left(\frac{x_H^\rho}{\rho} - \frac{x_L^\rho}{\rho}\right)^{\alpha(\mathcal{P})} + \frac{\lambda}{\alpha(\mathcal{P})}\left(\frac{x_H^\rho}{\rho} - \frac{c^\rho}{\rho}\right)^{\alpha(\mathcal{P})} + \frac{1}{\alpha(\mathcal{P})}\left(\frac{c^\rho}{\rho} - \frac{x_L^\rho}{\rho}\right)^{\alpha(\mathcal{P})},$$

and

$$C = -\frac{1}{\alpha(\mathcal{P})}\left(\frac{c^\rho}{\rho} - \frac{x_L^\rho}{\rho}\right)^{\alpha(\mathcal{P})} - \frac{c^\rho}{\rho} + \frac{x_L^\rho}{\rho}.$$

Initial values are identical to Figure 2 and reflect standard values. We also estimate an EU model with preferences given by $u(x) = \frac{x^\rho}{\rho}$. Our estimation equation for EU is

$$p_H = \frac{u(c) - u(x_L)}{u(x_H) - u(x_L)}.$$

Table 7 provides summary statistics for the individual estimates of the model parameters. We caution the reader that the *stochastic* loss aversion parameter is not the same construct as the loss aversion parameter arising from the deterministic model that is commonly used by prior studies. A rule of thumb to relate loss aversion parameters is that the stochastic model's parameter is one more than the loss aversion parameter from the deterministic model (DellaVigna, 2009). Therefore, our median estimated parameter for loss aversion (λ) is consistent with values published in prior studies, see Brown, Imai, Vieider, and Camerer (Brown et al.).

Consistent with prior reports, our own estimate for risk aversion parameter under EU have an individual median value for risk aversion of .5918 (95% CI:[.5323,.6426]). The lower curvature under our model is the result of controlling for loss-aversion and context-dependence. As our theory suggests, higher risk aversion observed in laboratory studies appears to be driven by context. For instance, certainty equivalents often yield curvature estimates near the risk-neutral benchmark. Please note that identifying latent intrinsic preferences

Table 7: Individual Parameters for KR w/ Context-Dependent Sensitivity

parameter	median	95% CI
ρ	0.758	[0.658, 0.913]
λ	2.594	[1.629, 4.931]
α(Pricing)	1.735	[1.514, 2.018]
α(Comparing)	0.407	[0.296, 0.546]

Notes: Note, ρ is the latent risk aversion parameter, λ is the loss aversion parameter, and $\alpha(context)$ measures the context-dependent sensitivity of loss-gain utility for each type of choice list. Estimates are for 302 producers who reported a unique switch point for every choice list. For five subjects parameters could not be estimated. Confidence intervals exhibit a substantial overlap if we use the first switching point instead (see Appendix B).

requires at least two distinct contexts. Prior studies assume latent utilities are linear to sidestep this issue.

As our theory suggests, the higher risk aversion observed in laboratory studies appears to be driven by context. For instance, certainty equivalents often yield curvature estimates near the risk-neutral benchmark. Please note that identifying latent intrinsic preferences requires at least two distinct contexts. This requirement is similar to loss aversion which requires both "losses" and "gains". Prior studies assume latent utilities are linear to sidestep Rabin's critique that these higher curvature estimates are dubious (Rabin, 2000).

In addition to estimating the EU model and the KR model with context-dependent sensitivity, we estimate a parametric version of the KR model with constant sensitivity, as in Sprenger (2015). With constant sensitivity, loss attitudes only affect behavior in the comparing tasks and thus the parameter values are elicited using only those tasks. The individual median value for loss aversion is 6.884 (95% CI: [6.131,7.444]). This value would imply losses lead to sevenfold increase in the disutility of a loss from an equivalent gain. This value is inconsistent with our point estimate for median loss aversion of 2.594 (95% CI: [1.629, 4.931]) and the rest of the literature. In the next section, we assess the ability to predict choices in the skewness task for the EU model, the constant sensitivity KR model, and our context-dependent sensitivity KR model.

4.4 Out-of-Sample Predictive Validity

In this section, we demonstrate that, in comparison to the EU model and the KR model with constant sensitivity, our KR model with context-dependent sensitivity does a better job of predicting behavior in a challenging out-of-sample decision environment. To assess the out-of-sample predictive validity of these models, we use skewness tasks, which were not used for the model calibrations in the previous section. Skewness tasks are challenging for most models of decision-making under uncertainty. For example, one may interpret Allais' and the St.

Petersbrug's paradoxes as reflecting a preference for skewness.[7] As described in our pre-analysis plan, we chose non-negative skewness tasks to examine the robustness of the endowment effect for risk with tasks that usually induce higher tolerance for risks.

To examine predictive validity, we evaluate differences between the producers' predicted (expected) risk premia and their observed premia. To calculate the distance between predictions and observations, we employ two procedures: one for pricing and another for comparing skewness choice lists. For pricing, we use predicted certainty equivalents to compute predicted risk premia and contrast them with the observed risk premia. For comparing, we use predicted probability equivalents to compute the expected risk premia. The expected risk premia is given by

$$\mathbb{E}[\text{Risk Premia}] = \mathbb{E}[\mathbf{p}] - \mathbb{E}[S].$$

Like standard risk premia, expected risk premia correlates higher positive values with higher risk aversion. In the next paragraph, we describe the general predictive model, for which the expected utility model and the KR model with constant sensitivity are special cases.

We denote a skewed lottery by $S = (p, s_H; 1-p, s_L)$ and the comparing lottery by $L = (q, x_H; 1-q, x_l)$, with $s_H > x_H > s_L > x_L$. We use c to label the sure amount. Under the KR model, utilities are given by

$$U(S|S) = q^2 u(s_H|s_H) + (1-q)^2 u(s_L|s_L) + q(1-q)\left(u(s_L|s_H) + u(s_H|s_L)\right),$$

$$U(L|S) = p\left(qu(x_H|s_H) + (1-q)u(x_H|s_L)\right) + (1-p)\left(qu(x_L|s_H) + (1-q)u(x_L|s_L)\right),$$

$$\text{and } U(c|S) = qu(c|s_H) + (1-q)u(c|s_L).$$

For the pricing choice lists, indifference is given by $U(c|S) = U(S|S)$. Numerically we find the roots for the following equation

$$c + q\mu\left(m(c) - m(s_H)\right) + (1-q)\mu\left(m(c) - m(s_L)\right) = U(S|S).$$

For the comparing choice lists, indifference is given by $U(L|S) = u(S|S)$. Solving yields the following equation

$$p = \frac{U(S|S) - U(x_L|S)}{U(x_H|S) - U(x_L|S)}.$$

We note that extreme risk tolerance can yield values higher than unity because the choice list for comparing is censored at the top. That is, we cannot measure preferences where the skewed lottery is always preferred to any probability equivalent for the fixed outcomes x_H and x_L.

The differences between predicted and observed values according to each model are presented in Figure 6. Both stochastic reference dependence models predict choices better than the expected utility model. The Spearman correlations for the KR model with constant sensitivity and our model are 0.334 and

[7] See Dertwinkel-Kalt and Köster (2020)

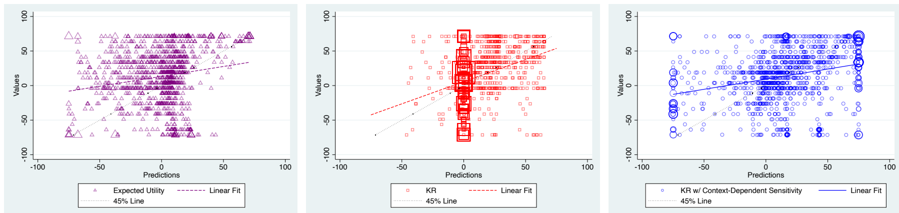


Figure 6: Predicted and Observed Values

Notes: Data is from 307 producers with a unique switch-point. Results are qualitatively unchanged if we use the first switching point instead.

0.308, respectively, which contrast favorably with 0.201 for the expected utility model.[8] The median squared errors are also lower for both KR models in comparison to the expected utility model (679 and 689 versus 917). Figure 7 summarizes the distribution of parameter values for our model and KR with constant sensitivity.

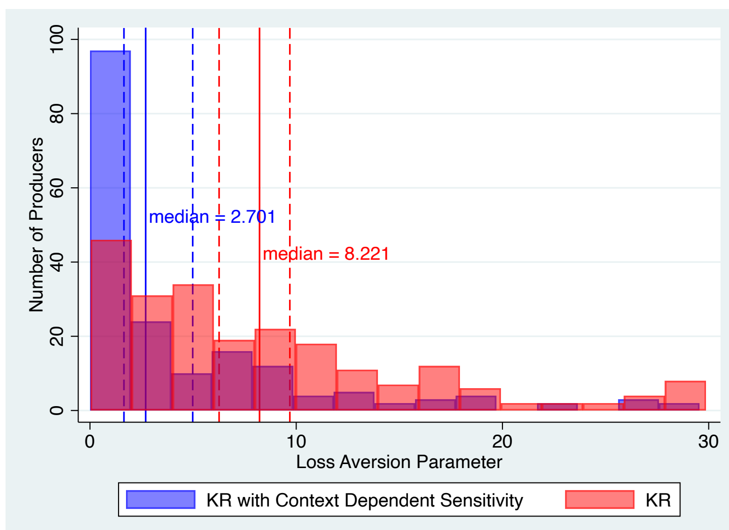


Figure 7: Loss-Aversion Parameter Values

Notes: Data is from 307 producers with a unique switch-point. Dashed lines are 95% confidence intervals. Picture restricts observation to values in [0,30) for readability, all summary statistics use the 307 producers. Dashed lines represent 95% confidence intervals.

Contrasting our results with the results in Sprenger (2015), two features emerge. First, our out-of-sample tasks are substantially more challenging than the out-of-sample prediction tasks used by Sprenger. Our skewness tasks fea-

[8]We use CRRA-type preferences throughout.

ture lower correlations and linear fit for all models than the out-of-sample tasks from Sprenger's study. Second, the overall predictive validity of our KR model with context-dependent sensitivity and the KR model with constant sensitivity are similar, but the loss aversion values for the KR model with constant sensitivity are problematic. We remind the reader that the loss aversion parameter measures how much more losses are felt than corresponding gains. Whereas, our model yields median loss aversion values (2.701) that are comparable with the prior literature (Brown, Imai, Vieider, and Camerer, Brown et al.), the KR model with constant sensitivity yields median values that are much larger (8.221). Thus, our model does a relatively better job of explaining the observed behavior in these challenging environments.

5 Discussion and Conclusion

By formally combining stochastic reference dependence from the economics literature and context-dependent sensitivity from the psychology literature, we develop a model that provides a new explanation for previously identified risk preference reversal patterns and an explanation for a new certainty effect for preference reversals. We also demonstrate that this new certainty effect cannot be explained by the expected utility model or the Koszegi-Rabin stochastic reference dependence model with constant sensitivity (Kőszegi and Rabin, 2006, 2007; Sprenger, 2015). Moreover, in comparison to these rival models, our model provides more plausible individual-level estimates of preference parameters and better predictions in an out-of-sample predictive validity exercise.

Any model that aims to explain risk preference reversals must explain the framing effect that depends on which attribute in an experimental choice list is changing across the choices. Consider an individual who, in the pricing choice list, chooses \$75 for sure rather than a 50/50 gamble that yields either \$150 or nothing but, in the comparing choice list, chooses the 50/50 gamble. As illustrated in Figure 8, the binary choices are identical across the pricing and comparing choice lists. However, the frame of the choices differs because, as one moves down the lists, the monetary amount is changing in the price list and the chance of a favorable outcome is changing in the choice list. The framing effects in our experiment cannot be explained by models that assume that differences across preferences over binary outcomes are either constant or purely stochastic. This assumption, however, is implicit in most behavioral models that aim to explain risk preference reversals, as we explain in the next paragraph.

Decades ago, Grether and Plott (1979) claimed that context dependence is the irrefutable explanation for preference reversals, a claim that spurred a wide range of efforts to eliminate or rationalize these reversals. However, popular competing explanations for reversals cannot explain the patterns that we observe in our experiments. These explanations include cognitive limitations concerning the probabilities (Enke and Graeber, 2019; Khaw et al., 2021), random mistakes and impreciseness (Blavatskyy, 2007; Butler and Loomes, 2007; Collins and James, 2015), salience (Bordalo et al., 2012) and complexity (Puri,

Pricing Tasks

	Different Choice Lists/Chances of $100										
	A1	A2	A3	A4	A5	A6	A7	A8	A9	*or*	B
1)	10 in 100	20 in 100	30 in 100	40 in 100	50 in 100	60 in 100	70 in 100	80 in 100	90 in 100		$10
2)	10 in 100	20 in 100	30 in 100	40 in 100	50 in 100	60 in 100	70 in 100	80 in 100	90 in 100		$20
3)	10 in 100	20 in 100	30 in 100	40 in 100	50 in 100	60 in 100	70 in 100	80 in 100	90 in 100		$30
4)	10 in 100	20 in 100	30 in 100	40 in 100	50 in 100	60 in 100	70 in 100	80 in 100	90 in 100		$40
5)	10 in 100	20 in 100	30 in 100	40 in 100	50 in 100	60 in 100	70 in 100	80 in 100	90 in 100		$50
6)	10 in 100	20 in 100	30 in 100	40 in 100	50 in 100	60 in 100	70 in 100	80 in 100	90 in 100		$60
7)	10 in 100	20 in 100	30 in 100	40 in 100	50 in 100	60 in 100	70 in 100	80 in 100	90 in 100		$70
8)	10 in 100	20 in 100	30 in 100	40 in 100	50 in 100	60 in 100	70 in 100	80 in 100	90 in 100		$80
9)	10 in 100	20 in 100	30 in 100	40 in 100	50 in 100	60 in 100	70 in 100	80 in 100	90 in 100		$90

Comparing Tasks

	Different Choice Lists/Sure Amounts										Chances of $100
	A'1	A'2	A'3	A'4	A'5	A'6	A'7	A'8	A'9	*or*	B'
1)	$10	$20	$30	$40	$50	$60	$70	$80	$90		10 in 100
2)	$10	$20	$30	$40	$50	$60	$70	$80	$90		20 in 100
3)	$10	$20	$30	$40	$50	$60	$70	$80	$90		30 in 100
4)	$10	$20	$30	$40	$50	$60	$70	$80	$90		40 in 100
5)	$10	$20	$30	$40	$50	$60	$70	$80	$90		50 in 100
6)	$10	$20	$30	$40	$50	$60	$70	$80	$90		60 in 100
7)	$10	$20	$30	$40	$50	$60	$70	$80	$90		70 in 100
8)	$10	$20	$30	$40	$50	$60	$70	$80	$90		80 in 100
9)	$10	$20	$30	$40	$50	$60	$70	$80	$90		90 in 100

Same Binary Choices

Figure 8: Pricing and Comparing Frames

2018). These competing explanations are ruled out by their inability to predict systematic differences across pricing and comparing frames. Middle-of-the-list effects are also ruled out because they predict symmetry in the deviations from expected utility generated by the pricing and comparing tasks, which we do not observe.[9] We can also reject heuristic-based theories that suggest a single reversal (e.g., the evaluation mode hypothesis in Hsee (1996)). Alternative normative explanations, like the lack of independence (Karni and Safra, 1987; Holt, 1986) or the failure of reduction (Segal, 1988) often shift the blame to the elicitation procedure. These explanations are correct in suggesting that non-expected utility models may lead people to hedge, which will distort incentive compatibility. However, these explanations only predict that reversals may happen. They do not explain why specific patterns arise. Moreover, Tversky et al. (1990) show that eliminating incentives for hedging, by using pricing tasks to only derive ordinal rankings between alternatives, does not eliminate reversals.

In addition to providing a concise, coherent explanation for preference reversals, our model also provides insights into when and why experience can

[9] In Figure 4 The deviations from the risk-neutral benchmark (45^o line) are not symmetric, nor are the deviations for probabilities above and below 50%.

eliminate preference reversals. Despite the abundant empirical evidence for preference reversals, economists tend to disregard them in theory and applications. That disregard may be motivated, in part, by a belief that market experience eradicates these reversals (List, 2002; Cox and Grether, 1996). For example, List (2003) reports that market experience eradicates the endowment effect (i.e., when a good's value increases after it becomes part of an individual's endowment; see also Tong et al. (2016)). Our model provides a potential explanation for the mechanism through which experience may affect preference reversals. Recall that the referent in our model is disciplined by the endowment – i.e., the fixed alternative in experimental elicitation tasks. We conjecture that, with additional experience, exogenous reference points will converge to endogenous (rational) expectations and preference reversals will decrease. One example of this convergence is KR's Choice-Acclimating Personal Equilibrium, where the optimal choice becomes the rational reference point. However, our model and experimental results also imply that economically meaningful preference reversals can persist in unfamiliar choice contexts or in familiar contexts that lack salient feedback on the outcomes of prior decisions.

Because our model provides an alternative to probability weighting as an explanation for the overweighting of low probability events, it also sheds light on why the empirical evidence concerning the effectiveness of lottery incentives is mixed. If individuals overweigh low probability events, then individuals should be more responsive to lottery incentives than fixed incentives with the same expected costs. Yet the limited use of lotteries by practitioners and policymakers suggests that leveraging probability distortions is challenging. Our model provides a reason for this challenge. Under our model, an increase in risk tolerance when the odds are unfavorable results in a utility boost from surprises. Thus, how individuals respond to lottery incentives will depend on how the choices and the alternatives are framed. In other words, our model predicts that, unless practitioners and policymakers have precise control over the choice context, lottery incentives will have unpredictable effects.

Finally, we note that our model's ability to separate utility into latent and loss-gain utility overcomes Rabin's Paradox (Rabin, 2000). Rabin's Paradox posits that moderate degrees of risk aversion can imply implausible choices. In our model, latent risk attitudes exhibit substantially less risk aversion than is assumed in standard calibrations, which rely on estimated values that are inflated by the effects of reference dependence. The separation of preferences into latent and loss-gain utility allows us to recover both stable (latent) and the labile (loss-gain) components of preferences. Future research should address whether our model can also be used to explain the observed lack of coherence among different risk preference elicitation tasks (Andreoni and Kuhn, 2019; Friedman et al., 2022).

In sum, our theoretical model incorporates the intuition from behavioral economists that initial endowments matter and the intuition from psychologists that individuals are sensitive to contextual features that change across choice options. The intuition for these insights is connected to two well-studied behavioral biases: loss aversion and context- dependent sensitivity. Hence, we can explain old behavioral anomalies from prior experiments and the new behavioral anomaly from our experiments without needing to create yet another "bias." Moreover, as described above, our model provides insights into when and why market experience can eliminate preference reversals, why field applications of lottery incentives have yielded conflicting results, and how prior risk parameter calibration critiques may be resolved. Nevertheless, the performance of our model in our challenging out-of-sample predictive validity environment using skewness tasks implies that further theoretical advances are needed. Our model provides one foundation for such advances.

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[Supplemental Material]

Appendix A Producers' Experimental Instructions and Choice Lists

Consent for Study: Behavioral Preferences about Uncertainty

You are invited to take part in a research study conducted by researchers at Johns Hopkins University. In this study, you will indicate your preferences for payments, some of which may be certain and some which may have an element of chance.

Your participation is voluntary and should take 30 minutes or less. We will keep your answers confidential and will not share your personal information with anyone outside the research team. For your participation, you will receive a $50 payment and an opportunity to receive another payment. Your payments will be loaded on a prepaid Visa card, which we will send to you in the mail. At the end of the study, you must provide a valid mailing address in the United States.

Questions? Please contact Dr. Paul Feldman at (218) 231-1331. If you have questions or concerns about your rights as a research participant, you can call the Homewood Institutional Review Board at Johns Hopkins University at (410) 516-6580.

If you want to participate in this study, click the Next button to start. If you do not wish to continue, simply close this window.

Next

Instructions

Please Watch the Entire 60-second Video. Click on video to pause. Click again to play. After the video has ended, a button will appear at the bottom of the page (scroll down to see it). You can click on "Watched Video" button or watch the video again.

VIDEO SCRIPT

Hello and Welcome!

This is a study about your preferences. There are no right or wrong choices.

The study has two parts. In the first part, you will complete 18 different tasks. In each task, you will decide between two options for earning money. After you have made all of your decisions, we will select one of your decisions at random to be paid for real.

Each decision is equally likely to be selected. So you should treat each decision carefully because your additional payment could depend on your choice in that decision.

The second part of the study is a short survey.

On the next few pages, you will see examples of the type of choices you will make and how you can earn additional money. Please go through the examples carefully and make sure you understand them. Once you begin the study, you will not be allowed to go back to the examples.

I have watched the video.

Options | Chances | Tables | Switching Row | Finalizing Decisions

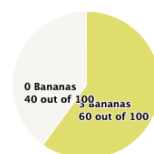
Choosing Between Two Options

Note: This decision about fruit is just an example. All choices in the study will be about money.

Important: You can adjust your screen at any time by pressing CTRL *and* + to zoom in or CTRL *and* - to zoom out. On a Mac, ⌘ Command *and* + or ⌘ Command *and* -, respectively.

Example: Would you prefer to have an Apple or the chance to have 3 bananas?

or



Now select your preference by clicking the radio button for Option A (Apple) or for Option B (Banana).

	Option A Certain Amount		*or*	Option B Chance of Three Bananas	 Chance of Zero Bananas	
12)	An Apple	A	*or*	60 in 100 chance	40 in 100 chance	B

Next

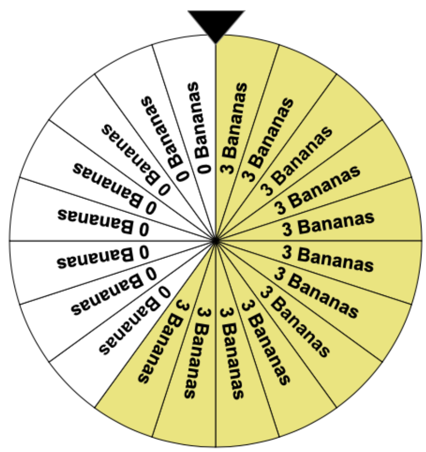
Options | Chances | Tables | Switching Row | Finalizing Decisions

Determining your chances

If you chose Option A you would get an Apple for sure.

If instead you chose Option B, chance would determine your earnings. You have a 60 in 100 chance of three bananas. To determine your outcome, please spin the wheel by clicking on it. The wheel below illustrates "how chance works".

Spin the Wheel



Note: In this example, you can spin the wheel as many times as you want. For the real decisions, you can only spin the wheel once. The stopping point on the wheel is truly random. It is not pre-determined. Our university prohibits us from deceiving participants in this study.

Important: You can adjust your screen at any time by pressing CTRL *and* + to zoom in or CTRL *and* - to zoom out. On a Mac, ⌘ Command *and* + or ⌘ Command *and* -, respectively.

Back | Next

Options Chances Tables Switching Row Finalizing Decisions

A sample table

As we described in the video, you will make multiple decisions, each time choosing between two options. The decisions will be in a table like the one below, with each decision in a row. Option A will be always be the same for all rows, but Option B will change across rows.

After you have made your decisions-–in other words, after you have chosen an option for every row in each table--we will select one numbered row from one table at random to determine your additional payment. Each row is equally likely to be chosen, so make each decision as if it is the one decision for which you will be paid.

	Option A Certain Amount		*or*	Option B Certain Amount	
	Five Apples	A	*or*	Zero Bananas	B
1)	Five Apples	A	*or*	One Banana	B
2)	Five Apples	A	*or*	Two Bananas	B

Important: You can adjust your screen at any time by pressing CTRL *and* + to zoom in or CTRL *and* - to zoom out. On a Mac, ⌘ Command *and* + or ⌘ Command *and* -, respectively.

Back Next

Options | Chances | Tables | Switching Row | Finalizing Decisions

Selecting a Switching Row

One way to make your choices is to pick the row in which you switch from preferring Option A to preferring Option B.

During the study you may select a switching row by entering a row number into the box. This will automatically fill in your choices.

Switching Row:

5

	Option A Certain Amount		or	Option B Certain Amount	
	Five Apples	A	*or*	Zero Bananas	B
1)	Five Apples		*or*	One Banana	
2)	Five Apples		*or*	Two Bananas	
3)	Five Apples		*or*	Three Bananas	
4)	Five Apples		*or*	Four Bananas	
5)	Five Apples		*or*	Five Bananas	
6)	Five Apples		*or*	Six Bananas	
7)	Five Apples		*or*	Seven Bananas	
8)	Five Apples		*or*	Eight Bananas	

Important: You can adjust your screen at any time by pressing CTRL *and* + to zoom in or CTRL *and* - to zoom out. On a Mac, ⌘ Command *and* + or ⌘ Command *and* -, respectively.

Back

Next

Options | Chances | Tables | Switching Row | Finalizing Decisions

Finalizing Your Decisions

Imagine you selected Row 5 as your *switching row*. Then, the computer would fill in the rest of the table as shown below. You can still manually change your decision in any row before submitting your decisions.

If you are ready to move on to the decisions, click on the End Examples button below. Otherwise, click Back to review the instructions.

	Option A Certain Amount		*or*	Option B Certain Amount	
	Five Apples	A	*or*	Zero Bananas	B
1)	Five Apples	A	*or*	One Banana	B
2)	Five Apples	A	*or*	Two Bananas	B
3)	Five Apples	A	*or*	Three Bananas	B
4)	Five Apples	A	*or*	Four Bananas	B
5)	Five Apples	A	*or*	Five Bananas	B
6)	Five Apples	A	*or*	Six Bananas	B
7)	Five Apples	A	*or*	Seven Bananas	B
8)	Five Apples	A	*or*	Eight Bananas	B

Important: You can adjust your screen at any time by pressing CTRL *and* + to zoom in or CTRL *and* - to zoom out. On a Mac, ⌘ Command *and* + or ⌘ Command *and* -, respectively.

Back | End Examples

Before we begin

- Once you click on the Next on any page you will not be able to go back to any previous page.

- Please use a laptop or desktop for the study. This study will be strenuous on a mobile device.

- If you close this window, you can return to the page where you left off by by logging in again to our study using your personal password or bookmarking this page.

- We encourage storing your password in a safe place until you get paid.

- Please take as many breaks as you need.

- You will make four different types of decisions. Before starting each type, you will see an example.

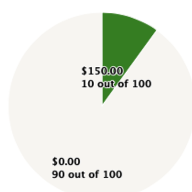
Next

Example 1

On the next page, your task will be to choose Option A or Option B. If you choose Option A, you will have a chance of receiving a large payment and a chance of receiving nothing. If you choose Option B, you will receive a specific amount of money for sure. Option A is fixed for every row. The amount you receive in Option B increases as you move down the rows. Here's an example of the next 7 tables.

	Option A			or	Option B	
	Chance of $150.00	Chance of $0.00			Certain Amount	
	10 in 100 chance	90 in 100 chance	A	or	$0.00	B
1)	10 in 100 chance	90 in 100 chance	A	or	$7.50	B
2)	10 in 100 chance	90 in 100 chance	A	or	$15.00	B
3)	10 in 100 chance	90 in 100 chance	A	or	$22.50	B
				.		
				.		
				.		
	10 in 100 chance	90 in 100 chance	A	or	$150.00	B

Imagine that, after you made your choices in every row, Row 3 was randomly selected to be the decision for which you can receive an additional **payment**. You would be paid based on what Option you chose. If you selected Option B, you would get $22.50 for sure. If you selected Option A, you would spin the wheel and get either $150.00 with a 10 in 100 chance or $0.00 with a 90 in 100 chance.



Note: You can adjust your screen at any time by pressing CTRL *and* + to zoom in or CTRL *and* - to zoom out. On a Mac, ⌘ Command *and* + or ⌘ Command *and* -, respectively.

Next

Table 1

Please read each row carefully. *Remember, any row can be chosen to be paid for real. So treat each row as if it could be the one that determines your final payment.*

In the Switching Row box below, you can select the row at which you would like to switch from Option A to Option B. The computer will then automatically fill in the buttons for Option B in your chosen row and all the subsequent rows. You can choose any switching row from 1 (choose Option B for every row) to 20 (choose Option A for every row).

If you want to manually select your preferred option for each row, just leave the 0 in the box and click "Next."

Switching Row:

0

Next

	Option A			or	Option B	
	Chance of $150.00	**Chance of $0.00**			**Certain Amount**	
	10 in 100 chance	90 in 100 chance	A	*or*	$0.00	B
1)	10 in 100 chance	90 in 100 chance		*or*	$7.50	
2)	10 in 100 chance	90 in 100 chance		*or*	$15.00	
3)	10 in 100 chance	90 in 100 chance		*or*	$22.50	
4)	10 in 100 chance	90 in 100 chance		*or*	$30.00	
5)	10 in 100 chance	90 in 100 chance		*or*	$37.50	
6)	10 in 100 chance	90 in 100 chance		*or*	$45.00	
7)	10 in 100 chance	90 in 100 chance		*or*	$52.50	
8)	10 in 100 chance	90 in 100 chance		*or*	$60.00	
9)	10 in 100 chance	90 in 100 chance		*or*	$67.50	
10)	10 in 100 chance	90 in 100 chance		*or*	$75.00	
11)	10 in 100 chance	90 in 100 chance		*or*	$82.50	
12)	10 in 100 chance	90 in 100 chance		*or*	$90.00	
13)	10 in 100 chance	90 in 100 chance		*or*	$97.50	
14)	10 in 100 chance	90 in 100 chance		*or*	$105.00	
15)	10 in 100 chance	90 in 100 chance		*or*	$112.50	
16)	10 in 100 chance	90 in 100 chance		*or*	$120.00	
17)	10 in 100 chance	90 in 100 chance		*or*	$127.50	
18)	10 in 100 chance	90 in 100 chance		*or*	$135.00	
19)	10 in 100 chance	90 in 100 chance		*or*	$142.50	
	10 in 100 chance	90 in 100 chance	A	*or*	$150.00	B

Table 1

Please read each row carefully. *Remember, any row can be chosen to be paid for real. So treat each row as if it could be the one that determines your final payment.*

If you are satisfied with your decisions, click on Next. If you wish to change any of your decisions, you can change them manually, and then click on Next.

	Option A			or	Option B	
	Chance of $150.00	**Chance of $0.00**			**Certain Amount**	
	10 in 100 chance	90 in 100 chance	A	or	$0.00	B
1)	10 in 100 chance	90 in 100 chance	A	or	$7.50	B
2)	10 in 100 chance	90 in 100 chance	A	or	$15.00	B
3)	10 in 100 chance	90 in 100 chance	A	or	$22.50	B
4)	10 in 100 chance	90 in 100 chance	A	or	$30.00	B
5)	10 in 100 chance	90 in 100 chance	A	or	$37.50	B
6)	10 in 100 chance	90 in 100 chance	A	or	$45.00	B
7)	10 in 100 chance	90 in 100 chance	A	or	$52.50	B
8)	10 in 100 chance	90 in 100 chance	A	or	$60.00	B
9)	10 in 100 chance	90 in 100 chance	A	or	$67.50	B
10)	10 in 100 chance	90 in 100 chance	A	or	$75.00	B
11)	10 in 100 chance	90 in 100 chance	A	or	$82.50	B
12)	10 in 100 chance	90 in 100 chance	A	or	$90.00	B
13)	10 in 100 chance	90 in 100 chance	A	or	$97.50	B
14)	10 in 100 chance	90 in 100 chance	A	or	$105.00	B
15)	10 in 100 chance	90 in 100 chance	A	or	$112.50	B
16)	10 in 100 chance	90 in 100 chance	A	or	$120.00	B
17)	10 in 100 chance	90 in 100 chance	A	or	$127.50	B
18)	10 in 100 chance	90 in 100 chance	A	or	$135.00	B
19)	10 in 100 chance	90 in 100 chance	A	or	$142.50	B
	10 in 100 chance	90 in 100 chance	A	or	$150.00	B

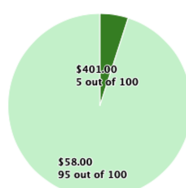
Next

Example 2

On the next page, your task will be to choose Option A or Option B. If you choose Option A, you will have a chance of receiving a large payment and a chance of receiving a smaller payment. If you choose Option B, you will receive a specific amount of money for sure. Option A is fixed for every row. The amount you receive in Option B increases as you move down the rows. Here's an example of the next 2 tables.

	Option A			or	Option B	
	Chance of $401.00	**Chance of $58.00**			**Certain Amount**	
	5 in 100 chance	95 in 100 chance	A	*or*	$0.00	B
			.			
			.			
			.			
9)	5 in 100 chance	95 in 100 chance	A	*or*	$67.50	B
10)	5 in 100 chance	95 in 100 chance	A	*or*	$75.00	B
11)	5 in 100 chance	95 in 100 chance	A	*or*	$82.50	B
			.			
			.			
			.			

Imagine that, after you made your choices in every row, Row 10 was randomly selected to be the decision for which you can receive an additional **payment**. You would be paid based on what Option you chose. If you selected Option B, you would get $75.00 for sure. If you selected Option A, you would spin the wheel and get either $401.00 with a 5 in 100 chance or $58.00 with a 95 in 100 chance.



Note: You can adjust your screen at any time by pressing CTRL *and* + to zoom in or CTRL *and* - to zoom out. On a Mac, ⌘ Command *and* + or ⌘ Command *and* -, respectively.

Next

Table 8

Please read each row carefully. *Remember, any row can be chosen to be paid for real. So treat each row as if it could be the one that determines your final payment.*

In the Switching Row box below, you can select the row at which you would like to switch from Option A to Option B. The computer will then automatically fill in the buttons for Option B in your chosen row and all the subsequent rows. You can choose any switching row from 1 (choose Option B for every row) to 20 (choose Option A for every row).

If you want to manually select your preferred option for each row, just leave the 0 in the box and click "Next."

Switching Row:

0

Next

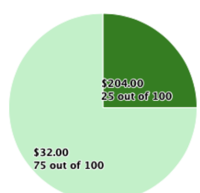
	Option A			*or*	Option B	
	Chance of $401.00	Chance of $58.00			Certain Amount	
	5 in 100 chance	95 in 100 chance	A	*or*	$0.00	B
1)	5 in 100 chance	95 in 100 chance		*or*	$7.50	
2)	5 in 100 chance	95 in 100 chance		*or*	$15.00	
3)	5 in 100 chance	95 in 100 chance		*or*	$22.50	
4)	5 in 100 chance	95 in 100 chance		*or*	$30.00	
5)	5 in 100 chance	95 in 100 chance		*or*	$37.50	
6)	5 in 100 chance	95 in 100 chance		*or*	$45.00	
7)	5 in 100 chance	95 in 100 chance		*or*	$52.50	
8)	5 in 100 chance	95 in 100 chance		*or*	$60.00	
9)	5 in 100 chance	95 in 100 chance		*or*	$67.50	
10)	5 in 100 chance	95 in 100 chance		*or*	$75.00	
11)	5 in 100 chance	95 in 100 chance		*or*	$82.50	
12)	5 in 100 chance	95 in 100 chance		*or*	$90.00	
13)	5 in 100 chance	95 in 100 chance		*or*	$97.50	
14)	5 in 100 chance	95 in 100 chance		*or*	$105.00	
15)	5 in 100 chance	95 in 100 chance		*or*	$112.50	
16)	5 in 100 chance	95 in 100 chance		*or*	$120.00	
17)	5 in 100 chance	95 in 100 chance		*or*	$127.50	
18)	5 in 100 chance	95 in 100 chance		*or*	$135.00	
19)	5 in 100 chance	95 in 100 chance		*or*	$142.50	

Example 3

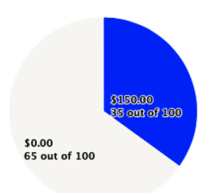
On the next page, your task will be to choose Option A or Option B. If you choose Option A, you will have a chance of receiving a large payment and a chance of receiving a smaller payment. If you choose Option B, you will have a chance of receiving a large payment and a chance of receiving nothing. Both options will be uncertain. Option A is fixed for every row. In Option B, the chance of receiving the larger payment will increase as you move down the rows while the chance of receiving $0 decreases. Here's an example of the next 2 tables.

	Option A			or	Option B		
	Chance of $204.00	Chance of $32.00			Chance of $150.00	Chance of $0.00	
	25 in 100 chance	75 in 100 chance	A	or	0 in 100 chance	100 in 100 chance	B
				.			
				.			
				.			
6)	25 in 100 chance	75 in 100 chance	A	or	30 in 100 chance	70 in 100 chance	B
7)	25 in 100 chance	75 in 100 chance	A	or	35 in 100 chance	65 in 100 chance	B
8)	25 in 100 chance	75 in 100 chance	A	or	40 in 100 chance	60 in 100 chance	B
				.			
				.			
				.			

Imagine that, after you made your choices in every row, Row 7 was randomly selected to be the decision for which you can receive an additional **payment**. You would be paid based on what Option you chose. If you selected Option A, you would spin the wheel and get either $204.00 with a 25 in 100 chance or $32.00 with a 75 in 100 chance.



If you selected Option B, you would spin the wheel and get either $150.00 with a 35 in 100 chance or $0.00 with a 65 in 100 chance.



Note: You can adjust your screen at any time by pressing CTRL *and* + to zoom in or CTRL *and* - to zoom out. On a Mac, ⌘ Command *and* + or ⌘ Command *and* -, respectively.

Next

Table 10

Please read each row carefully. *Remember, any row can be chosen to be paid for real. So treat each row as if it could be the one that determines your final payment.*

In the Switching Row box below, you can select the row at which you would like to switch from Option A to Option B. The computer will then automatically fill in the buttons for Option B in your chosen row and all the subsequent rows. You can choose any switching row from 1 (choose Option B for every row) to 20 (choose Option A for every row).

If you want to manually select your preferred option for each row, just leave the 0 in the box and click "Next."

Switching Row:

0

Next

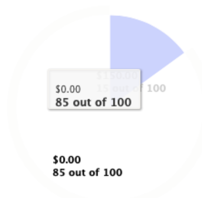
	Option A			or	Option B		
	Chance of $204.00	**Chance of $32.00**			**Chance of $150.00**	**Chance of $0.00**	
	25 in 100 chance	75 in 100 chance	A	*or*	0 in 100 chance	100 in 100 chance	B
1)	25 in 100 chance	75 in 100 chance		*or*	5 in 100 chance	95 in 100 chance	
2)	25 in 100 chance	75 in 100 chance		*or*	10 in 100 chance	90 in 100 chance	
3)	25 in 100 chance	75 in 100 chance		*or*	15 in 100 chance	85 in 100 chance	
4)	25 in 100 chance	75 in 100 chance		*or*	20 in 100 chance	80 in 100 chance	
5)	25 in 100 chance	75 in 100 chance		*or*	25 in 100 chance	75 in 100 chance	
6)	25 in 100 chance	75 in 100 chance		*or*	30 in 100 chance	70 in 100 chance	
7)	25 in 100 chance	75 in 100 chance		*or*	35 in 100 chance	65 in 100 chance	
8)	25 in 100 chance	75 in 100 chance		*or*	40 in 100 chance	60 in 100 chance	
9)	25 in 100 chance	75 in 100 chance		*or*	45 in 100 chance	55 in 100 chance	
10)	25 in 100 chance	75 in 100 chance		*or*	50 in 100 chance	50 in 100 chance	
11)	25 in 100 chance	75 in 100 chance		*or*	55 in 100 chance	45 in 100 chance	
12)	25 in 100 chance	75 in 100 chance		*or*	60 in 100 chance	40 in 100 chance	
13)	25 in 100 chance	75 in 100 chance		*or*	65 in 100 chance	35 in 100 chance	
14)	25 in 100 chance	75 in 100 chance		*or*	70 in 100 chance	30 in 100 chance	
15)	25 in 100 chance	75 in 100 chance		*or*	75 in 100 chance	25 in 100 chance	
16)	25 in 100 chance	75 in 100 chance		*or*	80 in 100 chance	20 in 100 chance	
17)	25 in 100 chance	75 in 100 chance		*or*	85 in 100 chance	15 in 100 chance	
18)	25 in 100 chance	75 in 100 chance		*or*	90 in 100 chance	10 in 100 chance	
19)	25 in 100 chance	75 in 100 chance		*or*	95 in 100 chance	5 in 100 chance	

Example 4

On the next page, your task will be to choose Option A or Option B. If you choose Option A, you will receive a specific amount of money for sure. If you choose Option B, you will have a chance of receiving a large payment and a chance of receiving nothing. Option A is fixed for every row. In Option B, the chance of receiving the larger payment will increase as you move down the rows while the chance of receiving $0 decreases. Here's an example of the next 7 tables.

	Option A		or	Option B		
	Certain Amount			Chance of $150.00	Chance of $0.00	
	$37.50	A	or	0 in 100 chance	100 in 100 chance	B
1)	$37.50	A	or	5 in 100 chance	95 in 100 chance	B
2)	$37.50	A	or	10 in 100 chance	90 in 100 chance	B
3)	$37.50	A	or	15 in 100 chance	85 in 100 chance	B
		.				
		.				
		.				
	$37.50	A	or	100 in 100 chance	0 in 100 chance	B

Imagine that, after you made your choices in every row, Row 3 was randomly selected to be the decision for which you can receive an additional **payment**. You would be paid based on what Option you chose. If you selected Option A, you would get $37.50 for sure. If you selected Option B, you would spin the wheel and get either $150.00 with a 15 in 100 chance or $0.00 with a 85 in 100 chance.



Note: You can adjust your screen at any time by pressing CTRL *and* + to zoom in or CTRL *and* - to zoom out. On a Mac, ⌘ Command *and* + or ⌘ Command *and* -, respectively.

Next

Table 12

Please read each row carefully. *Remember, any row can be chosen to be paid for real. So treat each row as if it could be the one that determines your final payment.*

In the Switching Row box below, you can select the row at which you would like to switch from Option A to Option B. The computer will then automatically fill in the buttons for Option B in your chosen row and all the subsequent rows. You can choose any switching row from 1 (choose Option B for every row) to 20 (choose Option A for every row).

If you want to manually select your preferred option for each row, just leave the 0 in the box and click "Next."

Switching Row:

0

Next

	Option A		or	Option B		
	Certain Amount			Chance of $150.00	Chance of $0.00	
	$37.50	A	or	0 in 100 chance	100 in 100 chance	B
1)	$37.50		or	5 in 100 chance	95 in 100 chance	
2)	$37.50		or	10 in 100 chance	90 in 100 chance	
3)	$37.50		or	15 in 100 chance	85 in 100 chance	
4)	$37.50		or	20 in 100 chance	80 in 100 chance	
5)	$37.50		or	25 in 100 chance	75 in 100 chance	
6)	$37.50		or	30 in 100 chance	70 in 100 chance	
7)	$37.50		or	35 in 100 chance	65 in 100 chance	
8)	$37.50		or	40 in 100 chance	60 in 100 chance	
9)	$37.50		or	45 in 100 chance	55 in 100 chance	
10)	$37.50		or	50 in 100 chance	50 in 100 chance	
11)	$37.50		or	55 in 100 chance	45 in 100 chance	
12)	$37.50		or	60 in 100 chance	40 in 100 chance	
13)	$37.50		or	65 in 100 chance	35 in 100 chance	
14)	$37.50		or	70 in 100 chance	30 in 100 chance	
15)	$37.50		or	75 in 100 chance	25 in 100 chance	
16)	$37.50		or	80 in 100 chance	20 in 100 chance	
17)	$37.50		or	85 in 100 chance	15 in 100 chance	
18)	$37.50		or	90 in 100 chance	10 in 100 chance	
19)	$37.50		or	95 in 100 chance	5 in 100 chance	
	$37.50	A	or	100 in 100 chance	0 in 100 chance	B

Table 12

Please read each row carefully. *Remember, any row can be chosen to be paid for real. So treat each row as if it could be the one that determines your final payment.*

If you are satisfied with your decisions, click on Next. If you wish to change any of your decisions, you can change them manually, and then click on Next.

	Option A		or	Option B		
	Certain Amount			Chance of $150.00	Chance of $0.00	
	$37.50	A	or	0 in 100 chance	100 in 100 chance	B
1)	$37.50	A	or	5 in 100 chance	95 in 100 chance	B
2)	$37.50	A	or	10 in 100 chance	90 in 100 chance	B
3)	$37.50	A	or	15 in 100 chance	85 in 100 chance	B
4)	$37.50	A	or	20 in 100 chance	80 in 100 chance	B
5)	$37.50	A	or	25 in 100 chance	75 in 100 chance	B
6)	$37.50	A	or	30 in 100 chance	70 in 100 chance	B
7)	$37.50	A	or	35 in 100 chance	65 in 100 chance	B
8)	$37.50	A	or	40 in 100 chance	60 in 100 chance	B
9)	$37.50	A	or	45 in 100 chance	55 in 100 chance	B
10)	$37.50	A	or	50 in 100 chance	50 in 100 chance	B
11)	$37.50	A	or	55 in 100 chance	45 in 100 chance	B
12)	$37.50	A	or	60 in 100 chance	40 in 100 chance	B
13)	$37.50	A	or	65 in 100 chance	35 in 100 chance	B
14)	$37.50	A	or	70 in 100 chance	30 in 100 chance	B
15)	$37.50	A	or	75 in 100 chance	25 in 100 chance	B
16)	$37.50	A	or	80 in 100 chance	20 in 100 chance	B
17)	$37.50	A	or	85 in 100 chance	15 in 100 chance	B
18)	$37.50	A	or	90 in 100 chance	10 in 100 chance	B
19)	$37.50	A	or	95 in 100 chance	5 in 100 chance	B
	$37.50	A	or	100 in 100 chance	0 in 100 chance	B

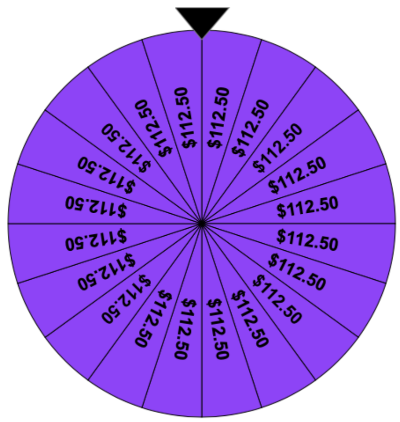
Next

Earnings

Row 15 from task 4 was selected as the decision-that-counts. You selected Option B or a 100 in 100 chance of $112.50 and a 0 in 100 chance of $0.00.

Please spin the wheel.

Spin the Wheel



Next

Appendix B Robustness Test

Pending

Appendix C Discussion of our Pre-analysis Plan

Pending