Certain Reversals*

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Abstract

In a lab-in-the-field experiment with experts facing risky, high-stakes decisions, experts exhibit context-dependent reversals in their attitudes towards risk and these reversals are affected by the likelihood of a better outcome, i.e., the direction of preference reversals is affected by the proximity of a better outcome to certainty. Although these patterns cannot be explained by leading models from economics and psychology, they can be explained by a model that combines stochastic reference dependence from economics and context-dependent sensitivity from psychology. The interaction of these two mechanisms may explain the perplexing inconsistencies in people's choices, including those attributed to probability weighting.

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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, Kunreuther, and Schoemaker, 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, Griffin, and Tversky, 1990; Loomes and Sugden, 1982).

Although theory suggests the two anomalies are related to each other (Schmidt, Starmer, and Sugden, 2008; Bordalo, Gennaioli, and Shleifer, 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 proximity to certainty exerts over preference reversals and we 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 proximity to certainty on reversals. Second, we use a within-subjects design for the elicitation of equivalent risk premia, where we also randomize the initial tasks, either pricing or comparing, between subjects. The within-subject data allow us to measure the magnitude of individual welfare losses from reversals. Third, we increase the stakes five-fold to a maximum of \$150 and, in addition to recruiting student subjects, we recruit experts in risky decision-making (commercial agricultural producers). 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 near-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.

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

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, Sattath, and Slovic, 1988; Slovic, Griffin, and Tversky, 1990; Tversky, Slovic, and Kahneman, 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 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 near-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 near-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), 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 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, when pricing lotteries, an agent with KR preferences and constant sensitivity to loss-gain utility is indistinguishable from an agent with expected utility preferences given by the Bernoullian utility function $m(\cdot)$.

For a stochastic referent, with binary outcomes ($r_H > r_L$) with a fixed

[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.

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

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

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

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

Multiplying out and rearranging the terms on the left-hand side of the equivalence,

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

and factorizing q out gives us

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

The multiplicative and additive terms on both sides of the equation are equal, and thus we conclude

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

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, when comparing lotteries, an agent with KR preferences and constant sensitivity exhibits more risk aversion than an agent with expected utility preferences given by the Bernoullian utility function $m(\cdot)$. 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 that 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 $p^* > p^*_{EU}$ 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 $\lambda > 1$. Summarizing, a loss-averse individual with KR preferences and constant loss-gain utility and latent utility $m(\cdot)$ is more risk-averse than an agent with EU preferences given by the Bernoulli utility function $m(\cdot)$.

2.4 KR Preferences and Multiple Reversals

We have argued that the model with KR preferences gives 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 near-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, Feldman, and Sprenger, 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, Slovic, and Kahneman (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 Tversky, Slovic, and Kahneman (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 near-certainty effects for pricing choice lists.

In the next section 2.6, we propose an extension to KR that can accommodate near-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 that 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, more precisely, procedural invariance. Violations of procedural invariance have been previously documented (Tversky, Slovic, and Kahneman, 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

[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.

consistent with Lichtenstein and Slovic's initial insight, but, in our extension, individuals are more sensitive to outcomes only through their loss-gain utility. The psychology behind context-dependence is that individuals will be more sensitive to the changing attribute than the fixed attribute. Clearly, pricing induces more sensitivity to changes in the outcomes than the probabilities.

By integrating context-dependent sensitivity into 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.

Our KR model with context-dependent sensitivity is

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

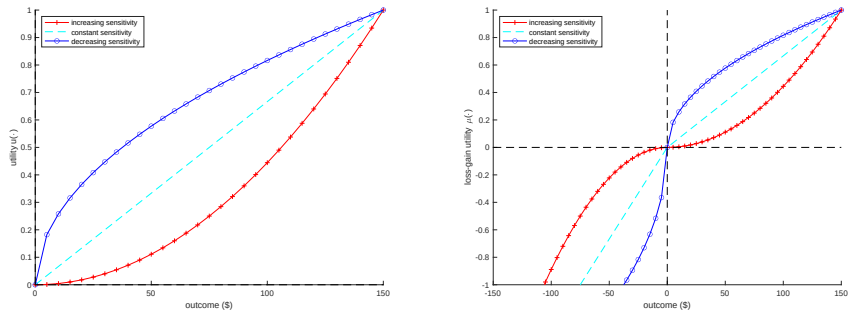
with,

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

$G(r)$ 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 determined by the context (e.g., the increasing alternative in the choice list). Both the theory and the empirical data from preference reversals suggest $\alpha(pricing) > 1 \geq \alpha(comparing)$. Put simply, 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. Figure 1b represents the extension for loss-gain utility.

Our model is different from models that include probability weighting. Inverse S-shaped probability weighting is one of the leading behavioral explanations for near-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 near-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



(a) Stimulus-Response Compatibility Theory

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

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

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 a known near-certainty effect, a known preference reversal, and a novel preference reversal near certainty. First, the model predicts that individuals, when pricing lotteries, will be risk-tolerant when the probabilities are unfavorable and become risk-averse as the probabilities become favorable. Second, the model predicts that individuals tend to be more risk-averse when comparing lotteries than when pricing lotteries with sufficiently unfavorable odds. In other words, when the odds are sufficiently unfavorable, individuals prefer certainty more when comparing lotteries than when pricing them. Third, the model predicts that individuals, when comparing lotteries, will be risk-averse when the probabilities are unfavorable and become risk-tolerant as the probabilities become favorable. In other words, when the odds are sufficiently favorable, individuals prefer certainty less when comparing lotteries than when pricing them.

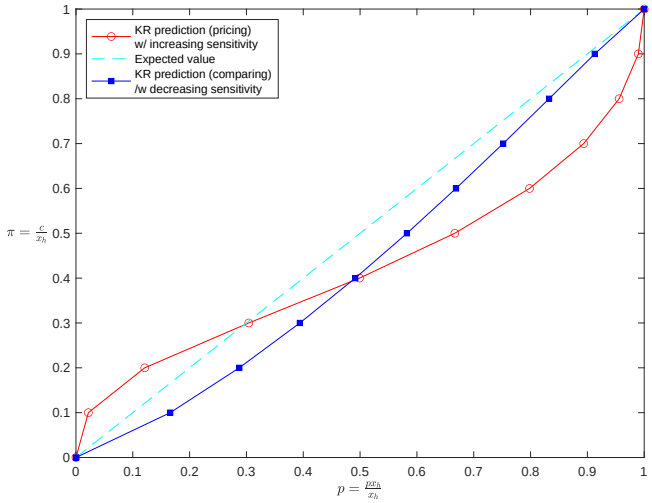


Figure 2: KR with Context-Dependent Sensitivity

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

3 Experimental Design

The primary motivation for our experimental design was to determine whether reversals exhibit a near-certainty effect. A secondary motivation was to assess the external validity of previous results. 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 the low stakes of prior experiments and the high stakes of our experiment with producers. For this reason, the student experiment had more choice lists than the producer experiment. With these students and low stakes, our results 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 in terms of features that were common for both subject types. We then describe features that differed across subject types. 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. The option on the left-hand side of the list is fixed while the option on the right-hand side 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	☐
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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	☐
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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 increments. 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			Option B	
	Chance of $401	Chance of $58		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	☐
.					
.					
.					
18)	5 in 100	95 in 100	☐ or	$135.00	☐
19)	5 in 100	95 in 100	☐ or	$142.50	☐

	Option A			Option B	
	Chance of $401	Chance of $58		Chance of $150	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 ☐
.					
.					
.					
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 3 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 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

[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 $skew(L_{s^M}) = 1.15$.

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 design where the first choice list type seen by a subject is randomly selected. 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, Schonger, and Wickens, 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 38 minutes and the median producer took 51 minutes. The average experimental 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, Sadiraj, and Schmidt, 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.

Under expected utility, this procedure is incentive-compatible whether subjects think of each binary comparison in isolation[7] or they consider each choice list in isolation and integrate all binary choices within a list (see Azrieli, Chambers, and Healy (2018)). However, reversals in binary choices may be incompatible with treating binary choices in isolation. When isolation does not hold, non-expected utility preferences may not be elicited truthfully, and even if there exists a procedure to elicit such preferences, it may be quite involved and likely to be misunderstood by subjects (Azrieli, Chambers, and Healy, 2018; Drichoutis, Palma, and Feldman, 2024).

Some economic models rule out "multiple switching behavior" in choice lists

[7]See Cubitt, Starmer, and Sugden (1998); Starmer and Sugden (1991) for an in-depth discussion of how considering binary choices in isolation can preserve the incentive compatibility of paying for one choice at random for non-expected utility models.

like the ones we use in our design. Letting subjects exhibit this behavior, however, may reveal stochastic preferences (Chew, Shen, and Zhong, 2015; Feldman and Rehbeck, 2022). 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 subsections. 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

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

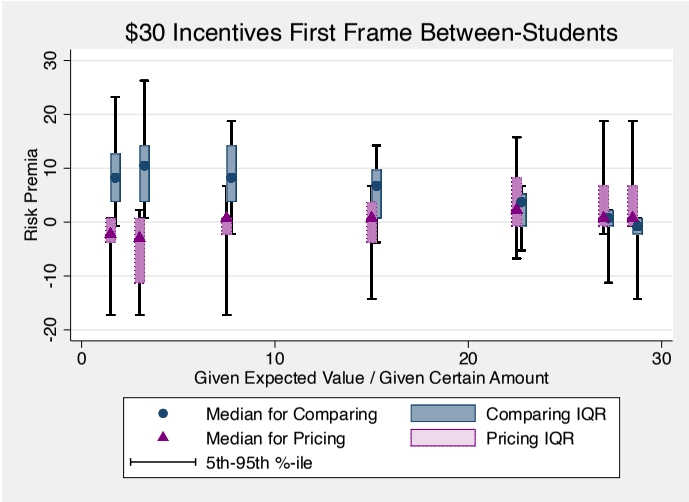
Bold letters denote the value elicited by the choice list, and non-bold letters denote the fixed attribute. We use risk premia to measure risk attitude reversals in two ways.

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

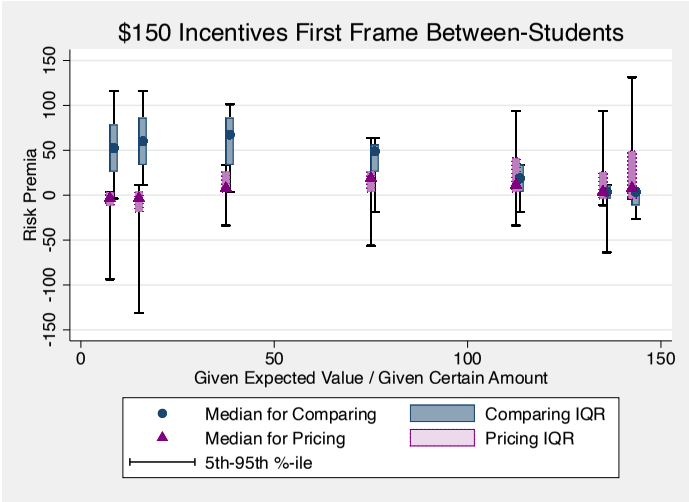
Table 5: Producers' Reversals by Value of the Fixed Alternative

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

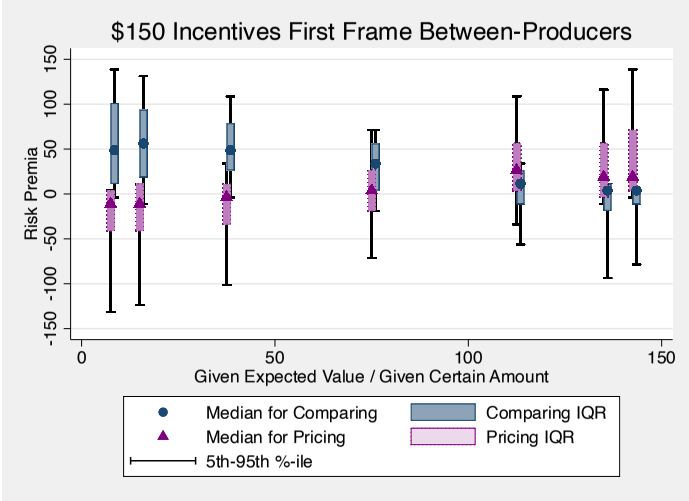
The first measure of risk attitude reversals is the sign of the risk premia differences between pricing and comparing choice lists. The sign provides a coarse measure of reversals. When the odds are unfavorable, producers exhibit a higher risk premium for comparing tasks (Table 5). However, when the odds are favorable, producers exhibit the opposite pattern. This pattern reversal implies a *near-certainty effect for preference reversals.*



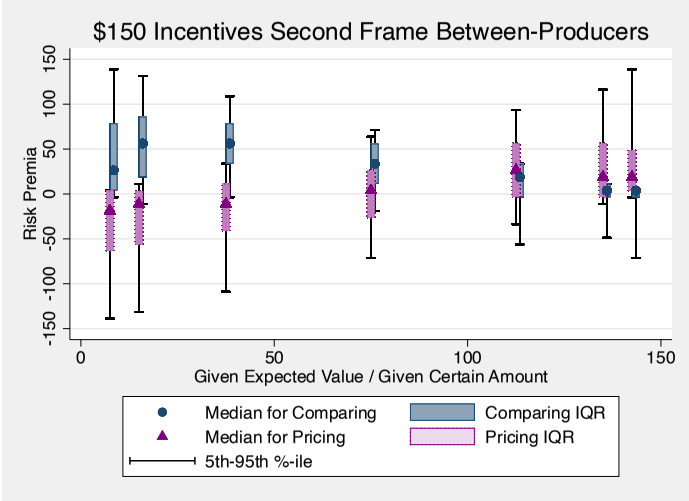
(a) Low Stakes for Students



(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).

The second measure of risk attitude reversals is the distribution of risk premia across the pricing and comparison tasks (Figure 3). To facilitate contrasting the two types of 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: when the odds are unfavorable, subjects exhibit a higher risk premium for comparing tasks, but when the odds are favorable, subjects exhibit the opposite pattern. Figure 3 is a simple way to represent deviations from risk neutrality; however, differences between the measures appear less substantial because 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 producers exhibit similar reversal patterns regardless of whether they already did one of the other task types or not.

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 subjects are comparing rather than 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. We also find relatively modest effects from either increasing the sure amounts (for comparing tasks) or from increasing the expected values (for pricing tasks).

We conclude by pooling all of our producer data together and graphically showing the near-certainty effect for risk. 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.

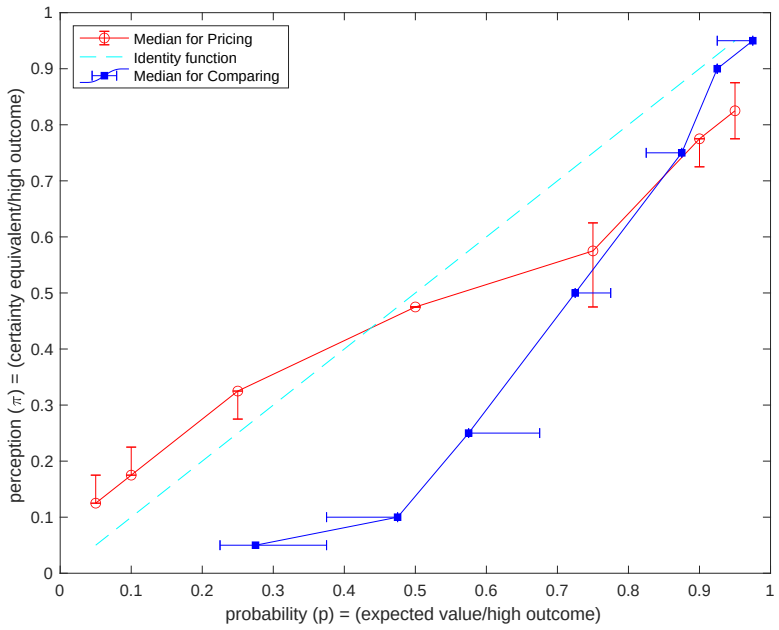


Figure 4: Normalized Median Choices by Choice List Type

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

We emphasize three main takeaways from Figure 4. First, we observe 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 rather than pricing near certainty. To our knowledge, this behavioral pattern had not been previously documented, and other behavioral models that explain preference reversal would struggle to accommodate this pattern (see Section 5 and Appendix C).

Table 6: Interval Regressions for Comparisons

Dependent Variable: Risk Premia Interval				
	Producers		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	-14,071.670	-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.

4.2 Within-Subject Differences

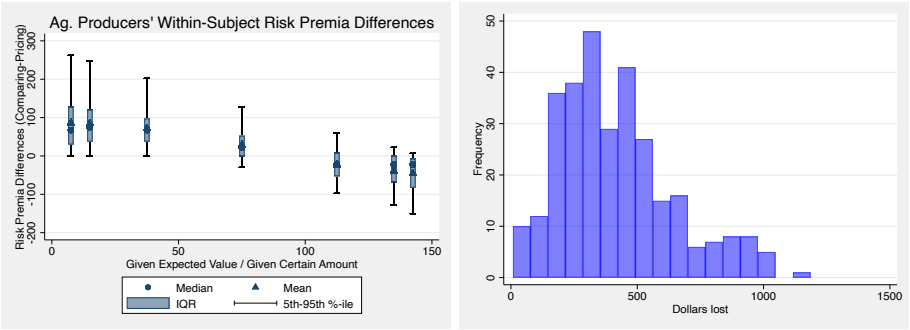
In this section, we show that the magnitude of the welfare losses due to risk attitude reversals is potentially large. To estimate this magnitude, we combine the within-subject data and a money-pump (dutch-book) type argument that assumes producers would exhibit these reversals in repeated decisions.

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, Chambers, and Healy, 2018; Cox, Sadiraj, and Schmidt, 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 11a summarizes the (expected) welfare loss due to a single prefer-

ence 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.

Figure 5: Welfare Loss Due to Reversals



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

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

Notes: Data is from 307 producers who reported a unique switch point for every choice list. Results are qualitatively unchanged if we instead use all 398 producers 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 in the pricing task, and $\alpha(comparing)$ is the analog in the comparing task.

To estimate parameters at the individual level, we use nonlinear least squares 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. Solving for the positive root for equation 1 equal to equation 2 gives the estimating equation for the pricing choice list. We use the following calibrating equation:

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

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 these 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 et al. (2023).

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

parameter	median	95% CI
ρ	0.758	[0.661, 0.915]
λ	2.689	[1.641, 4.977]
α(Pricing)	1.757	[1.557, 2.082]
α(Comparing)	0.400	[0.292, 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 303 producers who reported a unique switch point for every choice list. For four producers parameters could not be estimated. Confidence intervals exhibit a substantial overlap if we use the first switching point instead (see Appendix B).

Consistent with prior reports, the estimated individual median value for the risk aversion parameter under EU is .592 (95% CI:[.532,.643]). The lower curvature under our model is the result of controlling for loss-aversion and context-dependence.

As our theory suggests, the higher risk aversion observed in laboratory studies appears to be driven by context.[8] For instance, certainty equivalents often yield curvature estimates near the risk-neutral benchmark. Note that identifying latent intrinsic preferences requires at least two distinct contexts (similar to how identifying loss aversion requires both "loss" and "gain" contexts).

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 8.221 (95% CI: [6.260,9.692]). This value would imply losses lead to eight-fold increase in the disutility of a loss from an equivalent gain. This value is inconsistent with our point estimate for median loss aversion of 2.689 (95% CI: [1.641, 4.977]) and the rest of the literature. In the next section, we assess how well

[8] Prior studies assume latent utilities are linear to sidestep Rabin's critique that these higher curvature estimates are dubious (Rabin, 2000).

the EU model, the constant sensitivity KR model, and our context-dependent sensitivity KR model predict choices in the skewness task.

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 the expected utility model's inability to predict specific preferences for skewness.[9] As described in our pre-analysis plan, we chose non-negative skewness tasks because they usually induce higher tolerance for risks and we wanted to examine the robustness of the endowment effect for risk.

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, which we contrast 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

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

As in the case of standard risk premia, higher positive expected risk premia imply more 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

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

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

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

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

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. In other words, we cannot measure preferences where the skewed lottery is always preferred to any probability equivalent for the fixed outcomes x_H and x_L.

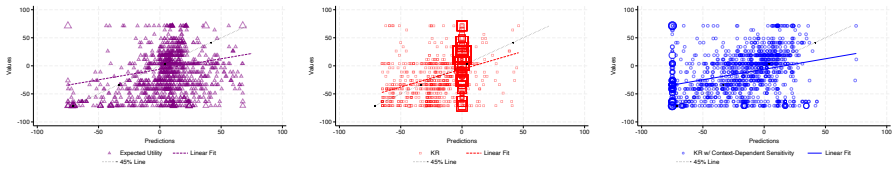


Figure 6: Predicted and Observed Values

Notes: Data is from 303 producers for KR with context-dependent sensitivity and 307 producers for KR, both with a unique switch-point. Results are qualitatively unchanged if we use the first switching point instead (see Appendix B). For four producers, parameters could not be estimated for KR with context-dependent sensitivity.

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 0.353 and 0.320, respectively, which contrast favorably with 0.239 for the expected utility model.[10] The median squared errors are also lower for both KR models in comparison to the expected utility model (487 and 503 versus 728). Figure 7 summarizes the distribution of parameter values for our model and KR with constant sensitivity.

[10] We use CRRA-type preferences throughout.

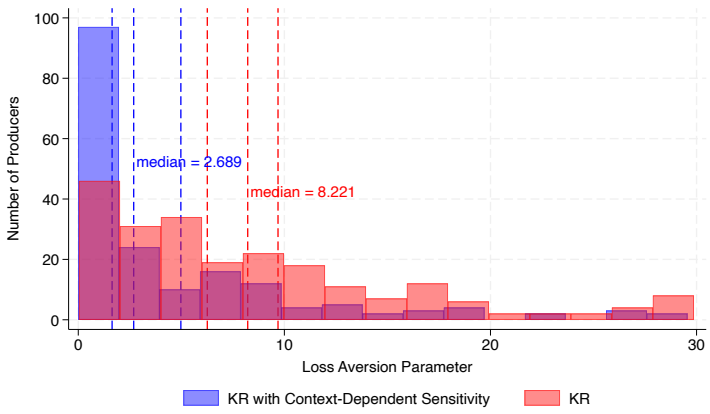


Figure 7: Loss-Aversion Parameter Values

Notes: Data is from 303 producers for KR with context-dependent sensitivity and 307 producers for KR, both with a unique switch-point. Picture restricts observation to values in [0,30) for readability. All summary statistics are calculated with the full sample of unique switchers whose parameters could be calculated. Dashed lines represent 95% confidence intervals. Results are qualitatively unchanged if we use the first switching point instead (see Appendix B).

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 feature 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 (2.761) that are comparable with the prior literature (Brown et al., 2023), 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 near-certainty effect for preference reversals. We also demonstrate that this new near-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, Li, and Woodford, 2021), random mistakes and impreciseness (Blavatskyy, 2007; Butler and Loomes, 2007; Collins and James, 2015), salience (Bordalo, Gennaioli, and Shleifer, 2012) and complexity (Puri, 2018). These competing explanations are ruled out by their inability to predict systematic differences across pricing and comparing frames. Explanations based on middle-of-the-list effects are also

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									*or*	Chances of $100
	A'1	A'2	A'3	A'4	A'5	A'6	A'7	A'8	A'9		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

Figure 8: Pricing and Comparing Frames

ruled out because they predict symmetry in the deviations from expected utility generated by the pricing and comparing tasks, which we do not observe.[11] 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, Slovic, and Kahneman (1990) show that eliminating incentives for hedging, by using pricing tasks to only derive ordinal rankings between alternatives, does not eliminate reversals.

[11] 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%.

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

Some may argue that our model bends over backward to use loss aversion as an explanation for phenomena that are much more readily explained by probability weighting. Probability weighting can not explain preference reversals or stochastic reference points. For this reason, Schmidt, Starmer, and Sugden (2008) propose third-generation prospect theory. In Appendix C, we

evaluate third-generation prospect theory's ability to explain the behavioral patterns explained by our model. We provide the punchline here. Although third-generation prospect theory can mathematically explain a near-certainty effect, doing so requires at least two different probability weighting functions from the two-parameters specification discussed in Prelec (1998). Moreover, commonly observed parameter values do not fit our data. Specifically, losses must be felt less than twice as gains ($\lambda_{PT} < 2$) and one of the probability weighting functions will not be inverse-S shaped.

Our model's intuition can also be repurposed to explain other deterministic economic environments. Consider the recent "shrinkflation" phenomenon, where companies reduce the quantities of goods instead of increasing their prices to defend their profit margins. Our model predicts that consumers' lower sensitivity to quantity changes is due to an endowment effect for money and to less sensitivity to changes in their purchasing power. Perhaps more interestingly, it also predicts a limit to how much these reduction strategies can be leveraged. As consumers' purchased goods shrink, their reference point may switch to the goods they expect to possess, and consequently, they will be more sensitive to their diminishing size and less sensitive to increasing prices.

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 estimates arising from 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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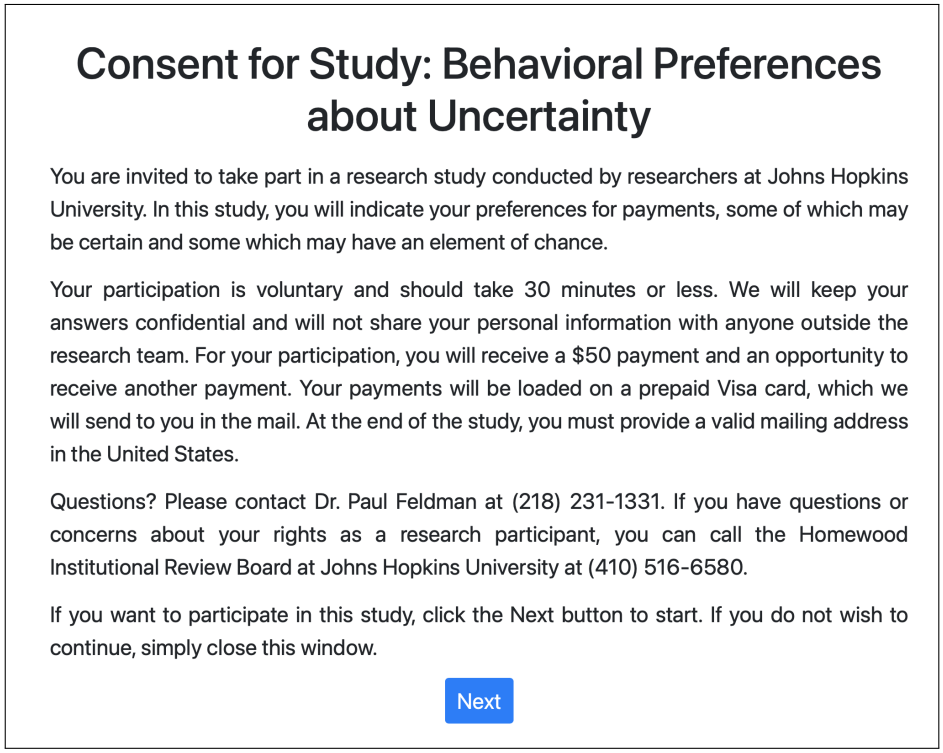
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[Supplemental Material]

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

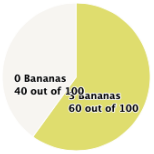
Note: This decision about fruit is just an example. All choices in the study will be about money.

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

Next

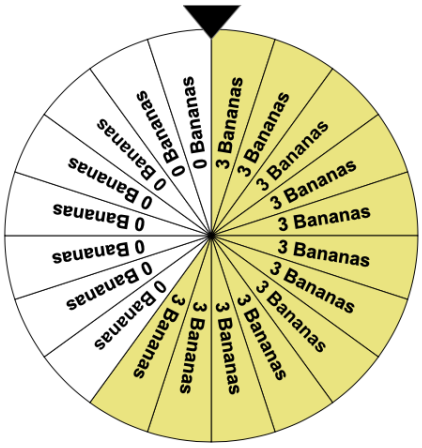
Options | Chances | Tables | Switching Row | Finalizing Decisions

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".

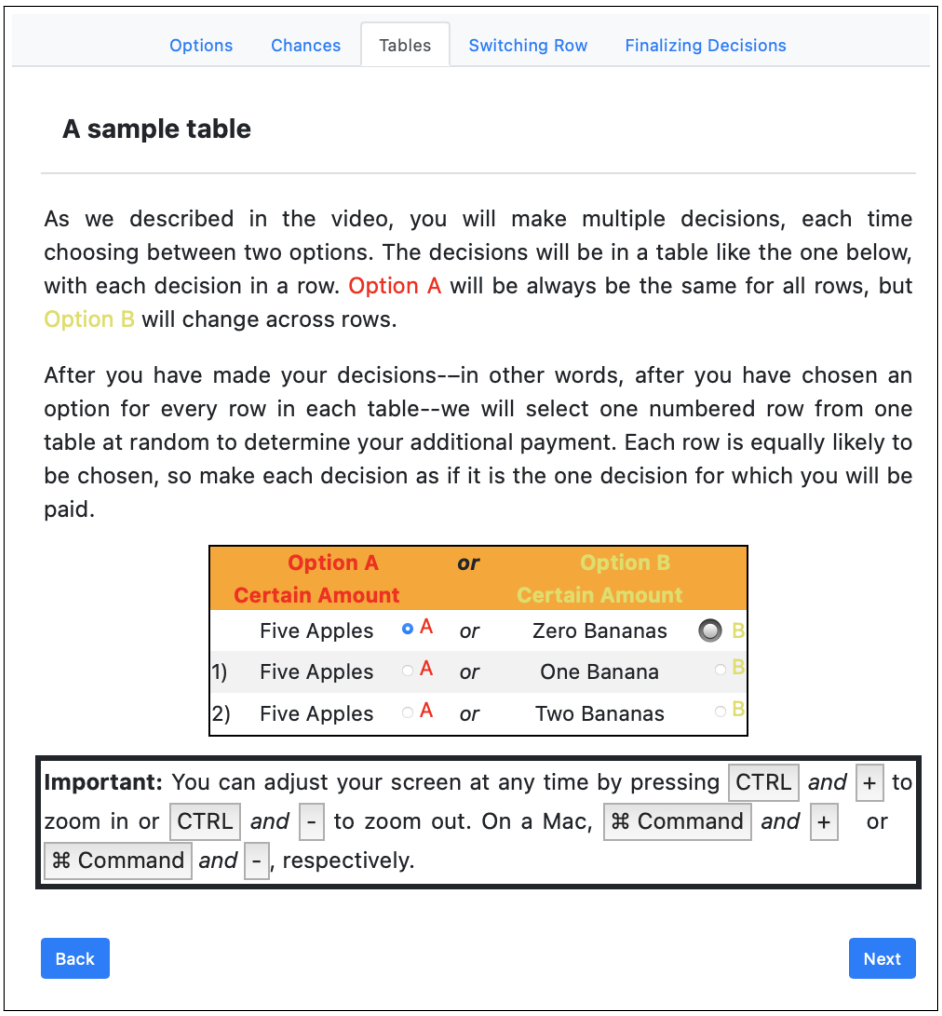
Spin the Wheel

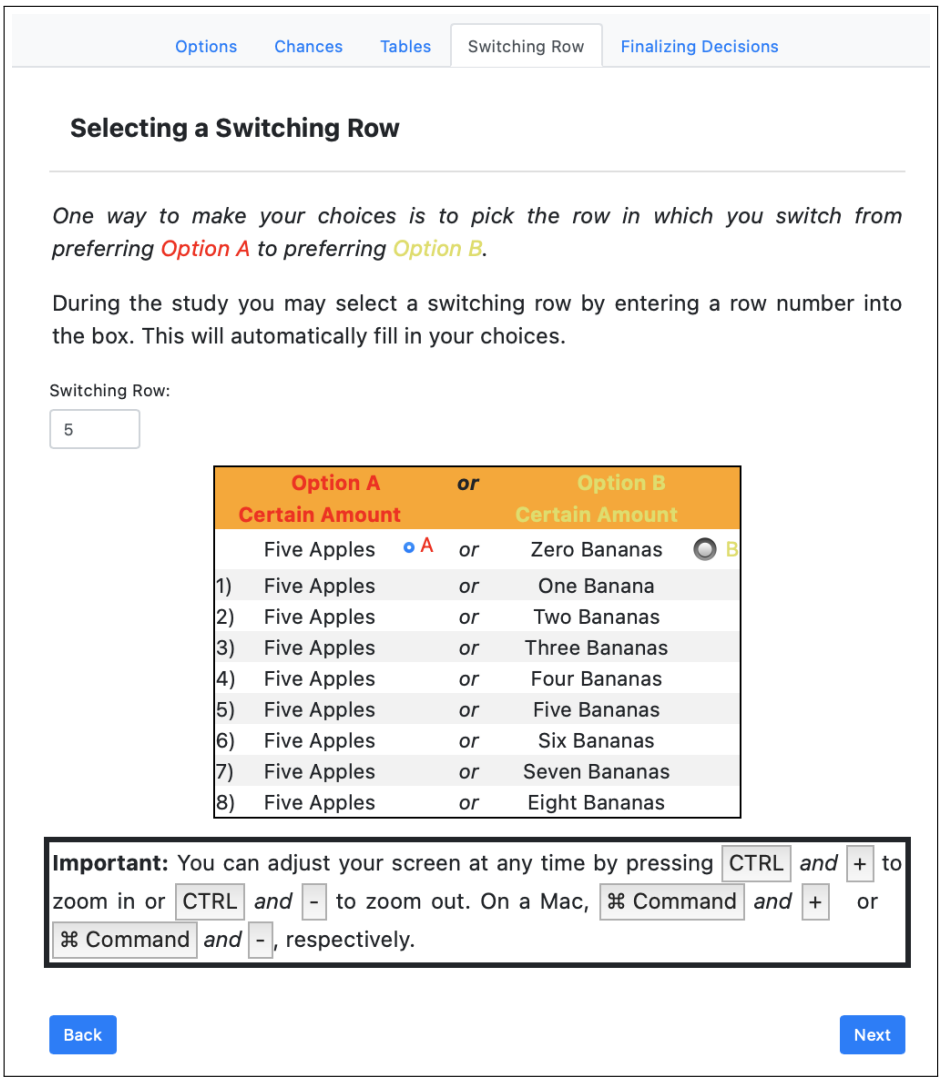


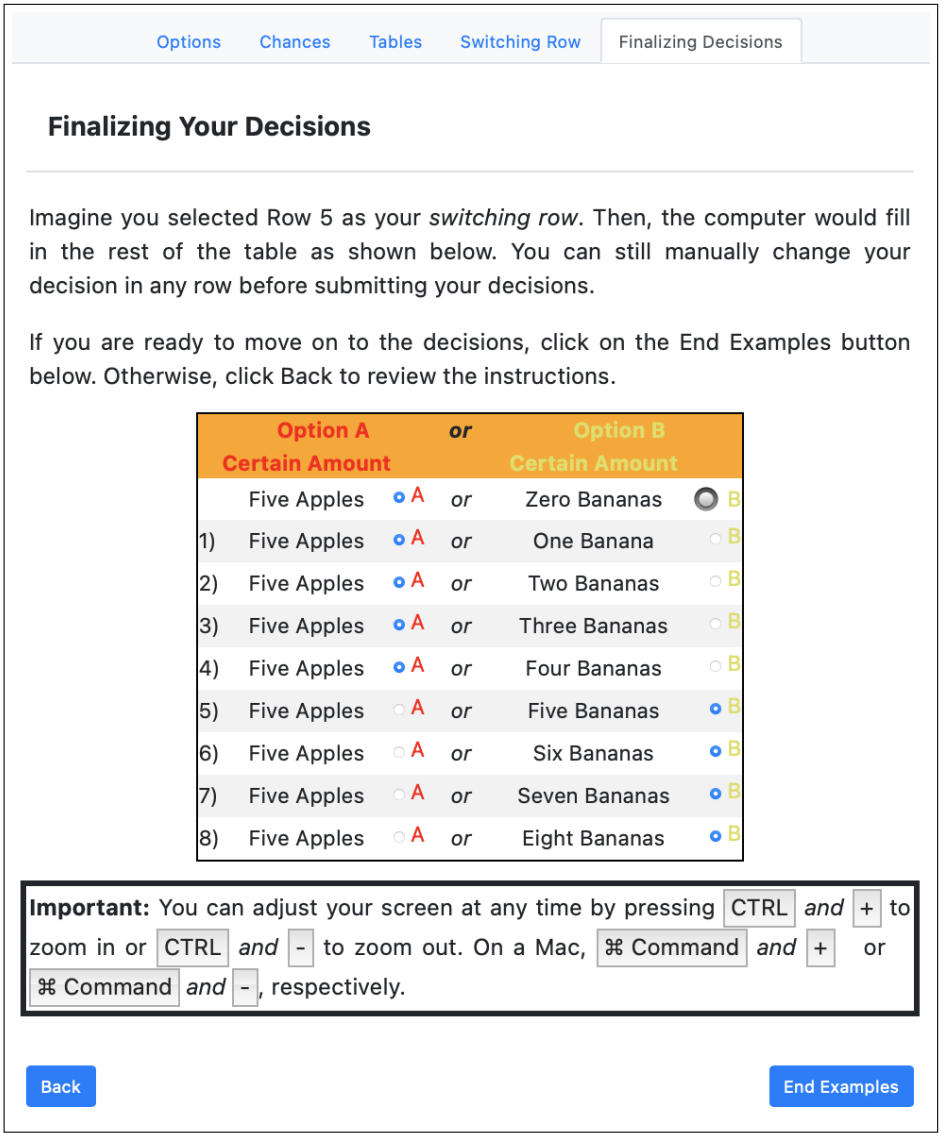
Note: In this example, you can spin the wheel as many times as you want. For the real decisions, you can only spin the wheel once. The stopping point on the wheel is truly random. It is not pre-determined. Our university prohibits us from deceiving participants in this study.

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.

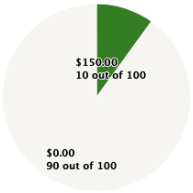
Next

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

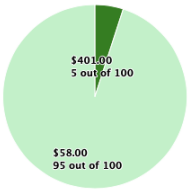
Next

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

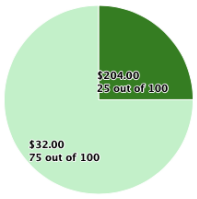
	Option A			or	Option B	
	Chance of $401.00	Chance of $58.00			Certain Amount	
	5 in 100 chance	95 in 100 chance	A	*or*	$0.00	B
1)	5 in 100 chance	95 in 100 chance		*or*	$7.50	
2)	5 in 100 chance	95 in 100 chance		*or*	$15.00	
3)	5 in 100 chance	95 in 100 chance		*or*	$22.50	
4)	5 in 100 chance	95 in 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

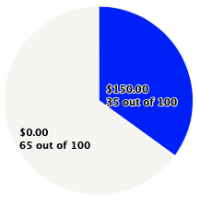
On the next page, your task will be to choose Option A or Option B. If you choose Option A, you will have a chance of receiving a large payment and a chance of receiving a smaller payment. If you choose Option B, you will have a chance of receiving a large payment and a chance of receiving nothing. Both 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

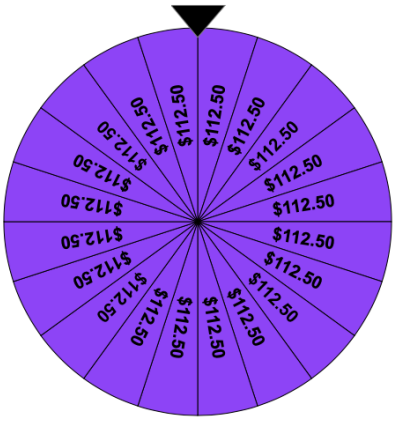
Next

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

All results below replicate results from Section 4 without dropping any subjects. We dropped multiple switchers from the main analysis. In this appendix, we use their first switch point on the choice list.

Table 8: Interval Regressions for Comparisons

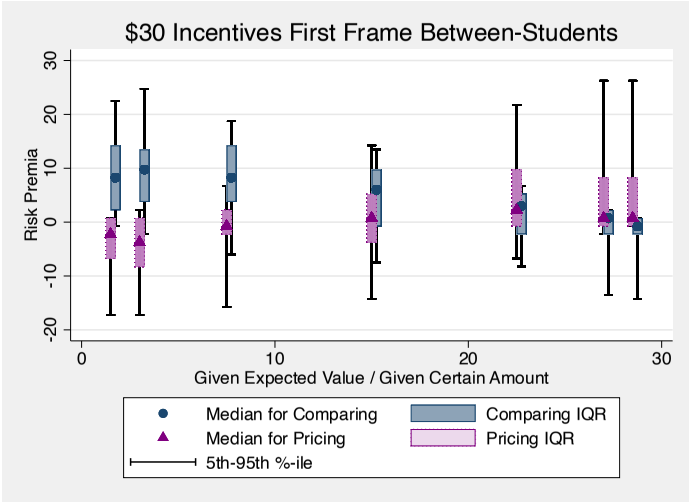
Dependent Variable: Risk Premia Interval				
	Producers		Students	
	(1)	(2)	(1)	(2)
	$X_{max} = \$150$	$X_{max} = \$150$	$X_{max} = \$150$	$X_{max} = \$150$
Comparing	13.116	13.116	13.332	13.332
Choice List	[2.346]	[2.346]	[2.139]	[2.139]
$C_{comparing}$ or	.015	.015	-.060	-.060
$EV_{pricing}$	[.011]	[.011]	[.017]	[.017]
Pricing first		-3.898		1.876
dummy		[2.150]		[3.249]
Constant	3.522	5.647	16.779	15.800
	[1.834]	[2.214]	[2.293]	[2.727]
Observations	5,572	5,572	1,610	1,610
Clusters	398	398	115	115
Log likelihood	- -18,779.152	-18,775.382	-4,906.3598	-4,905.8758

Notes: Data is from 398 producers and 115 students using their first switching point. Standard errors are reported in square brackets.

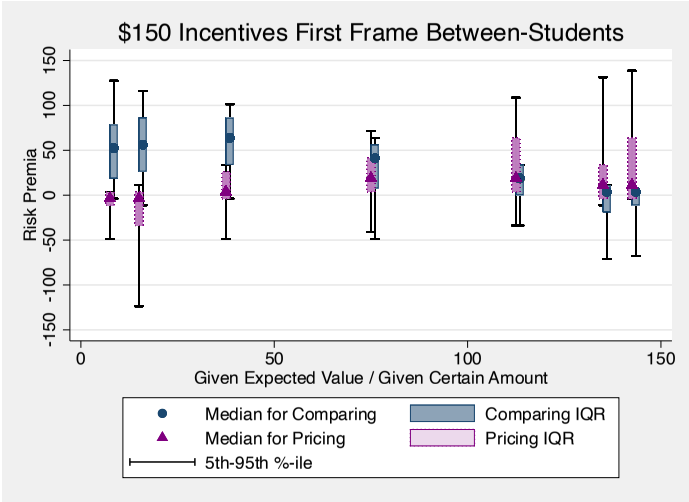
p / c	More Risk Averse when Comparing $\#(RP_{\mathcal{C}} \geq RP_{\mathcal{P}})$	Less Risk Averse when Comparing $\#(RP_{\mathcal{C}} < RP_{\mathcal{P}})$
5% / \$7.50	378	20
10% / \$15.00	369	29
25% / \$37.50	366	32
50% / \$75.00	292	106
75 % /\$112.50	119	279
90% / \$135.50	95	303
95% / \$142.50	81	317

Table 9: Producers' Reversals by Value of the Fixed Alternative

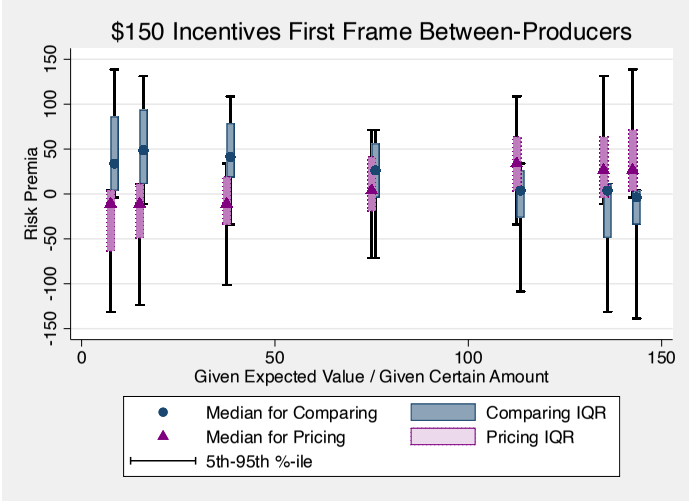
Notes: Data is from 307 producers. RP=Risk premia, $\mathcal{C}$=comparing choice list, and $\mathcal{P}$=pricing choice list.



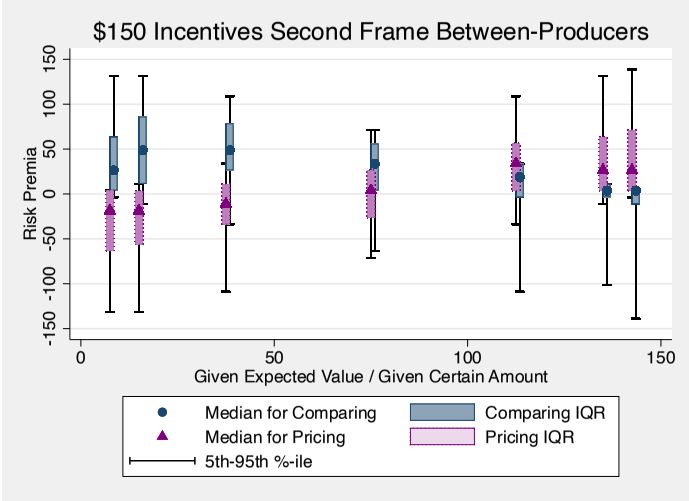
(a) Low Stakes for Students



(b) High Stakes for Students



(c) First Frame for Ag. Producers



(d) Second Frame for Ag. Producers

Figure 9: Comparisons by Stakes, Populations, and Context Ordering

Notes: Data is from 398 producers and 115 students and their first switching point.

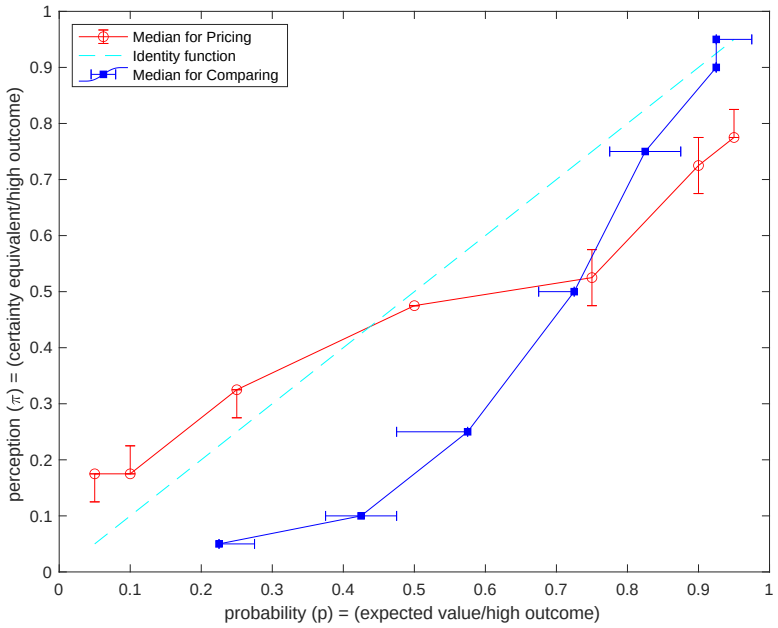
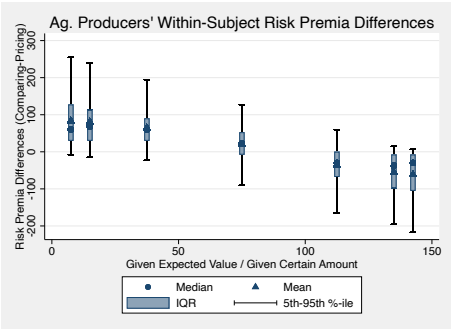
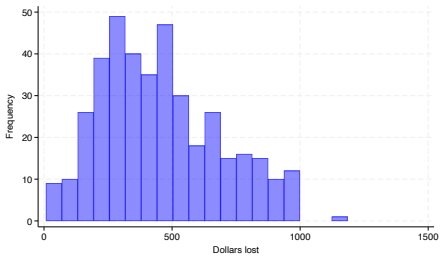


Figure 10: Normalized Median Choices by Choice List Type

Notes: Data is from 398 producers using their first switching point. Error bars represent 95% confidence intervals for median values.



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



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

Notes: Data is from 398 producers and 115 students using their first switching point.

Table 10: Individual Parameters for KR w/ Context-Dependent Sensitivity

parameter	median	95% CI
ρ	0.768	[0.683, 0.911]
λ	1.917	[1.353, 3.102]
α(Pricing)	1.677	[1.387, 1.936]
α(Comparing)	0.361	[0.255, 0.465]

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 390 producers' first switch point for every choice list. For eight producers, parameters could not be estimated.

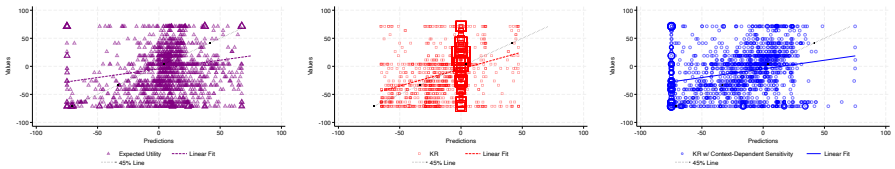


Figure 12: Predicted and Observed Values

Notes: Data is from 390 producers for KR with context-dependent sensitivity and 398 for KR and EU, using the first switching point. For eight producers, parameters could not be estimated for KR with context-dependent sensitivity.

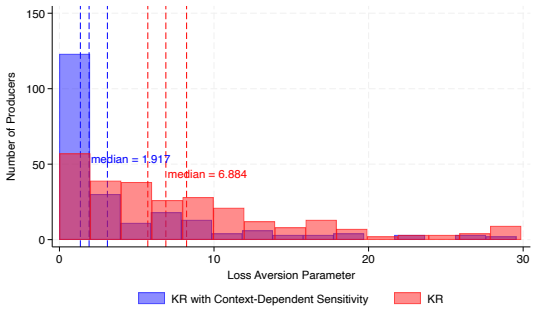


Figure 13: Loss-Aversion Parameter Values

Notes: Data is from 390 producers for KR with context-dependent sensitivity and 398 producers for KR, using their first switch-point. Picture restricts observation to values in [0,30) for readability. All summary statistics are calculated with the full sample whose parameters could be calculated. Dashed lines represent 95% confidence intervals. For eight producers, parameters could not be estimated for KR with context-dependent sensitivity.

Appendix C Third Generation Prospect Theory

A specific model that is a natural candidate to explain our behavioral patterns is third-generation prospect theory Schmidt, Starmer, and Sugden (2008). Second-generation prospect theory is the leading explanation for the pricing patterns that we observe and third-generation prospect theory was developed to generalize it to be able to account for stochastic referents and preference reversals. Therefore, one would hope it could explain the pattern we identify. We find it struggles to explain our behavioral pattern.

To see why, let f, and g be two different acts. An act is a function ($f : s \to \$x$) from states of the world to consequences (monetary outcomes in our context) and is more general than the notion of a prospect/lottery. Then, $PT^3(f, g) = v(f(s), g(s))\pi_i$, where v is a state-contingent reference-dependent utility function and π_i, are the rank-dependent probability weights. For the following result, we assume the standard form for loss aversion or $v(-x) = -\lambda v(x)$. First, note that because $v(f(s), f(s)) = v(g(s), g(s))$ we have that $PT^3(c, c) = PT^3(L, L)$ for any certain amount c and lottery L.

C.1 PT^3 Preferences when Pricing Binary Lotteries

Assume the underlying preferences are given by $c \sim (q_h, x_h; (1 - q_h), x_l)$ for some fixed lottery. We begin by normalizing $PT^3(c, c) = 0$. Then we get $P(c, c) = PT^3(q_h, x_h; (1 - q_h), x_l, c)$ which yields $\frac{v(c,x_l)}{-\lambda v(x_h,c)} = -\frac{\pi_(q_h)}{1-\pi_(q_h)}$. We can rewrite this as $\frac{v(c,x_l)}{v(x_h,c)} = \lambda\frac{\pi_(q_h)}{1-\pi_(q_h)}$.

C.2 PT^3 Preferences when Comparing Binary Lotteries

Assume we elicit the lottery such that $(p_h, x_h; (1 - p_h), x_l) \sim c$ fixed amount c from the previous exercise. Since

$$PT^3(c, c) = PT^3\left((p_h, x_h; (1 - p_h), x_l), (p_h, x_h; (1 - p_h), x_l)\right),$$

its value is zero. Then, using $PT^3(q_h, x_h; (1 - q_h), x_l, c) = P(c, c)$ we get $-\lambda\frac{v(c,x_l)}{v(x_h,c)} = -\frac{\pi(p_h)}{1-\pi(p_h)}$. We can rewrite this as $\frac{v(c,x_l)}{v(x_h,c)} = \frac{1}{\lambda}\frac{\pi(p_h)}{1-\pi(p_h)}$.

Since the fixed amount is the same across both contexts, we get $\frac{\pi(p_h)}{1-\pi(p_h)} = \lambda^2\frac{\pi(q_h)}{1-\pi(q_h)}$. Since π is strictly increasing under the standard rank-dependent assumptions, the probability equivalent (p_h) from comparing is larger than (q_h). This relation is equivalent to the risk premia from the pricing tasks being higher

than the risk premia from the comparing tasks. Since this predicts that comparing tasks always induce more risk aversion, it cannot rationalize a reversal near the certainty of the favorable (high) outcome or that comparing tasks will induce less risk aversion near favorable certainty.

C.2.1 PT^3 Predictions with Loss and Gain Probability Weighting Functions

Wakker (2010) argues that the probability weighting function is different for losses (π^-) and for gains (π^+). Perhaps less well-known, as discussed in his book, is the surprising mathematical result that as long as they change at zero one can preserve dominance even with two distinct probability weighting functions. To make this work, one also needs to employ the standard cumulative fixing inherent in rank-dependent models. In the results above, we assumed a single probability weighting function sufficed; it did not, but perhaps two can do the trick.

Our answer to whether two probability weighting functions can explain a near-certainty effect is twofold. On the one hand, the result is mathematically plausible. On the other, the parameters necessary to fit the data are at odds with generally observed values (Brown et al., 2023; Vieider et al., 2019). To highlight the former, we provide an equation that must hold between the pricing and comparing contexts and a condition on preferences that may explain our results. To emphasize the latter, we discuss a parametric restriction that works and provide some intuition as to the conditions this type of restriction necessitates.

As in Section C.1, we begin by fixing a lottery. In this instance, we get $\frac{v(c,x_l)}{v(x_h,c)} = \lambda_{PT}\frac{\pi^-(q_h)}{1-\pi^+(q_h)}$. Similarly, as in Section C.2, we fix the certain amount c from the previous exercise and this yields the following condition of $\frac{v(c,x_l)}{v(x_h,c)} = \frac{1}{\lambda_{PT}}\frac{\pi^+(p_h)}{1-\pi^-(p_h)}$.

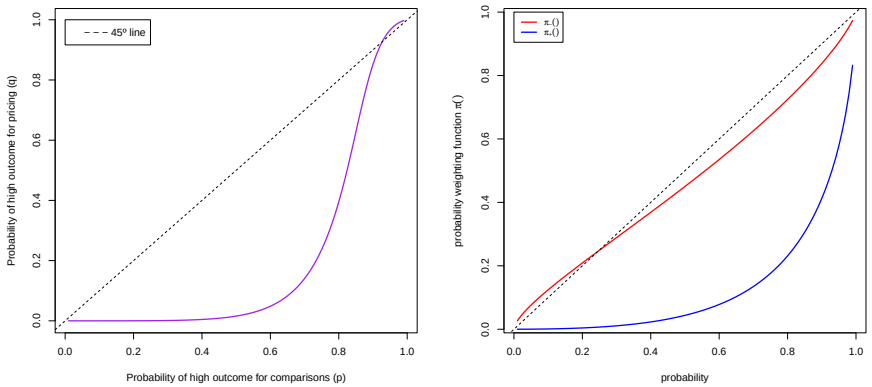
Putting both together for a common certain amount c yields

$$\frac{\pi^+(p_h)}{1-\pi^-(p_h)} = \lambda_{PT}^2\frac{\pi^-(q_h)}{1-\pi^+(q_h)}. \tag{12}$$

More risk seeking for pricing than for comparing implies that for a fixed c we must have that $q_h < p_h$. If pricing induces more risk aversion, then we get $q_h > p_h$. One way to see this is to fix a value on the y-axis (c/high outcome) in Figure 4 and compare the x-values from pricing and comparing. Hence, to explain the pattern of choices, we observe we need for $q_h < p_h$ initially, then for

$q_h = p_h \approx .85$, and $q_h < p_h$ for all higher values (equality should also hold at the endpoints).

If we assume loss aversion ($\lambda > 1$), then many strictly increasing functional specifications will satisfy $q_h < p_h$. The trickier part is getting the relation to flip to ($q_h > p_h$). One way to achieve this is for the probability weighting function for losses to be substantially flatter (more concave) than the probability weighting for gains that must be substantially steeper (more convex). The adjective substantial is employed as the strictly increasing specifications for the one-parameter family $\pi(p) = \frac{p^\gamma}{(p^\gamma+(1-p)^\gamma)^{\frac{1}{\gamma}}}$ will fail to exhibit sufficient bending. Moreover, with losses looming twice as much as gains ($\lambda = 2$), one really needs to push the $\pi^+(\cdot)$ towards forming a right angle at the southeast corner of the positive orthant (See Figure 14b) to generate any flip whatsoever. Figure 14 shows the most sensible example we were able to construct using values that are near observed values.



(a) Predicted Relationship between Pricing (q_h) and Comparing (p_h)

(b) Probability Weighting Functions for Losses and Gains

Figure 14: Third Generation Prospect Theory with Probability Weighting Functions for Losses and Gains

Notes: We assume $\lambda_{PT} = 1.5$ and using Prelec (1998)'s two-parameter specification we assume $(\alpha^+, \alpha^-) = (.8, .67)$ and $(\beta^+, \beta^-) = (4, 1.07)$.

Appendix D Discussion of our Pre-analysis Plan

Our pre-analysis plan was submitted to the AER RCT registry AEARCTR-0006951. Our experimental design is consistent with our pre-analysis. The total number of producers (398) is in line with our projected number (400) to detect a 20% decrease (-$10) in risk premia when compared to the student sample. Also true to our pre-analysis plan, we concentrate on risk premia and risk premia differences as the main outcome measures.

Our main hypothesis was that producers would exhibit smaller discrepancies in risk premia between the pricing and comparing tasks. Our data is inconsistent with this hypothesis, as shown in Figure 15. T-tests favor the opposite hypothesis or fail to reject a difference.

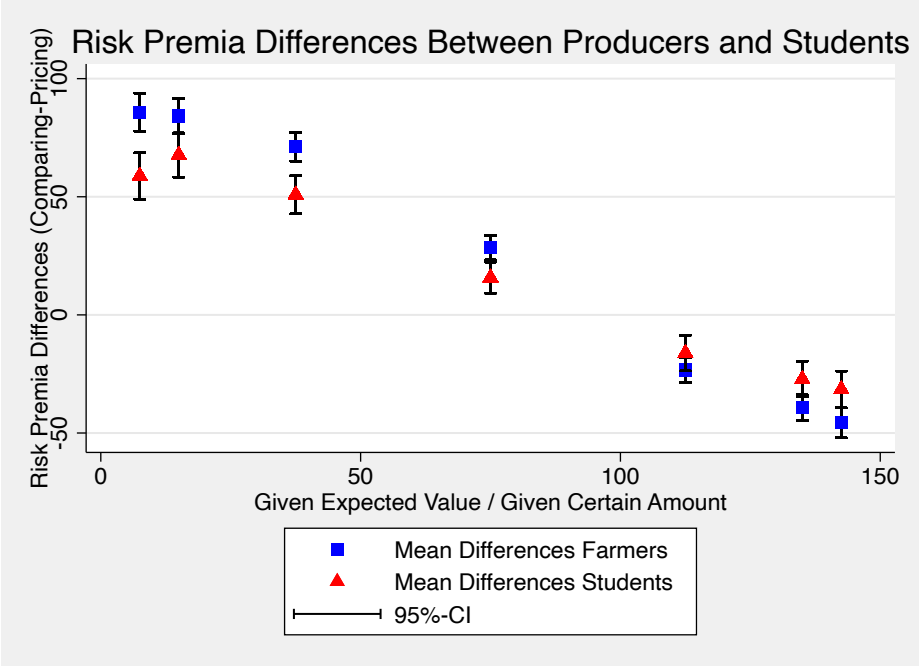


Figure 15: Risk Premia Differences by Expertise

Notes: Data is from 307 producers and 88 students using their first switching point. Error bars represent 95% confidence intervals.

D.1 Hypothesis from Pre-analysis Plan

Hypothesis 1: All subjects will be, on average, more risk-averse under com-

paring than under the pricing tasks. The null hypothesis is no difference in risk premia across the different elicitations.

Result 1: As can be glanced from 6, all subjects are on average at least 10% more risk averse when comparing than when pricing. All differences are statistically significant below the usual 1% threshold.

Hypothesis 2: For students, we expect that, on average, the difference in risk premia when subjects compare tasks versus when they price tasks would be different across the high and low incentive conditions. Our null was no difference in the risk premia differences across incentives.

Result 2: This hypothesis was confirmed by the results reported in Section 2 of our pre-analysis plan. We found a higher value for the differences in risk premia for higher incentives. For students, we found comparisons yielded a 10% higher risk premia for comparisons than for pricing tasks and that this percentage change was stable at the two incentive levels considered (max outcome=\$30 against max outcome=\$150). This relationship can be corroborated by contrasting Figure 3a and Figure 3b. Our point estimates from the interval regression are \$3.547 (\$0.503, s.e.) for the lower incentives and \$16.887 (\$2.268, s.e.) for the higher incentives. Producers only faced the higher incentives, so we can only conjecture a similar relationship holds.

Hypothesis 3: For the skewness tasks, all subjects will have, on average, higher risk premia under comparing that under the pricing tasks. The null hypothesis is no difference in risk premia across elicitations for the skewness tasks.

Result 3: We observe comparisons tend to increase risk premia for all subjects. Producers skewed lotteries had an expected value of \$75, while students had an expected value of \$15, and differences in risk premia reflect these magnitude differences. For producers, we find comparisons increase the 'implied'[12] risk premia by \$32.876 (\$3.132, s.e.) for the more skewed task and \$20.814 (\$3.178, s.e.) for the less skewed task. For students, we find comparisons increase the implied risk premia by \$5.816 (\$0.811, s.e.) and \$2.852 (\$0.850, s.e.) for the less skewed task.

Hypothesis 4: Producers will exhibit smaller differences in the absolute risk premia value from pricing and comparing tasks than students. The null hypothesis is no difference in risk premia elicitations across populations. **Result 4:** We omit the ordered probit and interval regression analysis outlined in our

[12] For probability equivalents, we use $\mathbb{E}[p] - \mathbb{E}[S]$.

pre-analysis as the results are quite clear and contrary to our hypothesis. Our evidence suggests producers exhibit bigger differences in absolute risk premia. Figure 15 is consistent with producers exhibiting a bigger difference in absolute risk premia.

Hypothesis 5: Positive skew will increase the differences in risk premia from pricing and comparing. The null is no difference in the risk premia differences from increasing skewness while keeping the other two first moments fixed.

Result 5: For this hypothesis, we find higher positively skewed lotteries increase risk premia differences between pricing and comparing. Evidence of this effect between no skew and lowered positively skewed is inconclusive. We use data from Result 3 and the 50/50 chance of \$150 (\$30) or \$0, the non-skewed lotteries from the main tasks. For producers the 50/50 chance of \$150 or \$0 increases risk premia from comparing by \$28.436 (\$2.625, s.e.) and \$3.920 (\$0.778, s.e.) for students. The p-values for the t-tests for producers' positive skew increasing risk premia differences are 0.0035 (high skew differences larger than low skew), 0.991 (low skew differences larger than no skew), and 0.080 (high skew no skew). The p-values for the t-tests for producers' positive skew increasing risk premia differences are 0.006 (high skew differences larger than low skew), 0.822 (low skew differences larger than no skew), and 0.047 (high skew differences larger than no skew).

Hypothesis 6: We will test two alternatives. First, that risk preferences from the comparisons are more informative than pricing risk preferences. Second, that pricing risk preferences are more informative. Our null hypothesis is that risk premia from the comparison tasks are equally informative as the risk premia from the pricing tasks for predicting prevented planting decisions.

Result 6: We intend to test this hypothesis in future work. We are still working on securing administrative data for prevented planting decisions.