Farmer Risk Aversion to Changing Weather

by

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Keywords: risk preferences, farmer behavior, adaptation decisions

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Introduction

Understanding farmer risk preferences is becoming more important than ever as farmers confront climate change. Many geographic regions, including the Midwestern United States, are experiencing extreme weather with greater frequency as sporadic drought and excessive rainfall become more common (Chen & Ford, 2023; Ford et al., 2021). Changing weather alters the location and shape of crop yield probability distributions (Lobell et al., 2011; Miller et al., 2021; Ortiz-Bobea, 2021; Schlenker & Roberts, 2009; Tack et al., 2012). Farmers have always managed production risk. But as climate changes, production risk is changing, and farmers must adapt. How they manage risk under these shifting conditions largely depends on their risk preferences. If the context of changing climate affects those risk preferences, then that context matters for climate change adaptation policy.

Apart from the early work of Von Neumann and Morgenstern (1947) on risk in game theory, much of the early thinking about decision making under risk was done by psychologists (Edwards, 1953, 1961; Tversky, 1967). Economists John Pratt (1964) and Kenneth Arrow (1965) provided the conceptual foundation for expected utility theory (EUT) and its mathematical expression. The functions that model risk preferences have evolved with the associated EUT. Early empirical studies estimated mean-variance utility functions (Dillon & Scandizzo, 1978; Officer & Halter, 1968) where concavity implied risk aversion, consistent with the theoretical work of Von Neumann and Morgenstern (1947).

Following the development of expected utility functions that exhibit constant absolute (CARA) and relative (CRRA) risk aversion based on wealth (Arrow, 1971; Pratt, 1964), these functions and variants were used to estimate risk aversion levels based on elicited risk preferences and risky choices (Binswanger, 1980; Dillon & Scandizzo, 1978). The expo-power function, introduced by Saha (1993) nests both the CARA and CRRA forms, enabling the direct modeling of risk aversion that decreases or increases with wealth or changes in income. Holt and Laury (2002) adapted the expo-power function for maximum likelihood estimation (MLE) using information elicited about acceptable price levels. Innovations in choice experiments to elicit risk preferences from lottery choices enable MLE of expected utility functions for individuals (Harrison & Rutström, 2008).

Economic choice experiments have shown that behavior is affected by both who makes the choice (the experimental population) and what they are choosing (the domain). It is now well established that for most populations of decision makers, "who" makes a difference: Field experiments with the relevant population are more informative than lab experiments with university students (Levitt & List, 2007). Growing evidence indicates that context matters too, because risky choices in the abstract are often different than similar choices in a familiar domain (Cerroni, 2020; Nguyen et al., 2022). For farmers exposed to changing climate risk, the farming context may influence their risk preferences and risk management choices.

Agricultural economists have a long history of using choice experiments in the field to elicit farmer attitudes toward risk. The earliest field research used simulated games against nature to elicit indifference curves for pairs of risky choices based on general gambles (Officer & Halter, 1968). Within a decade, Dillon and Scandizzo (1978) elicited risk preferences in an agricultural domain using a paired sample of small-scale landowners and sharecroppers. Shortly thereafter, Binswanger pioneered experimental lottery choices connected to real payoffs (Binswanger, 1980). Over recent decades, significant advances have enabled the estimation of expected utility functions using random lottery pairs (Hey & Orme, 1994) and MLE from limited dependent variable data (Harrison & Rutström, 2008).

Using these methodological tools, this research aims first to estimate expected utility functions and associated risk preferences for an aggregate sample of farmers presented with lottery choices in an abstract, general domain compared to choices in the context of agricultural investments driven by weather risk. We focus on agricultural investments related to water management because climate change in Michigan (where the research was conducted) is expected to make precipitation less frequent and more intense, increasing risk of seasonal drought and excess moisture. To our knowledge, this is the first paper to frame risk preference elicitation in the context of climate change conditions that impact crop yields.

Second, we compare the dispersion of individual risk preferences between the general and agricultural domains. A recent meta-analysis enables us to compare risk preferences not just for sample means, but across individuals sampled (Garcia et al., 2024). Third, we estimate the determinants of individual risk aversion levels for both domains. Prior studies have found risk aversion to be affected by age (Holt & Laury, 2002; Mata et al., 2011; Meissner et al., 2023; Tanaka et al., 2010), income (Holt & Laury, 2002; Meissner et al., 2023), wealth (Garcia et al., 2024), and education (Donkers et al., 2001; Gächter et al., 2022; Garcia et al., 2024; Harrison et al., 2007; Vieider et al., 2019; Von Gaudecker et al., 2011). Of special interest is the effect of wealth on risk aversion, as wealth effects could influence policy design. Fourth and last, we suggest how the traits of weather-driven agricultural risk aversion and its determinants can inform climate change adaptation policy.

To preview the results, we find that farmers are risk averse. The farmers interviewed were more risk averse for weather-driven, agricultural investment decisions than for general, context-free lottery choices under the CARA and expo-power functions, although the difference was not statistically significant at the 0.10 level under the CRRA function. Farmers' individual CRRA risk aversion coefficients were more heterogeneous for weather-driven agricultural investments than for general lottery choices. In both domains, the degree of risk aversion decreased with cropland acreage, a measure of wealth. In the general lottery domain, age was also a determinant, with risk aversion increasing quadratically up to age 70 and decreasing thereafter.

These findings suggest that risk aversion affects agricultural investment decisions related to climate change adaptation. The wide dispersion of risk attitudes implies that adaptation communications and policies should be tailored to the degree of risk aversion. For the largest-scale farmers (managing more than a few thousand acres), messaging about climate change adaptation should focus on relatively risk-neutral profit maximization and returns on investment. By contrast, messaging to smaller-scale farmers should focus on limiting down-side revenue risk.

We structure the remainder of this paper as follows. We first provide an overview of EUT and define relevant functional forms. Next, we describe our econometric estimation methods. Then, we explain our sampling approach, data collection process, structure of the interviews, and experimental design. Finally, we present our results and discuss the policy implications summarized above.

Conceptual and Empirical Framework

Conceptual Framework

The mathematician Bernoulli was the first to discuss risk preferences in 1738 (Bernoulli, 1738 [1954]). Bernoulli stated that to understand the value an individual places on something, one needs to measure the value based on utility as opposed to price. Since then, the experimental psychology and economics literatures have explored the concept of risk preferences extensively (Mata et al., 2018). In both cases, risk preferences refer to the tradeoffs that individuals are willing to make between rewards and losses. To model risk preferences, one can build upon of Bernoulli's concept of utility with the expected utility theory (EUT).

Von Neumann and Morgenstern (1947) illustrated how to obtain the EUT from three axioms about decision-maker preferences: 1) that preferences can be ordered, 2) that they are continuous, and 3) that the order is independent of irrelevant alternatives. Given these assumptions, the EUT posits that an expected utility function exists for each decision maker based on objective probabilities. The utility function can be nonlinear, where concavity connotes risk aversion and convexity connotes risk preferring. We denote utility for individual n as $U_n(w_{ij})$, where w_{ij} represents the lottery payoff j for lottery alternative i. Eq. (1) defines the expected utility for lottery i given the exogenously defined payoff, w_{ij}, and corresponding exogenous probability, p_{ij}, for each j lottery outcome.

$$EU_{ni} = \sum_{l=1}^{j} p_{ij} U_n(w_{ij}) \tag{1}$$

Since Von Neumann and Morgenstern (1947) posited the EUT, advances have been associated with measuring the degree of risk aversion, the shape of utility functions, and the empirical methods for estimating the corresponding risk parameters of the assumed utility functions. In order to quantify the degree of risk preferences, one can analyze the Arrow-Pratt Indexes of Absolute Risk Aversion and Relative Risk Aversion (Arrow, 1965; Pratt, 1964).

Two functions that are compatible with EUT and that exhibit constant risk preferences are the constant absolute risk aversion (CARA) and constant relative risk aversion (CRRA) functions (Pratt, 1964). CARA implies preference equivalence sets for lottery pairs that differ by an additive shift, meaning that the preference between two lotteries is unaffected if the same amount increases the payoffs (Wilcox, 2008). In this case, preferences between \$100 versus \$120 are the same as \$200 versus \$220 since the same additive term has increased all outcomes. Meanwhile, CRRA preferences imply preference equivalence sets for lottery pairs that differ by a proportional shift (Wilcox, 2008). Hence, under the CRRA assumption, the preferences for \$100 versus \$200 are the same as \$200 versus \$400, given that the same multiplicative term increases both outcomes.

We follow common practice in using the negative exponential function to model CARA preferences, with the risk preference parameter represented by α, as shown in Eq. (2). We utilize the power function to model CRRA preferences, with the risk aversion parameter represented by r in Eq. (3).

$$U(w) = -e^{-\alpha w} \tag{2}$$

$$U(w) = \frac{w^{1-r}}{1-r} \tag{3}$$

For the negative exponential function defined by Eq. (2), the Arrow-Pratt Index of Absolute Risk Aversion reduces to the constant term of α. Similarly, for the power function defined by Eq. (3), the Arrow-Pratt Index of Relative Risk Aversion reduces to the constant term of r. Under both CARA and CRRA, a negative risk aversion parameter represents risk-loving behavior, a positive risk parameter represents risk-averse behavior, and preferences approach risk neutrality as the risk aversion parameters approach zero.

Previous work relied on nonlinear approximations of the utility function (Kaylen et al., 1987; Lambert & McCarl, 1985) or non-nested tests (Vuong, 1989) to choose the best model fit between CARA (Eq. 2) and CRRA (Eq. 3) preferences. Saha (1993) introduced the expo-power utility function, a flexible form that can model relative and absolute risk aversion. Holt and Laury (2002) modified Saha's (1993) function to the version shown in Eq. (4) that demonstrates alternative risk preferences based on the parameter signs and values. The expo-power function in Eq. (4) allows for nested tests, considering that it represents CARA as $r \to 0$ and CRRA as $\alpha \to 0$. These reductions can be shown by calculating the associated Arrow-Pratt Indexes, which are provided in the supplemental material.

$$U(w) = \frac{1 - exp\,(-\alpha w^{1-r})}{\alpha} \tag{4}$$

When the expo-power function cannot be simplified to one of the nested CARA or CRRA functions, it displays risk aversion that changes over the magnitude of the stakes of the risky gambles.

Both the parameter α from the exponential function (Eq. 2) that represents CARA and r from the power function (Eq. 3) that represents CRRA can be found in the nested expo-power function (Eq. 4) that provides a flexible form containing both α and r. However, we cannot straightforwardly compare these parameter estimates, because the α of the nested expo-power function (Eq. 4) does not directly represent the Arrow-Pratt Index of Absolute Risk Aversion, nor does the r from Eq. (4) represent the Arrow-Pratt Index of Relative Risk Aversion. The α and r estimated for the expo-power function must be plugged into the corresponding equations to calculate the Arrow-Pratt Indexes of Absolute and Relative Risk Aversion.

Empirical Framework

A fundamental challenge in measuring risk attitudes is that we cannot observe an individual's utility function directly. However, we can make statistical inferences from the preferences revealed by how a decision maker makes choices. While there are various elicitation methods, we utilize the random lottery pair method as it is easy to explain to participants, applicable to production risk, and incentive-compatible (Charness et al., 2013; Harrison & Rutström, 2008).

The random lottery pair method presents subjects with one pair of lotteries at a time, and the participants must make multiple choices in a random sequence (Hey & Orme, 1994). Risk preferences elicited using lotteries have been shown to predict market behavior more reliably than values elicited using self-reported psychometric scales (Pennings & Smidts, 2000). Unlike the multiple price list method popularized by (Holt & Laury, 2002), one cannot directly infer risk preferences from the responses for random lottery pairs. Researchers must use estimation methods, such MLE, to calculate risk preferences (Harrison & Rutström, 2008). The random lottery pair method allows us to estimate risk preferences in the context of production risk that is the focus of this research, while the multiple price list method focuses on prices (Anderson et al., 2007).

The random lottery pair method enables the econometric estimation of functions $U_n(w_{ij})$, such as Eq. (2-4), for decision maker n from choices between pairs of risky gambles. In this research, we offer two sets of risky gambles, where w_{ij} represents the lottery payoff j for lottery alternative i. The first set of lottery pairs comprises context-free choices where the decision maker must choose between two lotteries, each of which has two payoffs with associated probabilities. The second set of lotteries involves choices in an agricultural domain where participants make decisions regarding investments to manage weather-driven, crop yield risk.

The random utility framework provides the theoretical underpinning for econometric estimation. It models an individual's preferences between the available alternatives as the choice that results in the highest expected utility for the individual (McFadden, 1973). In this framework, the dependent variable is the binary choice, where $y_i = 1$ indicates the lottery chosen. The probability that decision maker n chooses alternative i instead of alternative k depends on the exogenous payoffs, w_{ij} and w_{kj}, and probabilities, p_{ij} and p_{kj}, associated with each lottery choice.

$$P(y_i = 1 | \, w_{ij}, p_{ij}, w_{kj}, p_{kj}) = Prob[EU_{ni} > \, EU_{nk}] \; \forall \; \mathrm{i} \neq \mathrm{k} \tag{5}$$

Because utility is not directly observable, one can only predict the probability that a decision maker selects a given lottery. We apply MLE to a binary response model using a choice probability equation. We then estimate the parameters of the utility function that maximize the probability that the observed choice of the individual maximizes their expected utility compared to the option they did not choose. In particular, we maximize a function of the difference between expected utilities for each binary lottery choice. We can rewrite Eq. (5) as

$$P(y = 1 | \, w_{ij}, p_{ij}, w_{kj}, p_{kj}) = Prob[EU_{ni} - \, EU_{nk} > 0] \; \forall \; \mathrm{i} \neq \mathrm{k} \tag{6}$$

The utility functions of Eq. (2-4) each enter the EUT function of Eq. (1) separately to create the latent index. The latent index is then linked to the observed choices using a standard cumulative normal distribution function $\Phi(EU_{ni} - \, EU_{nk})$. We construct a log-likelihood equation (Eq. 7) to obtain parameter estimates given the bivariate probit index function. The log-likelihood equation depends upon the utility theory being evaluated, the functional form of the utility function, and an indicator variable that specifies the lottery choice from the set. Therefore, for each decision maker, n, we can estimate risk preferences from lottery choices as follows:

$$LL\big(U_n(w); \, w_{ij}, p_{ij}, w_{kj}, p_{kj}\big) = \tag{7}$$

$$\textstyle\sum_i [\ln(\Phi(EU_{ni} - \, EU_{nk})) * \boldsymbol{I}(y = 1) + \, \ln(\Phi(-(EU_{ni} - \, EU_{nk}))) * \boldsymbol{I}(y = 0)] \; \forall \; \mathrm{i} \neq \mathrm{k}$$

where $\mathbf{I}(.)$ is the indicator function and y indicates the lottery choice. Through MLE, we can estimate $\hat{\alpha}$ from Eq. (2), $\hat{r}$ from Eq. (3), or $\hat{\alpha}$ and $\hat{r}$ from Eq. (4), depending on which utility function is used for the latent index.

Once we have parameterized Eq. (2-4), we can evaluate which utility model best suits each lottery domain. For the aggregate sample we compare results from all three expected utility models. For evaluation of the distribution of individual farmer risk aversion levels, however, we first select a preferred model using both theoretical and empirical criteria. From a conceptual perspective, Lau (1986) identifies five key criteria: theoretical consistency, factual conformity, computational facility, flexibility, and domain of applicability. To these we add parsimony of parameters and readily interpreted parameters (Frank et al., 1990).

The exponential function (Eq. 2) that represents CARA, the power function (Eq. 3) that represents CRRA, and the nested expo-power function (Eq. 4) that provides a flexible form were all constructed to provide theoretical consistency and factual conformity under EUT. For the computational facility criterion, the single-parameter exponential (Eq. 2) and power (Eq. 3) functions allow for more straightforward model estimation and parsimony of parameters. However, the complexity of the expo-power function (Eq. 4) allows for greater flexibility and more complex risk preferences than CARA or CRRA, giving it a broader domain of applicability. Finally, the CARA and CRRA models offer constant risk aversion parameters that are more readily interpreted.

We apply nested choice-of-model tests as empirical measures of goodness-of-fit to expected utility functions estimated individually (for each farmer) as well as in aggregate (for the whole sample). Specifically, we evaluate whether the more complex expo-power model has added explanatory power that justifies its use over the simpler CARA or CRRA models by applying the

Wald test (Wald, 1943) of the null hypotheses $r = 0$ (implying CARA preferences) and $\alpha = 0$ (implying CRRA preferences).

Our objectives in evaluating the attitudes of Midwestern U.S. farmers toward weather risk are to test two exploratory hypotheses. The first tests the importance of the domain or context. In null form, it states that risk preferences are the same regardless of context, no matter whether elicited with a general lottery or with weather-related agricultural lottery data.[1] Using the frequency distribution of individual estimates, we select a preferred expected utility functional form and consider whether the context affects the mean level of risk aversion as well as the median and the spread. The literature abounds with evidence that contextual instructions can matter in experimental economics (Alekseev et al., 2017; Meraner et al., 2018; Rommel et al., 2019), so we wished to determine whether a weather-driven, agricultural yield risk context affects farmer risk preferences.

Our lottery experiment can be defined as a framed field experiment. Framed field experiments present subjects with risky decisions in their areas of expertise in a natural but controlled setting (Harrison & List, 2004). By adding context familiar to the participants, framed field experiments often introduce the background, exogenous risks, and endogenous risks explicitly presented within the experiment (Eeckhoudt et al., 1996).

Our second null hypothesis is that risk preferences are inherent and thus unrelated to potential determinants that are externally observable. To estimate the effects of decision-maker traits on

[1] The psychology and economics literature have developed cumulative prospect theory (CPT) as an alternative to EUT (Bocquého et al., 2014; Finger et al., 2024). CPT can accommodate more nonlinearities given the additional parameters. However, the estimation therefore requires many lottery choice observations. Given we were already comparing two lottery domains, we opted not to risk inducing cognitive fatigue by including additional lottery questions.

decisions, we include a vector of traits, $\boldsymbol{X'} = [X_1 \cdots X_j]$, in the MLE equation that estimates the risk aversion coefficient(s). For the CRRA risk aversion coefficient, this would look like,

$$\hat{r} = \hat{\beta}_0 + \hat{\beta}_j \boldsymbol{X} \tag{8}$$

We are particularly interested in whether risk aversion changes with wealth, as there is prior evidence for risk aversion decreasing with wealth, that wealthier individuals have a safety net (Garcia et al., 2024). Our study uses income intervals, acres operated, and debt-to-asset ratio intervals to proxy for wealth.

Data

This framed field experiment is based on interviews of Michigan crop farmers at county-level meeting places, including restaurants and county offices of Michigan State University Extension. We selected interviewees from the population of Michigan corn-soybean farmers who operated at least 300 acres in 2022 and devoted a portion of this land to growing corn for grain. We chose a minimum of 300 acres to ensure that the producers relied on farming as a major source of income (USDA-NASS, 2022). As such, our participants would take seriously risk management to safeguard their income. We also wanted participants to be the primary farm decision maker on crop production, as we asked questions about corn production and commodity prices. Michigan State University Extension educators helped with recruitment, resulting in 44 farmer interviews between September 2022 and April 2023.

We conducted computer-assisted, in-person interviews, with the general lottery directions presented to the group before individual completion of the online survey with Qualtrics. Graduate students from the Department of Agricultural, Food, and Resource Economics at Michigan State University facilitated the personal interviews by answering questions and assisting with navigating the online survey. The first and second portions of the study comprised the lottery-based experiments. The first section contained 25 binary lottery choices in a general domain, while the second section presented 18 lottery choices in the context of farm investment decisions related to weather-driven crop yield risk.

We presented the 25 general lottery pairs in random order to prevent ordering effects; they included payoffs that were both positive, both negative, and a mix of the two. The general lottery experimental design is based on Pedroni et al. (2017) to ensure adequate variation across payoffs and probabilities. Each general lottery had two potential outcomes denoted by bar graphs to visually represent the corresponding probabilities for each outcome. For example, Figure 1 depicts that Lottery A offers 40% odds of winning $100,000 versus 60% odds of losing $80,000, while Lottery B offers 25% odds of winning $10,000 versus 75% odds of losing $40,000.

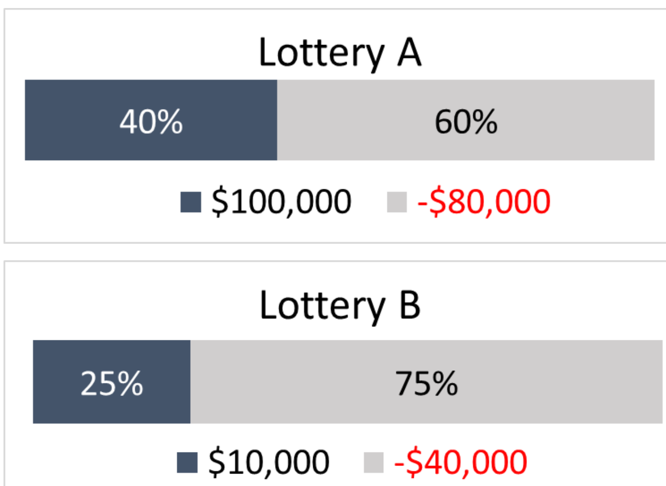

Figure 1: Example of visual representation of lottery bar graphs.

Before beginning the general lottery experiment, we provided each participant with a $50 participation payment plus a $40 endowment from which they could gain or lose money, given that the lottery outcomes included negative payoffs. We informed participants that the computer would randomly select one of the questions to determine a payoff, with a conversion from hypothetical dollars to real money of $4,000 to $1. In extreme cases, the payoff could double or erase the $40 endowment. The supplemental information includes the complete set of general lotteries, the experimental procedures, and example questions for each payoff type.

The agricultural lottery experiment framed the 18 lottery choices as investment decisions to mitigate revenue loss due to excessive moisture or drought. We informed participants that payoffs were based on revenue of $24,000 for the hypothetical 40-acre field. The payoffs in the agricultural lottery domain were grounded in potential corn yield outcomes under Michigan production conditions, so the design lacks the full orthogonality of the general lottery payoffs. The lotteries offered choices between taking no action or investing in drainage, irrigation, drought-tolerant seeds, or crop insurance. For example, a participant had a 30% chance of their hypothetical field flooding in the upcoming season and a 70% chance that the field does not flood. They could invest in tile drainage at 60ft spacing with an annualized cost of $1,600 for the 40-acre field. If the participant chose not to invest in tile drainage, they had a 70% chance of the flood not occurring, corresponding to receiving the total gross income of $24,000 for the 40-acre field. They also had a 30% chance of the flood occurring, in which case they would hypothetically receive $20,000 due to crop yield loss. The payoffs related to investing in tile drainage at 60-foot spacing reflected a 70% chance of receiving $22,400 (the gross crop revenue minus the annualized investment cost if the flooding event does not occur) versus a 30% chance of receiving $21,200 (the gross crop revenue less the annualized investment cost and a smaller percentage of crop yield if flooding does occur). Given the high cost associated with irrigation, we also included four irrigation lottery questions with a higher baseline crop revenue of $48,000 to reflect higher potential mean yields.

Each investment category had a 2x2 experimental design with combinations of high and low probability of adverse weather outcomes and high and low investment costs to provide variation in the lottery questions. The one exception to the 2x2 design was drought-tolerant seeds. There was only one level of investment intensity (to buy the seed), but there was still a high and a low probability question while holding intensity constant. These combinations resulted in a set of 14 agricultural lotteries with four questions relating to tile drainage, four relating to crop insurance, two about drought-tolerant seeds, and four for irrigation investments. With the four additional irrigation investments at a higher revenue level, we have a total of 18 agricultural lotteries.[2] We consulted with Michigan State Extension agents to ensure realistic investment costs and intensities. The proportion of crop yield loss in the event of adverse weather without investment was taken from Li et al. (2019).

To help with participant understanding, we grouped the questions for each investment type into a block of questions. For example, we grouped all drainage questions within a block. We then randomized the order of the questions within the block, so participants saw the drainage questions together in a random sequence. We also randomized the order of the blocks so that one individual might see the block of drainage questions first, while another may see the block of drainage questions as their third investment type. We include the complete set of agricultural lotteries in the supplemental information, along with example questions for each investment type. Given that the subject sample of 44 farmers completed 25 general lottery questions and 18 agricultural lotteries, the panel data include 1,100 and 792 observations under each lottery type.

The sample broadly represents Michigan corn-soybean farms that rely heavily on farming for household income. While the sample was selected purposively, participant farms are spread across the southern half of Lower Michigan, which is the region where corn and soybean are cash crops. Sample traits largely align with the 2022 Michigan Census of Agriculture (USDA-NASS, 2024a).

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[2] We have 18 agricultural lotteries as opposed to 25 to minimize cognitive fatigue. The agricultural lottery questions required participants to read background information to put the lottery choice into investment contexts. Therefore, we went with the 2x2 design experimental design.

Table S3 in the supplemental information provides a detailed comparison of sample characteristics to the 2022 Michigan Census of Agriculture. We have a similar racial composition compared to the state-level data for Michigan on the North American Industry Classification Code referring to oilseed and grain farming. Our sample contains more males (98%) than the census (77%), which may be because we asked to speak with the primary decisionmaker on crop production. Several participants remarked that their wives are business partners who handle the finances as opposed to crop production. Our sample also contains more producers in the 35-44 age group than the 2022 census. By design, the farms in our sample are significantly larger, given that we required respondents to operate 300 acres or more, whereas 57% of Michigan farms had under 200 acres.

Previous literature has found that age, education, and income or wealth can impact risk aversion. Given that it is challenging to measure wealth directly, we proxy wealth with income, acres in operation, and debt-to-asset ratio. Table 1 provides a breakdown of the main covariates of interest for data analysis. Age and acres in operation are continuous variables, while education, income, and debt-to-asset ratio are categorical variables. The education levels are defined as less than high school, high school diploma, some college, associate's degree, bachelor's degree, and master's degree or higher. Income and debt-to-asset ratio are defined as categorical variables, with income categories ranging from less than $25,000 to more than $1,000,000 and debt-to-asset ratio categories ranging from capital debt between 0% to 9% of current asset value up to capital debt greater than current asset value. Fuller details appear in supplemental information Table S3.

Table 1: Summary Statistics for Main Covariates

Variable	Units	Average	Median	Minimum	Maximum
age	years	56	57	25	92
education	categorical	Associate degree	Associate degree	High school diploma	Graduate degree
acres in operation	acres	2,420	1,650	335	17,000
income	categorical	$200,000-$500,000	$200,000-$500,000	$25,000-$50,000	$1,000,000<
debt-to-asset ratio	categorical	25%-32%	25%-32%	0%-9%	100%

Figure 2 depicts the counties where interview participants operate most of their acres. Given our requirement that they grow corn for grain, we recruited farmers in the lower half of Michigan. Corn produced in the northern half of Michigan is primarily for dairy silage.

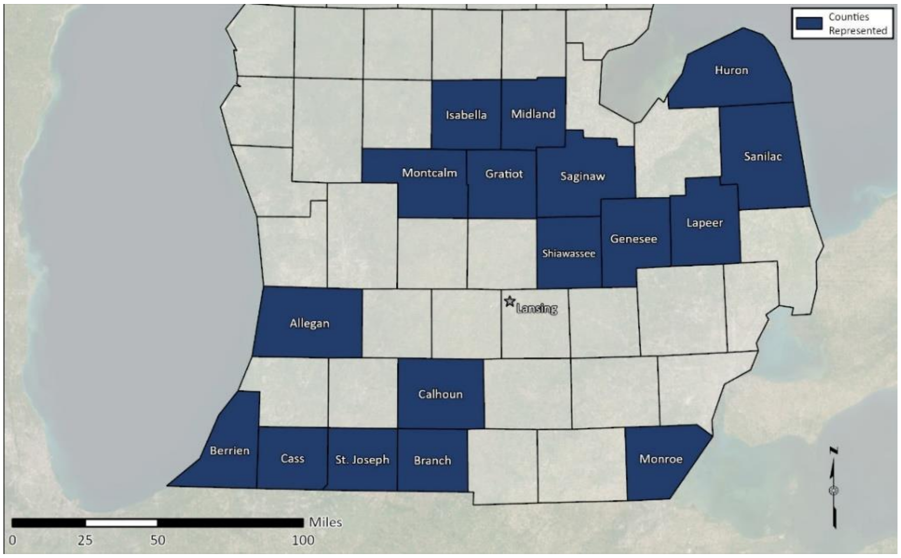

Figure 2: Counties represented in our sample indicated by our participants as the county where they operate most of their acres. (Map created by Justin Anderson.)

Results

We find that the farmers sampled were risk averse across both domains and all expected utility models. Under two of the three expected utility functions, farmers were more averse to risk related to weather-driven crop yield management than to general risky gambles. Analysis of individual farmer risk preferences found greater heterogeneity of risk preferences in the weather-driven agricultural context than in the general one.

Starting with the aggregate picture, Table 2 shows the whole-sample probit MLE results given the CARA exponential (Eq. 2), CRRA power (Eq. 3), and the nested expo-power (Eq. 4) functions with data from both standard, general lotteries and lotteries based on weather-driven agricultural investment decisions. In both lottery domains, the CARA $\hat{\alpha}$ coefficients are positive, displaying risk aversion. Compared to the general lottery CARA coefficient, the one for weather-driven agricultural investments is larger by an order of magnitude, implying that farmers display higher risk aversion when making decisions about weather risk to crop revenue. While both of the CARA model $\hat{\alpha}$ estimates are quite small, these magnitudes are typical for this model (Raskin & Cochran, 1986).

Table 2: Whole-Sample Probit Models of Lottery Choices Given CARA Exponential, CRRA Power, and Nested RRA and ARA Expo-Power Functions.

	CARA	CRRA	Nested RRA and ARA	
	$\hat{\alpha}$	$\hat{r}$	$\hat{\alpha}$	$\hat{r}$
General	7.67e-6***	0.862***	-0.295***	0.852***
	(3.79e-7)	(0.007)	(0.002)	(0.003)
Agricultural	4.60e-5***	0.890***	0.041***	0.641***
	(6.36e-7)	(0.023)	(0.007)	(0.029)
Log-pseudolikelihood				
General	-749.37	-865.01	-694.85	
Agricultural	-693.09	-662.61	-662.34	

Note: Standard errors in parentheses, *** p < 0.01, ** p < 0.05, * p < 0.10

The aggregate CRRA results likewise show risk aversion in both lottery domains. However, their 95% confidence intervals overlap, so we cannot reject the possibility that the risk aversion coefficients, $\hat{r}$, are equal. The magnitude of these CRRA $\hat{r}$ estimates matches estimates in the literature (Lilleholt, 2019).

The whole-sample results for the expo-power functional form (Table 2) indicate that participants display both relative and absolute risk aversion. Notwithstanding the negative coefficient estimate for α in the expo-power function[3], the associated index of absolute risk aversion (Eq. S2) is positive over the full range of lottery choice values offered (Figure S13 in Supplemental Information). Indeed, the expo-power estimates of the index of relative risk aversion (Eq. S3) over the range of lottery choice values reveals that are not only are they positive in both domains, but they are also much larger in the agricultural than the general domain.

In order to compare levels of risk aversion between the two domains at the individual level, we first conducted choice-of-model tests among the three expected utility functional forms. Wald tests gave evidence for preferring the CRRA form for nearly all individuals in both the general and the weather-driven agricultural lotteries (see Tables S4, S5, and S6, as well as accompanying text in Supplemental Information). The CRRA model ranks first, followed by the expo-power model, while the CARA model places last. Given the evidence from these individual-level analyses, we focus the remainder of the Results section on estimates from the CRRA power model of exponential utility.

In comparing the frequency distributions of the CRRA $\hat{r}$ coefficient estimates in the two domains, the most striking feature is the much wider dispersion of risk aversion levels in the context of weather-driven agricultural lotteries. Whereas the $\hat{r}$ values range from 0.68 to 0.97 in the general lotteries, they span 0.56 to 1.02 in the weather risk-driven agricultural lotteries (Figure

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[3] Note that the interpretations of the coefficient values of the expo-power utility function are not equivalent to those of the exponential or power utility functions, given the Arrow-Pratt Indexes for the expo-power function do not reduce to constant terms. Hence the need to compute values, as in Figure S13.

3). The two frequency distributions of CRRA $\hat{r}$ coefficient estimates with bin sizes of 0.025 differ at the 0.10 significance level, based on a χ^2 test. Reflecting this, the standard deviation of the $\hat{r}$ estimates is 0.066 for the general domain versus 0.125 for the weather-driven agricultural one.

Central tendencies differ little between the general and agricultural frequency distributions in Figure 3. This finding should not surprise, given the small difference between CRRA $\hat{r}$ estimates from the aggregate sample in Table 2. The median $\hat{r}$ values for the general and agricultural distributions of individual farmer estimates are 0.855 and 0.843, respectively. The mean from the agricultural domain is also slightly lower (0.810) than the general domain (0.843), reflecting the left-skewed tail in the weather-driven agricultural context (Figure 3).

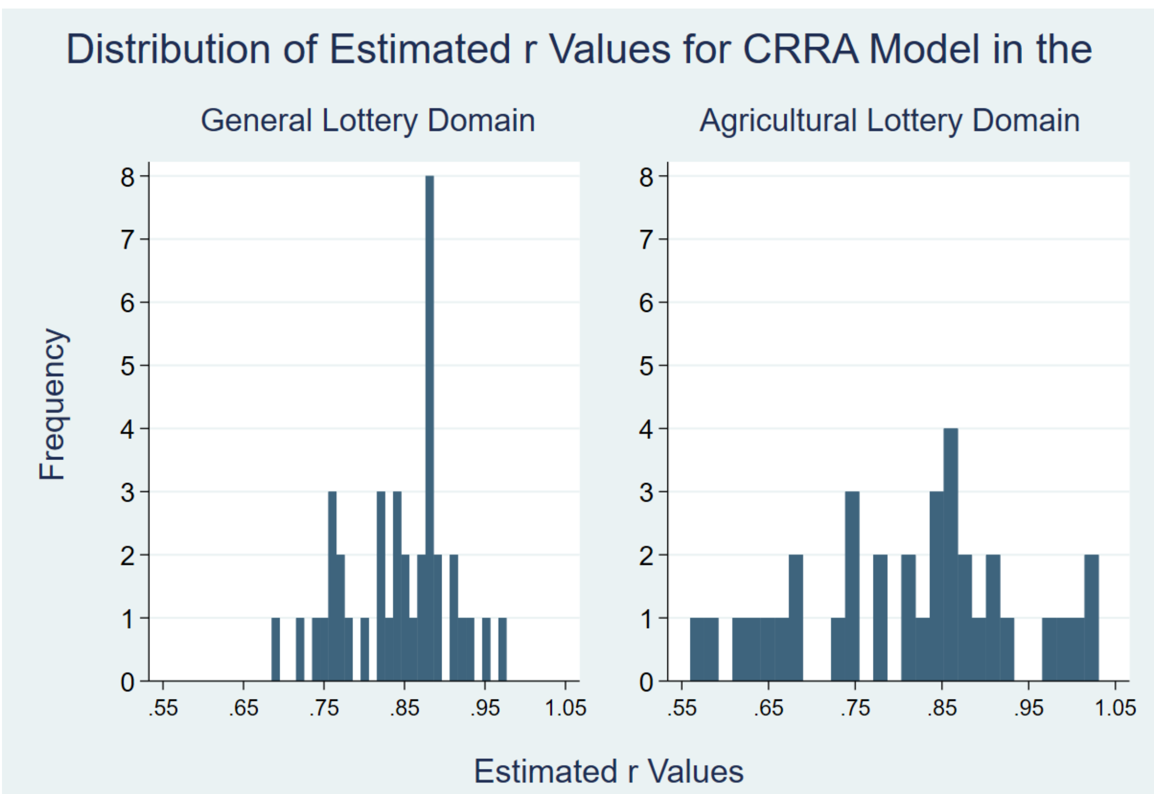

Figure 3: A comparison of estimated r values at the individual-level for both lottery domains.

To understand what is driving differences in participants' risk aversion measures, we test our second hypothesis and estimate CRRA risk preference parameters as functions of demographic and farm characteristics following Eq. (8). The preferred specification shown in Table 3 was the most parsimonious that was directly comparable across general and agricultural lottery samples. (Results for alternative specifications are provided in supplemental information Tables S8 and S9.)

Table 3: Probit Model of Lottery Choices Given CRRA Power Function, 44 Michigan Corn-Soybean Farmers, 2022-23.

	General Lottery		**Agricultural Lottery**	
Constant	0.862*** (0.007)	0.556*** (0.089)	0.890*** (0.023)	0.759* (0.446)
age	---	0.009*** (0.002)	---	-0.006 (0.016)
age^2	---	-6.39e-5*** (1.89e-5)	---	6.45e-5 (1.61e-4)
education level	---	-0.003 (0.005)	---	0.032 (0.019)
acres operated	---	-3.60e-6*** (1.35e-6)	---	-1.70e-5*** (6.02e-6)
income	---	0.007 (0.005)	---	0.039 (0.029)
Log-pseudolikelihood	-865.01	-849.29	-731.43	-702.12

Note: Standard errors in parentheses, *** p < 0.01, ** p < 0.05, * p < 0.10

Both the general and the agricultural lottery results reveal that demographic and farm resource variables significantly influence risk preferences (Table 3). But both models also reveal clear risk aversion inherent to the decision maker, as captured by the constant terms in the specifications that include covariates.

Two farmer traits influenced the risk aversion estimates. Wealth mattered in both lottery domains, with acres operated decreasing the degree of relative risk aversion in the preferred model. Although, the acres operated effect was not robust across all specifications, it was significant and negative in the two agricultural models where it appeared in linear form as well as one of the two general models where it appeared in linear form. Our sample's average acreage in operation is 2,420 acres, and the median is 1,650 acres. The coefficient estimates in Table 3 imply that an increase of 1,000 in acres operated is, on average, associated with a .65% decrease in risk aversion in the general lottery domain and a 2.24% decrease in the agricultural lottery domain. In both lottery domains, the levels of education and income do not impact risk aversion estimates.

The general lottery results show a clear quadratic age effect across all specifications, though the agricultural lottery results do not. The results for the general lottery domain imply that on average, risk aversion increases by about 2.33% as a farmer ages from 50 to 60 years old. However, the quadratic term means that risk aversion is increasing at a decreasing rate. Once the risk aversion estimate reaches its maximum at 70 years old, an increase in the average farmer's age from 70 to 80 years results in a 0.67% decrease in risk aversion.

With and without covariates included, the results in Table 3 indicate that we cannot reject the possibility that the risk coefficients, *r*, are equal across lottery types at a 5% significance level. The coefficient estimates in Table 3 along with evidence from the dispersion of risk aversion levels suggest that differences between general and agricultural domains are driven by individual traits, notably age and wealth. This could explain why we see stronger evidence that farmers are more risk averse in the agricultural domain for the aggregate CARA and expo-power functions as shown in Table 2.

Discussion and Conclusion

In order to understand farmer risk attitudes in the context of changing climate, we compare risk preferences elicited from general versus weather-driven agricultural lottery domains. The general domain simply asks respondents to choose between pairs of risky gambles. Given predictions of increased incidence of seasonal drought and excess moisture, the agricultural domain focuses on investments in water management, including drainage tile to remove excess water, irrigation and drought-tolerant seed varieties to manage insufficient water, and crop insurance to provide revenue protection.

We find that the climate context matters. In our aggregate sample of 44 respondents, farmers responded differently to risk in the context of weather-driven agricultural risk than in the general, abstract domain. While not evident under the CRRA function, they showed greater risk aversion in the agricultural domain under CARA function (Table 2). Under the expo-power function, where risk aversion levels vary with lottery payout levels, farmers consistently displayed greater risk aversion in the context of weather-driven agricultural investments compared to the general domain. This finding reinforces the message from Hudson et al. (2005), who found agricultural producers in Mississippi to be averse to crop yield and price risk, but risk-seeking behavior in a context-free auction. Our evidence about risk behavior differences between weather-driven agricultural and general settings is also consistent with Menapace et al. (2016) who determined that Italian apple producers' crop insurance purchases were better explained by risk preferences elicited from lotteries in the context of farm income explain farmer than elicitations from lotteries with no agricultural framing.

On risk attitudes in the whole-sample analysis, we find first that Michigan corn-soybean farmers are risk averse across all three expected utility functions evaluated (constant absolute risk aversion [CARA], constant relative risk aversion [CRRA], and expo-power). This finding is consistent with the preponderance of evidence from past studies that elicited risk attitudes of farmers in the United States (Barham et al., 2014; Hellerstein et al., 2013) and in Europe (Iyer et al., 2020; Meissner et al., 2023).

By estimating individual utility functions, we can compare the distributions of risk attitudes as well as the determinants of those attitudes between general and climate-related agricultural domains. Based on prior choice-of-model tests, we found that the CRRA function could not be rejected as equivalent to the expo-power function, whereas the CARA function was overwhelmingly rejected as less informative.

The frequency distribution of CRRA risk aversion coefficients was broader for agricultural investments than for general lottery choices. With $\hat{r}$ coefficient estimates ranging 0.68 to 0.97 in the general lotteries and 0.56 to 1.02 in the weather risk-driven agricultural lotteries, our findings correspond to the risk averse and highly risk averse ranges where Holt and Laury (2002) found 45% of their subjects' choices to fall in their 20x stakes lottery. The ranges overlap heavily with seven of the ten distributions of European farmer risk preferences reported by Garcia et al. (2024), although the mean $\hat{r}$ values here are higher (more risk averse) than the means reported there.

Upon re-estimation of CRRA coefficients as a function of age, education, wealth (proxied by acres operated), and income, we find that wealth matters in both the general and the agricultural domains. Specifically, we find decreasing relative risk aversion as a function of acres operated. This suggests that operators of larger farms, which are less vulnerable to bad outcomes, exhibit less risk aversion. Their level of risk aversion decreases faster for risky agricultural decisions than for general ones (albeit from a higher starting level, represented by the constant in these models) (Table 3). Other studies have also found evidence that wealth and risk aversion are negatively correlated (Holt & Laury, 2002; Meissner et al., 2023; Wik et al., 2004).

In the general domain (but not in the agricultural one), we find also that risk attitudes evolve with age. Risk aversion increases at a decreasing rate up to age 70, declining after that point. This pattern has been found elsewhere in the United States and in Spain (Ackert et al., 2009; Picazo-Tadeo & Wall, 2011), and it may be related to changing financial goals and vulnerability over a farmer's life cycle. A young farmer may aim to expand the farm operation, taking on substantial mortgage debt while also facing the financial obligations of a growing family. Farmers who have persisted in business past age 70 may have accomplished many of their goals and become more tolerant of financial risk. Additional work has separated risk preferences and loss aversion, with Tanaka et al. (2010) finding a negative relationship between age and risk aversion while Meissner et al. (2023) find a positive relationship between age and risk aversion but a negative relationship with loss aversion.

We do not find a significant relationship between education and risk preferences. This could be due to its mixed effect on risk attitudes, with some studies finding positive effects (Vieider et al., 2019; Von Gaudecker et al., 2011) while others have found negative effects (Donkers et al., 2001; Gächter et al., 2022; Harrison et al., 2007).

Two features of the experimental design invited robustness checks. First, the general lottery questions always preceded the agricultural ones. In order to determine whether the order of presentation affected risk aversion coefficient estimates, we estimated individual CRRA parameters from the first 13 general lotteries presented and compare them to those from the last 12 presented in Table S7 of the supplemental material. We find no evidence of ordering effects. Second, the general lotteries included losses among the outcomes, whereas the agricultural lotteries did not. To evaluate the effect of omitted losses on coefficient estimates, we estimated the whole-sample CRRA parameter from the subset of 10 general lotteries where all outcomes were positive amounts. The estimated value of 0.820 (s.d. 0.012) is lower than both the general CRRA estimate of 0.862 (0.007) and the agricultural CRRA estimate of 0.890 (0.023). While this finding indicates that omission of losses has a significant effect on coefficient estimates, that effect is to depress them. As the omission of losses leads to underestimation of CRRA risk aversion and one key finding is that risk aversion is slightly greater in the weather-driven agricultural domain, it appears that this finding would have been even stronger had we included losses in the agricultural lotteries.

The chief limitations of this research stem from the sample, which is small and not randomly selected. This is not uncommon for complex economic experiments on risk attitudes, especially when targeting a specific group of individuals such as farmers (Brunette et al., 2013; Cerroni, 2020; Hellerstein et al., 2013; Tevenart & Brunette, 2021). However, it remains a shortcoming, despite being mitigated by reasonably good tracking with the broader population of Michigan corn-soybean farmers as reported in the 2022 Census of Agriculture. The study was limited to corn-soybean farmers in Michigan, but growers of these crops have a large footprint in the wider scheme of things, as grain and oilseed farmers manage two-third of cropland in Michigan (67%) and in the United States as a whole (67%) (USDA-NASS, 2024a, 2024b).

As agricultural policy makers contemplate how to support farmers in confronting climate change, these findings offer three insights. First, farmers appear slightly more averse to risk in the context of decisions about agricultural investments related to climate risk than in a general domain that does not bear on their livelihood. Second, risk attitudes toward agricultural investments vary widely, so there is no one-size-fits-all policy prescription. Third, farmers display decreasing relative risk aversion: Those who operate large acreages are closer to being risk-neutral profit maximizers than smaller scale farmers. Hence, policies aimed at smaller scale farmers may build upon the assumption of risk aversion. However, policies aimed at large scale farmers—who operate a large share of U.S. acreage in commodity crops like corn and soybean (MacDonald et al., 2018)—should focus more on expected profitability, rather than down-side risk.

Future research into farmer risk attitudes and climate change adaptation would benefit by both broadening the data on risk preferences and applying the results to subjective probability distributions. The work reported here could be broadened by extending data collection over a wider agricultural geography where farmers face more varied climate conditions. A larger data set with greater data variability would likely enable testing a wider range of utility functions that includes variants of prospect theory (Eisele et al., 2021; Kahneman & Tversky, 1979; Tversky & Kahneman, 1992; Wakker, 2010). A more diverse geography could also potentially parse more clearly the determinants of risk attitudes.

A second valuable extension of this research would be to apply its estimates of risk aversion to climate change-related decisions. Subjective probability distributions of crop yields play an important role in adaptive management decisions. Past research by Menapace et al. (2013) found farmers' risk attitudes to affect how they estimated the probability of crop loss from pests. A worthwhile extension would be to evaluate whether and how farmer risk attitudes affect the way they perceive climate-driven changes in crop yield probability distributions.

Moving on to how risk aversion affects climate change adaptation decisions, how and how much does farmer risk aversion affect adaptive management decisions related to climate change? Studies have analyzed the relationship between risk aversion in decision making and technology adoption (Barham et al., 2014; Gilboa et al., 2008; Marra et al., 2003; Marra & Carlson, 2002). An important next step is to explore how risk attitudes affect the adoption of climate change adaptation technologies.

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SUPPLEMENTAL INFORMATION

S1: Lottery Experiments

Experimental Procedures

Before beginning the general lottery-based experiment, we presented the participants with a consent form that provided information regarding the survey, participation payment, voluntary participation, and confidentiality of responses. The survey's introduction includes two general lottery examples to introduce the lottery framework and explain the conversion for the lottery payment. In addition to the $50 participation payment, we provide participants with a $40 endowment from which they can earn or lose money. We present the 25 general lottery pairs in a random order to prevent ordering effects, and they include payoffs that are both positive, both negative, and a mix of the two. After completing the general and agricultural lottery sections, the random number generator built into Qualtrics selects a number from one to 25 to decide the general lottery question. We then see whether the participant chooses Lottery A or B. Qualtrics also generates a random number between one and 100 to represent the binding outcome within the chosen lottery.

For example, suppose the randomly drawn lottery question includes Lottery A, which offers 50% odds of winning $50,000 versus 50% odds of winning $20,000, and Lottery B, which offers 20% odds of winning $100,000 versus 80% odds of winning $10,000. We see that the participant selected Lottery B, depicted below. If the randomly generated outcome number falls between 1 and 20, the first payoff of $100,000 is binding. Similarly, if the randomly generated outcome number falls between 21 and 100, the second payoff of $10,000 is binding.

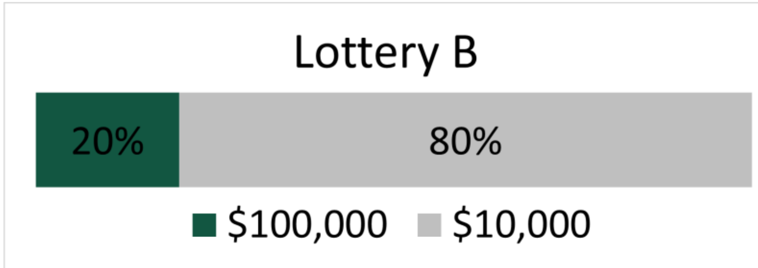


Figure S1: Example of general lottery outcome.

We divide the experimental payoffs by 4,000 to convert the lottery outcomes to real dollars that impact the participants' final payment. Therefore, by choosing Lottery B of the selected question, with an outcome number of 11 and the binding payoff of $100,000, the participant would receive $25. If the binding outcome is negative, we would subtract the converted payoff from the $40 endowment. The participants can potentially lose all of the $40 endowment or win up to $40 in addition to the endowment, meaning the minimum payment is the $50 participation payment, and the maximum is $130.

Table S1: General Lottery Set

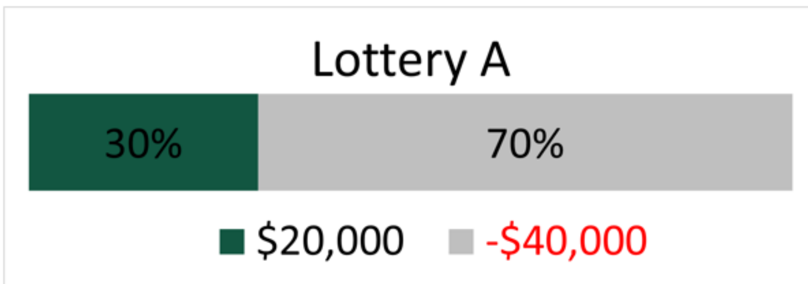
Lottery A				Lottery B			
Payoff	Probability	Payoff	Probability	Payoff	Probability	Payoff	Probability
$10,000	35%	$90,000	65%	$20,000	30%	$50,000	70%
$160,000	15%	$60,000	85%	$110,000	70%	$70,000	30%
$80,000	20%	$20,000	80%	$50,000	75%	$10,000	25%
$120,000	80%	$40,000	20%	$150,000	20%	$80,000	80%
$40,000	65%	$10,000	35%	$25,000	70%	$15,000	30%
-$90,000	65%	-$10,000	35%	-$50,000	70%	-$20,000	30%
-$160,000	15%	-$60,000	85%	-$110,000	70%	-$70,000	30%
-$80,000	20%	-$20,000	80%	-$50,000	75%	-$10,000	25%
-$120,000	80%	-$40,000	20%	-$150,000	20%	-$80,000	80%
-$40,000	65%	-$10,000	35%	-$25,000	70%	-$15,000	30%
$100,000	40%	-$80,000	60%	$10,000	25%	-$40,000	75%
$80,000	60%	-$100,000	40%	-$10,000	25%	$65,000	75%
$20,000	20%	-$100,000	80%	-$40,000	80%	-$110,000	20%
-$20,000	20%	$100,000	80%	$40,000	80%	$110,000	20%
-$30,000	60%	$40,000	40%	-$15,000	30%	$5,000	70%
$80,000	5%	$20,000	95%	$50,000	50%	$10,000	50%
$80,000	10%	$20,000	90%	$60,000	50%	$10,000	50%
$100,000	95%	$40,000	5%	$120,000	40%	$50,000	60%
$100,000	90%	$40,000	10%	$120,000	45%	$50,000	55%
$50,000	50%	$20,000	50%	$100,000	20%	$10,000	80%
-$80,000	5%	-$20,000	95%	-$50,000	50%	-$10,000	50%
-$80,000	10%	-$20,000	90%	-$60,000	50%	-$10,000	50%
-$100,000	95%	-$40,000	5%	-$120,000	40%	-$50,000	60%
-$100,000	90%	-$40,000	10%	-$120,000	45%	-$50,000	55%
-$50,000	50%	-$20,000	50%	-$100,000	20%	-$10,000	80%

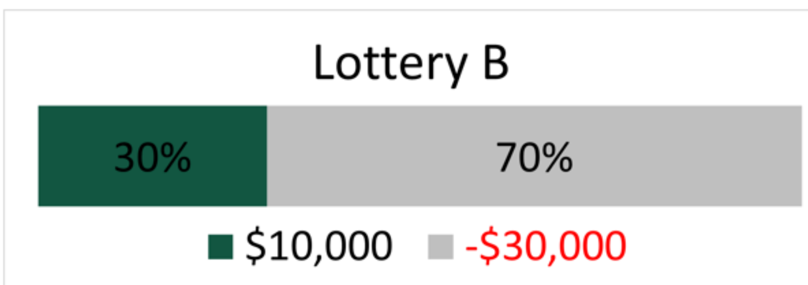
General Lottery Example Questions

In the first section of this interview, we will present you with 25 pairs of risky gambles. In each case, we will ask which one you prefer. There will be options with all positive payoffs, all negative payoffs, or a mix of positive and negative payoffs.

For example,
Lottery A might offer 30% odds of earning $20,000 versus 70% odds of losing $40,000, while Lottery B offers 30% odds of earning $10,000 versus 70% odds of losing $30,000.

We then ask, “Which lottery do you prefer?”





We would like you to think about these gambles like real investment choices in your farm business. So to encourage you to think that way, once we are done with all the gambles, we will pay you real money based on one of your answers. No one will know ahead of time which outcome will be selected.

We will do this in two steps: First, the computer will randomly pick one of the 25 questions; next, the computer will randomly choose one of the two outcomes.

We will then pay you an additional $40 plus any gain from that outcome or minus any loss from that outcome. Because our budget is limited, we will be dividing the gamble sums by 4,000 (so a $4,000 lottery payoff becomes a $1.00 payoff with us).

Figure S2: Survey instructions and an example for general lottery questions.

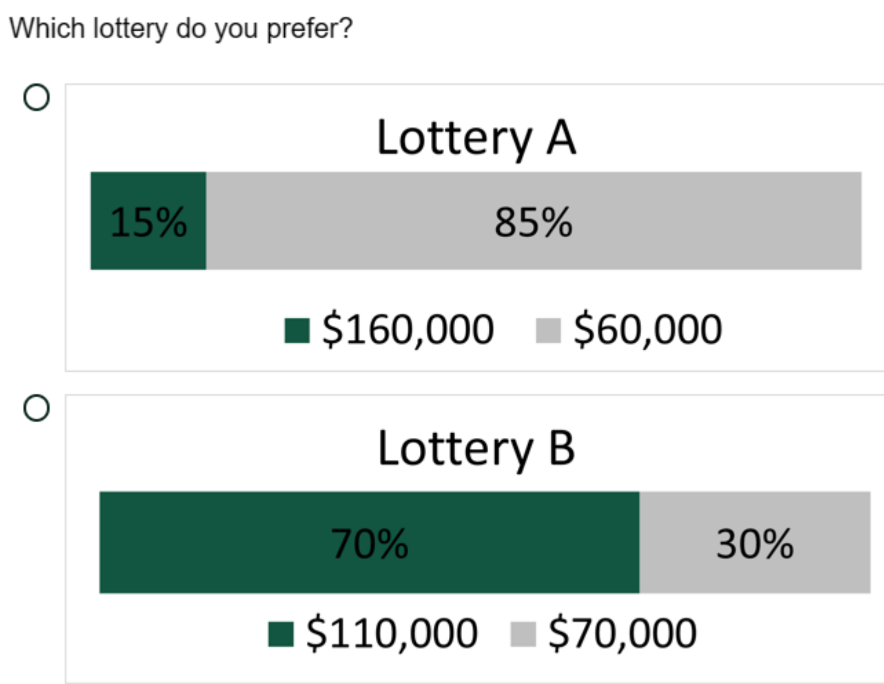


Figure S3: Example of a general lottery question with all positive payoffs.

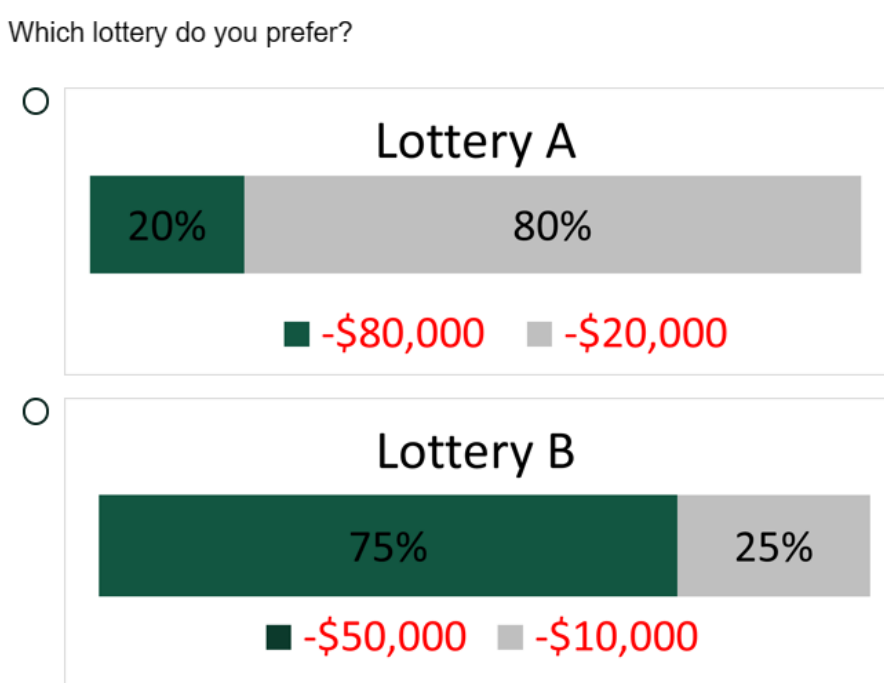


Figure S4: Example of a general lottery question with all negative payoffs.

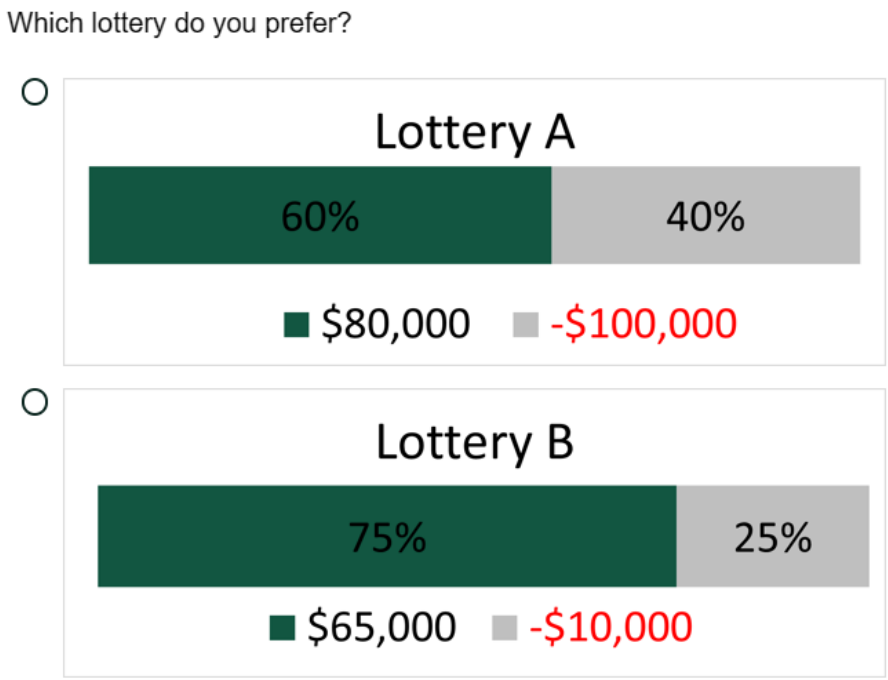


Figure S5: Example of a general lottery question with all mixed payoffs.

Table S2: Agricultural Lottery Set

	Invest				Do not invest			
	Payoff	Probability	Payoff	Probability	Payoff	Probability	Payoff	Probability
$4/bu								
Drainage	$ 21,600	100%	---	---	$20,000	30%	$24,000	70%
Drainage	$ 21,200	10%	$22,400	90%	$20,000	10%	$24,000	90%
Drainage	$ 21,600	100%	---	---	$20,000	15%	$24,000	85%
Drainage	$ 21,200	25%	$22,400	75%	$20,000	25%	$24,000	75%
Irrigation	$ 16,500	10%	$17,200	90%	$16,300	10%	$24,000	90%
Irrigation	$ 16,350	15%	$17,850	85%	$16,300	15%	$24,000	85%
Irrigation	$ 16,500	25%	$17,200	75%	$16,300	25%	$24,000	75%
Irrigation	$ 16,350	30%	$17,850	70%	$16,300	30%	$24,000	70%
DT seeds	$ 17,840	15%	$23,840	85%	$16,300	15%	$24,000	85%
DT seeds	$ 17,840	25%	$23,840	75%	$16,300	25%	$24,000	75%
Crop Insurance	$ 17,800	35%	$22,600	65%	$16,800	35%	$24,000	65%
Crop Insurance	$ 17,000	15%	$23,000	85%	$16,800	15%	$24,000	85%
Crop Insurance	$ 17,000	30%	$23,000	70%	$16,800	30%	$24,000	70%
Crop Insurance	$ 17,800	20%	$22,600	80%	$16,800	20%	$24,000	80%
$8/bu								
Irrigation	$43,450	10%	$44,800	90%	$32,600	10%	$48,000	90%
Irrigation	$42,500	15%	$45,450	85%	$32,600	15%	$48,000	85%
Irrigation	$42,500	30%	$45,450	70%	$32,600	30%	$48,000	70%
Irrigation	$43,450	25%	$44,800	75%	$32,600	25%	$48,000	75%

Agricultural Lottery Introduction

In this section, we present two lottery choices related to crop management in the face of drought or flooding risk.

The payoffs are framed as your gross crop revenue for a 40-acre field, before input costs are deducted. We assume that without investment costs or bad weather conditions your gross crop revenue would be $24,000 for the 40-acre field.

You will be presented with a probability of bad weather occurring. Then you will be asked whether or not you would like to invest in a production practice that will reduce your risk of receiving lower gross crop revenue for the field.

If you choose to invest in a way to reduce yield risk, the payoff represents your field's gross crop revenue minus the annual cost of the investment. If you choose not to invest, you have some probability of earning lower gross crop revenue for the field if bad weather occurs and some probability of earning the full gross crop revenue for the field if bad weather does not occur.

Even if the situation looks different from what you might see on your own farm, please answer as if you had to face the situation we describe.

An example of a question context is “Looking into the future, suppose there is a 30% chance that your field floods during the crop season and a 70% chance your field does not flood.”

If your farm has sandy soils that don’t flood, this may not seem realistic to you. But we’d like you to imagine that this is the reality that you have to deal with. Some questions are about drought, and there too, we’d like you to imagine that the costs and risks are exactly as presented in the question.

Please carefully consider the setting and choose whether you would invest or not based on the situation.

Figure S6: Survey instructions for agricultural lottery section with explanation of lottery framing.

Agricultural Lottery Example Questions

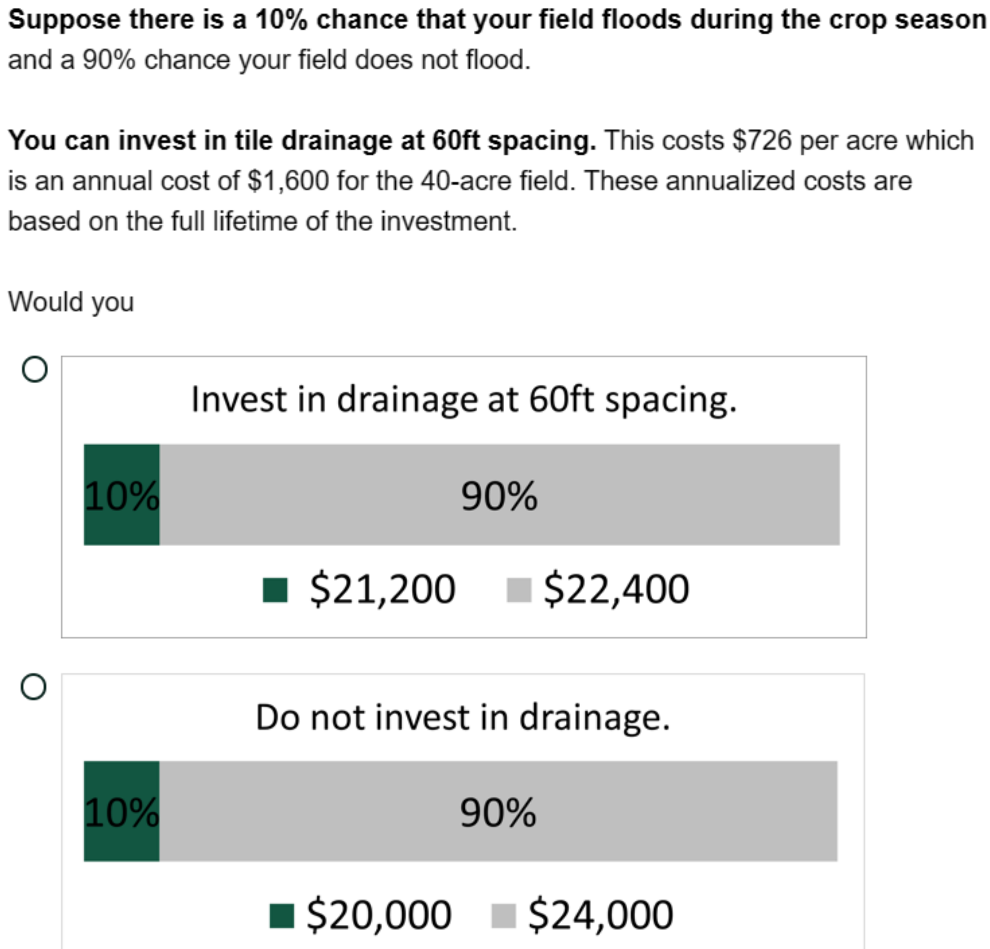


Figure S7: Example of drainage investment question in agricultural lottery experiment.

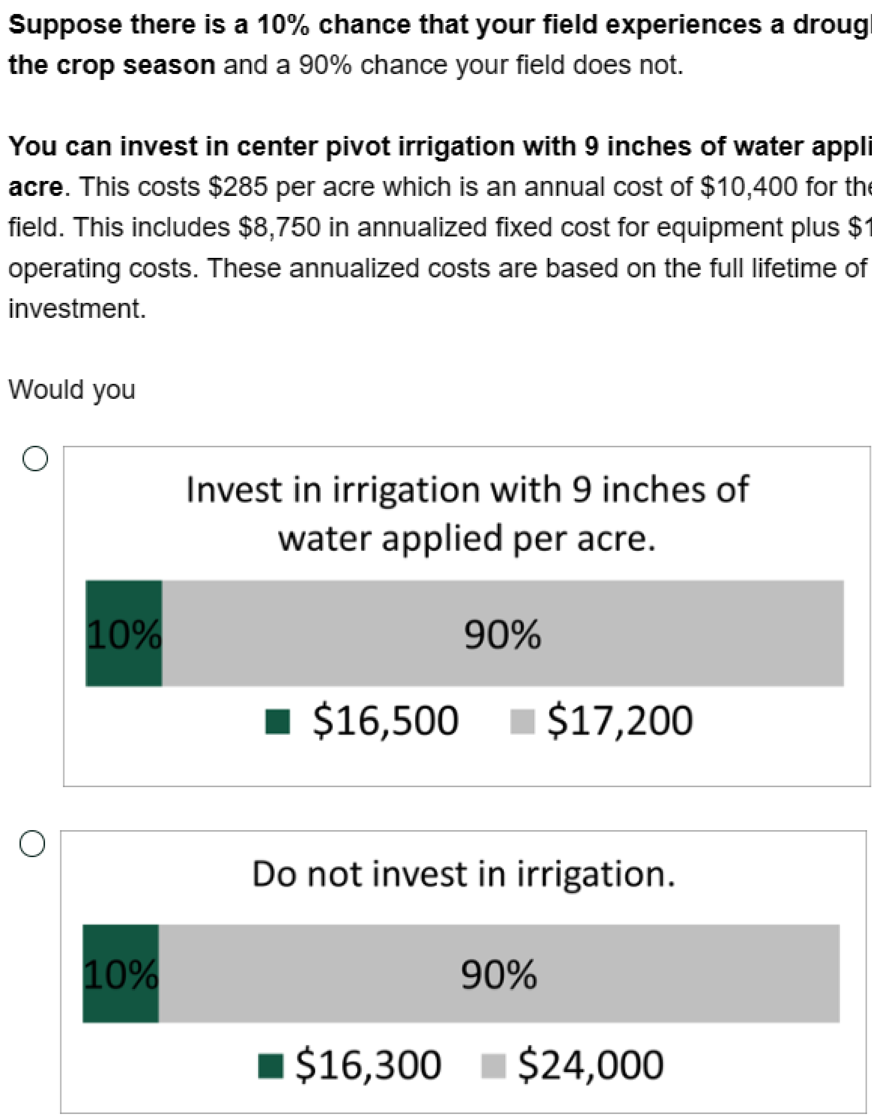


Figure S8: Example of irrigation investment question in agricultural lottery experiment.

Please note that we increased the base revenue in the case of investing in irrigation to account for the yield boost associated with the investment.

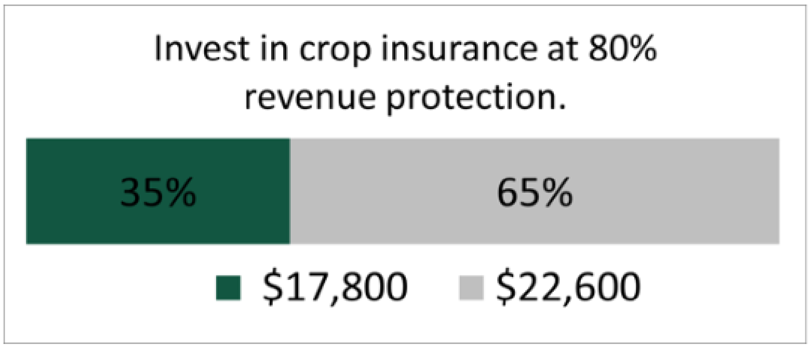
In the event of a severe drought (10% chance), you will earn $16,500 in gross crop revenue. $24,000*1.12 = $26,900 in gross crop revenue minus the annual investment of $10,400.

In the event of no severe drought (90% chance), you will earn $17,200 in gross crop revenue. $24,000*1.15 = $27,600 in gross crop revenue minus the annual investment of $10,400.

Suppose there is a 35% chance that your field experiences some form of severe weather next season that would cause crop damage, and a 65% chance your field does not.

You can invest in crop insurance at 80% revenue protection. This costs $35 per acre which is an annual cost of $1,400 for the 40-acre field.

Would you



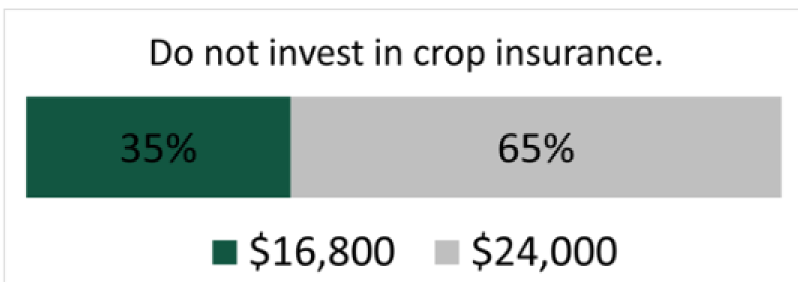


Figure S9: Example of crop insurance investment question in agricultural lottery experiment.

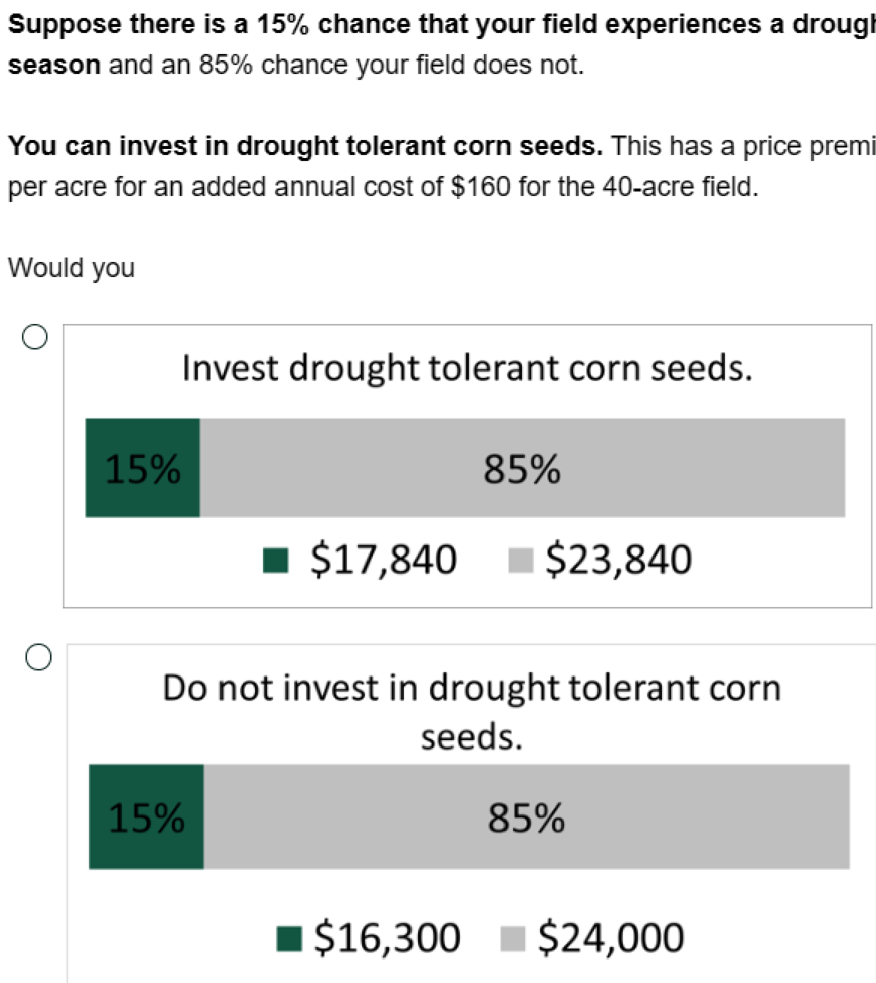


Figure S10: Example of drought tolerant seed investment question in agricultural lottery experiment.

Now suppose that corn prices are higher.

Instead of $24,000 in gross crop revenue from the 40-acre field, assume that your gross crop revenue was $48,000 if the weather was good and there were no investments to reduce risk.

Apart from the fact that the crop is worth twice as much, these decisions are just like the ones you just saw.

Figure S11: Higher corn price irrigation investment instructions.

Suppose there is a 10% chance that your field experiences a drought during the crop season and a 90% chance your field does not.

You can invest in center pivot irrigation with 9 inches of water applied per acre. This costs $285 per acre which is an annual cost of $10,400 for the 40-acre field. This includes $8,750 in annualized fixed cost for equipment plus $1,650 in operating costs. These annualized costs are based on the full lifetime of the investment.

Would you

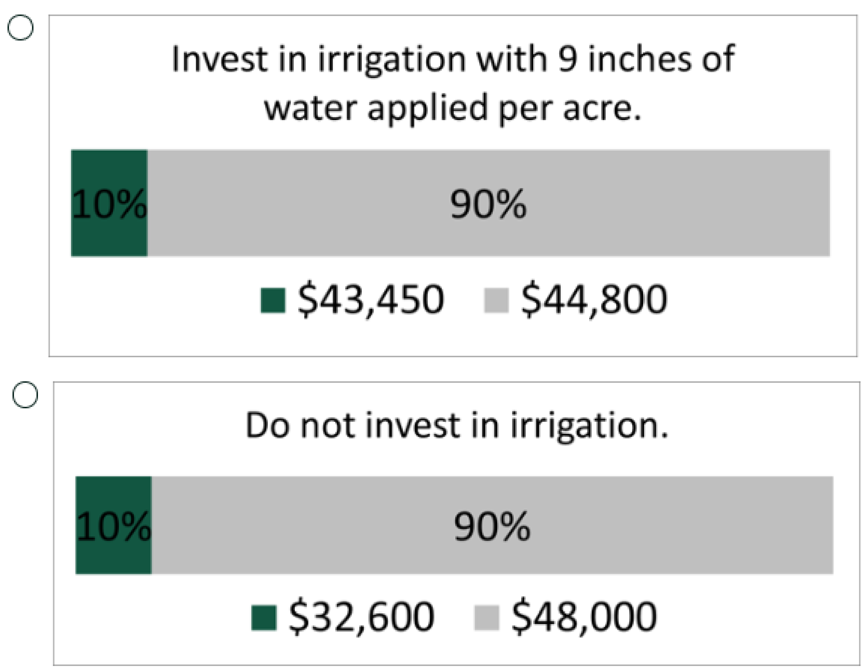


Figure S12: Example of a higher corn price irrigation investment question in agricultural lottery experiment.

S2: Conceptual Framework for Nested Expo-Power

The expo-power function (Eq. S1) allows for nested tests, considering that it represents constant absolute risk aversion (CARA) as $r \to 0$ and constant relative risk aversion (CRRA) as $\alpha \to 0$.

$$U(w) = \frac{1 - exp\,(-\alpha w^{1-r})}{\alpha} \tag{S1}$$

These reductions can be shown by the Arrow-Pratt Indexes. The Arrow-Pratt Index of Absolute Risk Aversion is represented by

$$A(w) = \frac{-U"(w)}{U'(w)} = \frac{r + \alpha(1-r)w^{1-r}}{w}. \tag{S2}$$

When $r = 0$, Eq. (S2) reduces to the CARA coefficient, α, with $A'(w) = 0$.

The Arrow-Pratt Index of Relative Risk Aversion is represented by

$$R(w) = \frac{-U"(w)w}{U'(w)} = r + \alpha(1-r)w^{1-r}. \tag{S3}$$

When $\alpha = 0$, Eq. (S3) reduces to the CRRA coefficient, r, and $R'(w) = 0$.

S3: Summary Statistics

We pull state-level statistics from the 2022 Michigan Census of Agriculture and focus on the North American Industry Classification Code referring to oilseed and grain farming (USDA-NASS, 2024). We compare the characteristics of our sample population and that of the 2022 Michigan Census of Agriculture in Table S3.

Table S3 Producer and Farm Characteristics: Sample (n=44 in 2023) vs. Michigan Agricultural Census (2022)

	Sample	MI Ag Census
Male	98%	77%
Age		
Under 25	0%	1%
25 to 34	5%	8%
35 to 44	25%	13%
45 to 54	14%	14%
55 to 64	25%	25%
65 to 74	20%	23%
75 and older	11%	15%
Ethnicity		
Caucasian	98%	99%
Hispanic or Latino	2%	1%
Education		
High school diploma	25%	---
Some college	20%	---
Associate degree	16%	---
Bachelor's degree	27%	---
Master's degree or higher	11%	---
Acres harvested		
1 to 199	0%	57%
200 to 499	7%	20%
500 to 999	7%	13%
1,000 to 1,999	52%	7%
2,000 or more	34%	4%
Average acres operated	2420	533
Total acres operated	106,499	5,333,742

S4: Model Comparison and Selection

By modeling the Arrow-Pratt indexes of Absolute and Relative Risk Aversion (S2-S3), we can see how estimates of risk preferences in the full sample change as a function of the estimated α and r values and lottery payoff levels. Figure S13 displays how the changing absolute risk aversion estimates from the expo-power function compared to their CARA and CRRA counterparts in both the general and agricultural lottery domains. The top two panes of the figure show point estimates and 95% confidence intervals (CIs) for the absolute risk aversion index, while the bottom two panes show the same for the relative risk aversion index. The horizontal lines depict the CARA and CRRA estimates from Table 2 of the main text for comparison with the expo-power estimates.

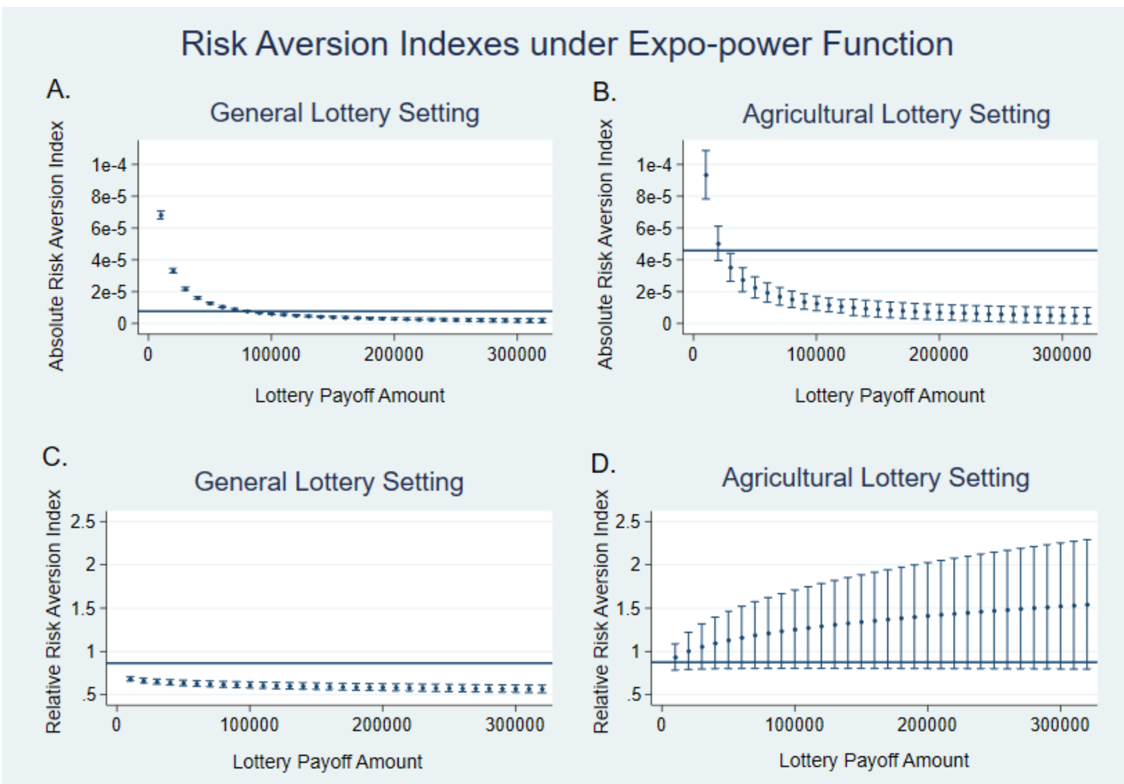


Figure S13: Risk aversion index estimates under the expo-power function and their 95% confidence intervals for a) absolute risk aversion under the general lottery setting, b) absolute risk aversion in the agricultural lottery setting, c) relative risk aversion in the general lottery setting, and d) relative risk aversion in the agricultural lottery setting. The solid horizontal lines represent the corresponding risk aversion estimates for the CRRA and CARA functions for comparison.

Side by side comparison of panels A vs B and C vs D reveals higher risk aversion in the agricultural than the general domain. The larger confidence intervals on the right side (panels B and D) sides shows that risk aversion levels in the agricultural domain are more heterogeneous than in the general domain (panels A and C). Overall, the negative exponential utility functions reveal that in the agricultural lottery setting, the relative risk aversion measure is consistently both greater and more heterogeneous than in the general lottery setting. In the context of weather-driven, agricultural yield risk, respondents are more risk averse than in a general (context-free) lottery by both measures.

After estimating each model for the whole sample, we performed individual-level analyses to measure the heterogeneity of risk preferences across the participants. We estimated risk preferences for each participant under the CARA exponential (Eq. 4), CRRA power (Eq. 5), and nested expo-power (Eq. 6) functions. Table S4 summarizes the individual-level analyses for each utility model under the two lottery settings. We report the total number of significant individual-level estimates for the CARA exponential (Eq. 4) and CRRA power (Eq. 5) functions in the corresponding columns. We then estimated the nested expo-power (Eq. 6) at the individual-level and performed Wald tests to evaluate whether risk attitudes could be represented by either of the two more parsimonious utility models. As noted above, rejection of the null hypothesis (Eq. 6) provides evidence of the null hypothesis of CARA (if $\hat{r}_n = 0$) or CRRA (if $\hat{\alpha}_n = 0$). Table S5 reports the full set of Wald Test results at the individual level.

While the whole sample estimates provide evidence of non-constant risk preferences, the results at the individual level in Table S4 provide strong empirical evidence of CRRA preferences in both lottery settings. For the general lottery data, Wald tests of individual models found CRRA to fit in all 39 cases that converged and to be preferred to the negative exponential in 38 of the 41 cases that converged. By contrast the CARA model fit only 2 of 44 cases that converged and was never preferred to the nested expo-power. For the agricultural lottery data, the CRRA model fits in 35 of the 42 cases that converged and in 17 of the 32 nested expo-power cases that converged. The CARA model fits in just 7 of 42 cases that converged and in 1 of the 32 instances where the expo-power function converged. No individual model with general lottery data and just four with agricultural lottery data failed to reject the null hypothesis that the nested expo-power model was superior to both CARA and CRRA.

Table S4: Individual Farmer Probit Models of Lottery Choices: Wald Test Results for the CARA, CRRA, and Nested Expo-Power Functions

Wald Test results by model type when max likelihood estimation converged	General Lotteries			Agricultural Lotteries		
	CARA (Eq. 4)	CRRA (Eq. 5)	Nested (Eq. 6)	CARA (Eq. 4)	CRRA (Eq. 5)	Nested (Eq. 6)
Converged	44	39	41	42	42	32
No significant results	42	0	3	35	7	10
Evidence of CARA	2	---	0	7	---	1
Evidence of CRRA	---	39	38	---	35	17
Evidence of ARA & RRA	---	---	0	---	---	4
Did not converge	0	5	3	2	2	12

While Table S4 summarizes the Wald test results, Table S5 provides the full Wald test results for the 44 individuals in our sample.

Table S5: Wald Test Results for Utility Model Selection at the Individual-Level

	Nested RRA and ARA			
	α		r	
id	**General**	**Agricultural**	**General**	**Agricultural**
1	0.37	---	109.18***	---
2	0.51	0.25	143.45***	3.98***
3	0.12	1.83	60.14***	10.84***
4	0.07	3.15*	16.58***	5.76**
5	0.11	0.15	55.14***	0.86
6	0.00	---	0.00	---
7	0.10	0.92	26.68***	3.41
8	0.73	0.35	50.40***	2.84*
9	2.63	0.02	42.00***	3.01*
10	1.03	5.45**	296.71***	6.24**
11	0.16	1.69	45.91***	16.25***
12	0.10	0.27	32.49***	1.88
13	0.10	---	2,389.54***	---
14	2.35	0.87	24.71***	2.68*
15	0.93	0.02	17.57***	4.93**
16	0.06	0.00	16.86***	5.21**
17	0.00	---	0.66	---
18	0.00	0.28	0.00	2.41
19	1.07	0.10	17.01***	25.25***
20	0.11	1.63	26.98***	4.85**
21	0.15	---	75.56***	---
22	0.88	---	362.79***	---
23	0.28	2.70*	87.38***	9.39***
24	0.02	0.11	7.92***	1.32
25	0.07	---	19.79***	---

Table S5 (cont'd)

26	0.14	---	40.09***	---
27	0.00	---	48.45***	---
28	0.10	0.79	54.89***	4.37**
29	0.28	2.42	93.81***	136.71***
30	0.12	0.00	63.80***	3.14*
31	0.18	0.65	78.54***	15.80***
32	---	0.02	---	4.67**
33	1.38	---	23.75***	---
34	1.51	---	20.46***	---
35	---	0.18	---	1.87
36	0.15	---	65.62***	---
37	0.41	136.71*	123.80***	2.19
38	---	0.14	---	27.84***
39	0.24	0.00	97.80***	0.64
40	0.16	0.00	74.21***	0.74
41	1.20	0.01	19.70***	0.06
42	0.03	0.49	10.10***	3.62*
43	0.11	0.00	47.44***	1.18
44	0.07	6.79***	14.74***	7.70***

Note: Standard errors in parentheses, *** p < 0.01, ** p < 0.05, * p < 0.10

In selecting the most suitable functional form for estimation of risk preferences, we followed the criteria of Lau (1986) and Frank et al. (1990), which include computational facility, flexibility, domain of applicability, parsimony of parameters, and readily interpreted parameters. Table S6 compares the models across these conceptual criteria along with results on goodness of fit at both aggregate and individual farmer levels. Based on these criteria, the CRRA model ranks first, followed by the expo-power model; the CARA model places last.

Table S6: Choice of Model Criteria: CRRA Preferred in Individual Models and Overall

Criterion	CARA	CRRA	Expo-Power
Computational facility	High	High	Medium
Domain of applicability	Constant risk aversion	Constant risk aversion	DARA, DRRA, IARA, IRRA, CARA, CRRA
Flexibility	Limited	Limited	High
Parsimony of parameters	High	High	Medium
Ease of interpretation	High	High	Medium
General: Goodness-of-fit, Aggregate (Wald)	Reject***	Reject***	Fail to reject
General: Goodness-of-fit, Individual (Wald)	38 of 41 reject*	0 of 41 reject*	N/A
Agricultural: Goodness-of-fit, Aggregate (Wald)	Reject***	Reject***	Fail to reject
Agricultural: Goodness-of-fit, Individual (Wald)	21 of 32 reject*	5 of 32 reject*	N/A

Note: We omit theoretical consistency and factual conformity, given that all models perform equally well.

S5: Robustness Checks

To test the potential for path dependency and learning effects, we compare risk preference parameter estimations of the CRRA function from the first half of the general lottery questions to the second half. For each individual, we identify the order in which they saw the general lottery questions and estimate individual risk preference parameters for the first 13 and the last 12 general lottery questions separately. The results are provided in Table S7. Of the 27 individual parameter estimations that converged for both sets of lottery questions, only one has evidence of a significant difference between the first and second half of lottery questions (ID 25).

Table S7: Testing Ordering Effect of General Lottery Questions to Identify Potential Path Dependency

		$\hat{r}$	
ID	Overall	First 13	Last 12
1	0.836*** (0.773, 0.900)	No convergence	0.927*** (0.741, 1.113)
2	0.765*** (0.708, 0.821)	0.751*** (0.668, 0.834)	0.775*** (0.691, 0.859)
3	0.880*** (0.822, 0.937)	3.200 (-1,541, 1,547)	0.743*** (0.671, 0.815)
4	0.738*** (0.691, 0.784)	No convergence	0.767*** (0.690, 0.844)
5	0.878*** (0.818, 0.937)	0.882*** (0.818, 0.945)	0.859*** (0.733, 0.985)
6	0.999*** (0.994, 1.006)	0.999*** (0.999, 1.000)	1.067** (0.165, 1.968)
7	0.771*** (0.712, 0.831)	0.796*** (0.713, 0.879)	0.713*** (0.655, 0.771)
8	1.168 (-0.829, 3.164)	1.168 (-0.829, 3.164)	0.999*** (0.999, 1.000)
9	0.926*** (0.773, 1.079)	0.994*** (0.692, 1.196)	0.909*** (0.720, 1.097)
10	0.753*** (0.702, 0.804)	0.802*** (0.714, 0.890)	0.681*** (0.641, 0.721)
11	0.782*** (0.695, 0.870)	0.782*** (0.695, 0.870)	0.781*** (0.688, 0.875)

Table S7 (cont'd)

12	0.820*** (0.750, 0.890)	0.824*** (0.742, 0.942)	0.759*** (0.668, 0.850)
13	0.821*** (0.746, 0.897)	0.838*** (0.709, 0.967)	0.810*** (0.721, 0.900)
14	0.855*** (0.764, 0.946)	0.877*** (0.709, 1.046)	0.837*** (0.720, 0.954)
15	0.932*** (0.765, 1.098)	0.931*** (0.615, 1.246)	4.720 (-12,752, 12,761)
16	0.765*** (0.709, 0.822)	0.754*** (0.680, 0.827)	0.780*** (0.683, 0.876)
17	No convergence	0.780*** (0.683, 0.876)	No convergence
18	0.955*** (0.748, 1.162)	0.957*** (0.623, 1.291)	0.954*** (0.690, 1.218)
19	0.914*** (0.772, 1.056)	0.873*** (0.755, 0.992)	1.582 (-22.939, 26.102)
20	0.7222*** (0.674, 0.770)	0.736*** (0.671, 0.801)	0.687*** (0.604, 0.770)
21	0.886*** (0.832, 0.940)	0.843*** (0.709, 0.976)	0.889*** (0.835, 0.943)
22	0.857*** (0.764, 0.949)	0.897*** (0.754, 1.040)	0.794*** (0.707, 0.881)
23	0.840*** (0.777, 0.904)	0.864*** (0.794, 0.933)	0.772*** 0.700, 0.844)
24	0.827*** (0.755, 0.898)	0.827*** (0.733, 0.921)	0.826*** (0.717, 0.935)
25*	0.762*** (0.709, 0.815)	0.675*** (0.636, 0.713)	0.813*** (0.726, 0.901)
26	0.804*** (0.734, 0.875)	0.778*** (0.698, 0.858)	0.832*** (0.721, 0.944)
27	0.766*** (0.710, 0.823)	0.771*** (0.693, 0.850)	0.760*** (0.676, 0.844)
28	0.882*** (0.825, 0.938)	1.738 (-40.321, 43.797)	0.795*** (0.682, 0.909)
29	0.855*** (0.790, 0.919)	0.767*** (0.687, 0.847)	0.873*** (0.808, 0.937)
30	0.882*** (0.824, 0.938)	0.786*** (0.693, 0.879)	0.786*** (0.693, 0.879)
31	0.877*** (0.818, 0.936)	9.021 (-48,085, 48,103)	0.765*** (0.674, 0.856)

Table S7 (cont'd)

32	0.893*** (0.845, 0.942)	0.870*** (0.801, 0.939)	6.396 (-337,457, 337,470)
33	0.977*** (0.725, 1.228)	0.938*** (0.744, 1.132)	0.999*** (0.999, 1.000)
34	0.907*** (0.775, 1.038)	0.926*** (0.729, 1.124)	0.878*** (0.712, 1.044)
35	0.892*** (0.842, 0.943)	0.999*** (0.827, 1.171)	0.881*** (0.819, 0.944)
36	0.874*** (0.815, 0.934)	0.749*** (0.665, 0.833)	1.106 (-0.273, 2.484)
37	0.843*** (0.778, 0.908)	0.771*** (0.689, 0.854)	0.860*** (0.791, 0.929)
38	0.999*** (0.999, 1.000)	0.999*** (0.999, 1.000)	0.840*** (0.713, 0.966)
39	0.878*** (0.821, 0.935)	1.632 (-38.502, 41.765)	0.858*** (0.785, 0.931)
40	0.881*** (0.825, 0.938)	0.782*** (0.689, 0.875)	1.956 (-110.674, 114.545)
41	0.999*** (0.975, 1.025)	1.029*** (0.417, 1.641)	0.999*** (0.999, 1.000)
42	0.816*** (0.744, 0.888)	0.789*** (0.686, 0.893)	0.831*** (0.738, 0.924)
43	0.868*** (0.807, 0.930)	0.848*** (0.761, 0.936)	0.910*** (0.735, 1.085)
44	0.685*** (0.648, 0.722)	0.729*** (0.658, 0.800)	No convergence

Tables S8 and S9 provide alternative results with different combinations of explanatory variables for comparison to Table 3 of the main text.

Table S8: Alternative Specifications of Probit Model (Eq. 5) of Lottery Choices Given Power Function for General Lotteries

	Preferred Specification	**(1)**	**(2)**	**(3)**	**(4)**
Constant	0.556*** (0.089)	0.552*** (0.092)	0.557*** (0.092)	0.607*** (0.060)	0.611*** (0.063)
age	0.009*** (0.002)	0.009*** (0.002)	0.009*** (0.002)	0.009*** (0.002)	0.008*** (0.002)
age^2	-6.39e-5*** (1.89e-5)	-6.52e-5*** (2.00e-5)	-6.52e-5*** (1.97e-5)	-5.82e-5*** (1.65e-5)	-5.62e-5*** (1.65e-5)
education level	-0.003 (0.005)	-0.003 (0.005)	-0.005 (0.005)	-0.008 (0.005)	-0.007 (0.005)
acres operating	-3.60e-6*** (1.35e-6)	-1.63e-6 (8.78e-6)	---	---	-1.80e-6 (2.18e-6)
acres operating^2	---	-1.47e-10 (4.80e-10)	---	---	---
income level	0.007 (0.005)	0.008 (0.006)	0.004 (0.006)	---	---
debt-to-asset ratio	---	-0.002 (0.002)	---	-0.001 (0.002)	---
Log-pseudolikelihood	-830.51	-829.26	-831.57	-849.14	-849.29
Wald test of omitted variables	1.68	---	1.78	1.83	3.24

Note: Standard errors in parentheses, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$

Table S9: Alternative Specifications of Probit Model (Eq. 5) of Lottery Choices Given Power Function for Agricultural Lotteries

	Preferred Specification	**(1)**	**(2)**	**(3)**	**(4)**
Constant	0.759* (0.446)	0.518 (0.484)	0.704** (0.324)	0.986*** (0.178)	1.189*** (0.262)
age	-0.006 (0.016)	0.002 (0.012)	-0.002 (0.009)	-0.008 (0.007)	-0.016 (0.011)
age^2	6.45e-5 1.61e-5)	-1.73e-5 (1.09e-5)	2.35e-5 (8.56e-5)	8.68e-5 (7.39e-5)	1.63e-4 (1.18e-4)
education level	0.032 (0.019)	0.037 (0.026)	0.030 (0.020)	0.015 (0.016)	0.016 (0.013)
acres operating	-1.70e-5*** (6.02e-6)	3.45e-5 (5.82e-5)	---	---	-1.25e-5*** (4.54e-6)
acres operating^2	---	-2.92e-9 (3.28e-9)	---	---	---
income level	0.039 (0.029)	0.025 (0.023)	0.024 (0.025)	---	---
debt-to-asset ratio	---	-0.001 (0.008)	---	-0.003 (0.006)	---
Log-pseudolikelihood	-702.12	-699.15	-705.96	-726.52	-724.20
Wald test of omitted variables	0.99	---	0.44	1.34	2.39

Note: Standard errors in parentheses, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$

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