UNDERSTANDING FARMER DECISIONS ABOUT CLIMATE CHANGE ADAPTATION AND CONSERVATION DECISIONS IN AGRICULTURE

By

Natalie R. Loduca

A DISSERTATION

Submitted to
Michigan State University
in partial fulfillment of the requirements
for the degree of

Agricultural, Food, and Resource Economics – Doctor of Philosophy

2024

ABSTRACT

As farmers adjust to the evolving climate, they alter their farming practices and technologies to manage the risks associated with changing crop yields. These adjustments can range from minor changes like tweaking crop insurance coverage to major investments such as adopting irrigation systems. Their responses are influenced by their risk preferences and perceptions of how climate change will affect the risks they face. Additionally, government incentives can play a role in shaping these behavioral responses. This research contributes to the existing body of knowledge by delving into the drivers of farmer decisions in the context of climate change.

The first chapter of this dissertation empirically estimates the risk aversion of 44 corn-soybean farmers in Michigan under different utility function assumptions. We then compare risk aversion across these utility functions and between general lottery choices and choices related to agricultural investments that can mitigate weather risk. We compare the fit of three utility models—constant absolute risk aversion (CARA), constant relative risk aversion (CRRA), and nonconstant risk preferences—and chose the CRRA model as the most suitable for our application. We estimate risk preferences at both the sample- and individual-level, to compare drivers of risk aversion in each lottery setting. While the sample-level estimates of CRRA are similar across lottery settings, individual-level comparisons reveal greater variability in risk preferences within the agricultural lottery setting. In the general lottery, participants' age significantly influences risk preferences, whereas wealth (measured by acres in operation) significantly impacts risk preferences in both lottery settings. Simply measuring farmers' risk preferences without considering contextual factors fails to capture the diversity in preferences and the factors driving this heterogeneity.

The second chapter of this dissertation explores the connection between farmers' risk preferences, perceptions of crop yields, and decisions regarding climate change adaptation. Drawing on the same 44 interviews, we construct perceived crop yield distributions under investment scenarios for tile drainage, center pivot irrigation, and drought tolerant seeds to identify the

perceived efficacy of these practices. We uncover that farmers foresee shifts in future crop yield distributions, anticipating rising means with greater variances. Individuals who perceive a larger increase in expected crop yield from irrigation adoption are more likely to be currently using center pivot irrigation or be considering adopting irrigation. Meanwhile, participants who believe that tile drainage will increase their crop yield variance are less likely to adopt drainage. Assessing risk preferences and subjective crop yield distributions across different technology scenarios enables us to identify the key factors influencing adaptation adoption decisions.

This dissertation's third and last part explores how the U.S. Department of Agriculture Natural Resource Conservation Service (NRCS) cost-share programs encourage the adoption of cover crops across the Midwest. Cover crops provide both public ecological benefits, such as improving air and water quality, and private benefits to farmers, such as improved soil health and reduced soil erosion. Analyzing NRCS cover crop contract county level data, we find that an increase in the cost-share proportion translates to an increase in enrolled acres, which provides evidence of additionality. Results also indicate that the basic single species cover crop contract is the most popular, and higher adoption rates correlate with lower precipitation levels in the preceding growing season. Using remote sensing data, we test the relationships between enrolled cover crop acreage and conservation tillage practices. We do not find positive learning and peer effects from previous enrollment in cover crop contracts, but we do see a positive relationship between cover crop and no-tillage acreage. These findings deepen our understanding of the drivers behind cover crop adoption and shed light on the effectiveness of government incentives in promoting sustainable agricultural practices.

ACKNOWLEDGMENTS

As my Ph.D. program ends, I would like to thank those that provided invaluable support along the way. Thank you to my advisor, Dr. Scott M. Swinton, for his continuous support and guidance. You have pushed me out of my comfort zone which has allowed me to learn and grow as a researcher. Thank you to Dr. James Sears for aiding in my understanding of panel data estimation methods. To my additional committee members, Drs. Frank Lupi and Robert Shupp, thank you for providing feedback along the way. Additional thanks to Dr. Rick Horan for valuable reviewer feedback in the early stages of the first chapter and Dr. Glenn Harrison for patient coaching on coding of maximum likelihood estimation of utility models. Dr. Harrison endured many emails from me as I sought to learn the necessary concepts and coding skills. Thank you to my fellow graduate students Dane Erickson, Drew Frommelt, Aaron Staples, and José Quintero for assisting with the interview process. The financial support of the National Science Foundation under the project, "LTER: The Ecology of Row Crop Ecosystems and Landscapes at the KBS LTER Site" made my graduate studies and survey work possible. Additionally, the A. Allan Schmid Fellowship provided funding for data used in the last chapter of this dissertation.

I would next like to thank those in my personal support system. Thank you to my mom for always supporting me as I have pursued my dreams. Growing up, she used to tell me that she did not care if I decided to be a goat herder in the mountains as long as I "made good cheese." At first, I thought this was a weird phrase until I learned the sentiment behind it. She has always wanted me to find happiness in my purpose in life, regardless of what that may be. Thank you to my best friends, Aley Herrera and Megan Meadows, for always being there when I need to vent or to remember who I am outside of academia. And last but not least, thank you to my amazing fiancé, Aaron Staples. You have believed in me when I do not believe in myself, consoled me when I have lost loved ones, and provided a guiding light when I have lost my way.

TABLE OF CONTENTS

LIST OF ABBREVIATIONS vii

CHAPTER 1: FARMER RISK AVERSION IN A GENERAL VS. AGRICULTURAL LOTTERY SETTING.... 1
1.1. Introduction 1
1.2. Risk Preferences and Their Measurement 5
1.3. Conceptual and Empirical Framework 8
1.4. Data 17
1.5. Results 22
1.6. Discussion and Conclusion 32
REFERENCES 35
APPENDIX 1 40

CHAPTER 2: THE INFLUENCE OF FARMERS' RISK PREFERENCES AND CROP YIELD BELIEFS ON CLIMATE CHANGE ADAPTATION DECISIONS 58
2.1. Introduction 58
2.2. Subjective Probabilities and Their Measurement 62
2.3. Conceptual and Empirical Framework 65
2.4. Data 75
2.5. Results 77
2.6. Discussion and Conclusion 91
REFERENCES 95
APPENDIX 2 99

CHAPTER 3: EXPLORING THE INFLUENCE OF NRCS COST-SHARE PROGRAMS ON COVER CROP ADOPTION IN THE MIDWEST 104
3.1. Introduction 104
3.2. Cover Crop Policy Background and Evaluation 110
3.3. Behavioral Model 112
3.4. Data 115
3.5. Estimation Methods 121
3.6. Results 124
3.7. Discussion and Conclusion 132
REFERENCES 136
APPENDIX 3 139

LIST OF ABBREVIATIONS

ARMS	Agricultural Resource Management Survey
CARA	Constant Absolute Risk Aversion
CRRA	Constant Relative Risk Aversion
CSP	Conservation Stewardship Program
DARA	Decreasing Absolute Risk Aversion
DRRA	Decreasing Relative Risk Aversion
EQIP	Environmental Quality Incentive Program
EUT	Expected Utility Theory
EV	Mean-Variance
FOIA	Freedom of Information Act
GDD	Growing Degree Days
IARA	Increasing Absolute Risk Aversion
IRRA	Increasing Relative Risk Aversion
MLE	Maximum Likelihood Estimation
MVP	Marginal Value Product
NRCS	Natural Resource Conservation Service
OpTIS	Operational Tillage Information System
PDF	Probability Density Function
PRISM	Parameter Regression Independent Slopes Model
RP	Risk Premium
SARE	Sustainable Agriculture Research and Education
SD	Standard Deviations
USDA	United States Department of Agriculture

CHAPTER 1: FARMER RISK AVERSION IN A GENERAL VS. AGRICULTURAL LOTTERY SETTING

Anticipated Coauthor: Scott M. Swinton

Abstract: As farmers adapt to changing climate, they modify practices and technologies to manage evolving crop yield risk. Understanding farmers' risk attitudes is critical to predicting their decisions about climate change adaptation. This research empirically estimates utility functions to measure the risk preferences of Michigan corn-soybean farmers. We elicit from farmers their choices between paired lotteries both in a general and an agricultural context and estimate utility functions that take negative exponential, power, and expo-power forms. Given conceptual and empirical criteria, we select the constant relative risk aversion (CRRA) model as the best-fitting model. Although our whole-sample CRRA risk aversion estimates do not differ statistically between the general and agricultural contexts, our estimates at the individual-level show greater variation in the agricultural context. The participants' age drives the heterogeneity in risk preferences for the general lottery. In contrast, wealth (measured by acres in operation) drives the heterogeneity in risk preferences for both lottery settings. Measuring farmers' risk preferences in a context-free setting fails to capture the heterogeneity in risk preferences that we observe for agricultural investment decisions.

1.1. Introduction

Farmer adaptation to climate risk depends on their risk attitudes and how evolving climate conditions change the distribution of risks they face. Past agricultural economic research has quantified risk aversion, but not in the context of climate change. Understanding farmer risk preferences in the face of climate change can allow policymakers and researchers to better identify how agricultural producers make decisions regarding risk-reducing adaptation investments. Climate change adaptation within agricultural production is vital to ensure crop yields, given that precipitation extremes are predicted to become more prevalent across Midwestern agricultural land in the long run, increasing soil erosion and nutrient leaching, flooding, and droughts (Chen & Ford, 2023; Ford et al., 2021). While temperature changes may increase the growing season length due to increases in frost-free days (Abendroth et al., 2019), drought conditions are predicted to negatively impact crop yields in the Midwest (Jin et al., 2017).

These unprecedented weather changes are shifting the nature of production risks that farmers face (Kimm et al., 2020; Shrestha et al., 2023). Previous work has highlighted the historical impacts extreme temperature and vapor pressure deficits can have on yield (Roberts et al., 2013; Tack et al., 2012), while more recent work shifted to projecting future crop yield distributions under climate change scenarios (Ortiz-Bobea et al., 2019; Van Klompenburg et al., 2020). Climate change is predicted to lower average crop yield and increase crop yield variability. However, the magnitude of this impact is difficult to pin down due to unknown variations in weather, regional differences, and future adaptation (Challinor et al., 2014; Ramsey, 2020). Annual precipitation has increased in the Midwest, and experts predict that the frequency and intensity of precipitation events will continue to increase (Easterling et al., 2017). A majority of Midwest cropland, the largest production region for corn and soybeans, is rainfed, making these farmers more vulnerable to changes in precipitation (Polasky et al., 2022). How agricultural producers manage risk under these shifting conditions largely depends on their risk preferences.

Originally, capturing risk preferences and understanding behavior through the lens of utility theory was primarily studied in psychology (Edwards, 1953, 1961; Tversky, 1967). The contributions of Von Neumann and Morgenstern (1947), Pratt (1964), and Arrow (1965) provided a foundation for utility measurement with advancements in experimental economics, allowing for the empirical estimation of risk parameters. Researchers in agricultural economics soon started to highlight the importance of deriving empirical utility functions to measure risk preferences and how these estimations can inform practical decision-making (Halter & Beringer, 1960; Officer & Halter, 1968). Officer and Halter (1968) discuss early work related to farmer utility analysis and underscore the importance of altering utility measurement methods to ensure suitability under field conditions. Early field experiments measured the risk preferences of subsistence farmers to unpack drivers of technology adoption decisions (Binswanger, 1980; Dillon & Scandizzo, 1978). There is a vast literature on the relationship between risk perceptions and the adoption of new technologies (Marra et al., 2003). More recent work has investigated how risk preferences impact climate change adaptation (Holden & Quiggin, 2017) and conservation decisions (Canales et al., 2024).

Experimental economics has advanced the elicitation and estimation methods to provide evidence of risk aversion. Economic experiments are generally conducted in a computer lab that provides researchers with a controlled environment to measure risk preferences, typically using undergraduate students as research subjects (Harrison & Rutström, 2008). By applying experimental methods in a lab setting, the researchers have more control over the environment. This can make it easier to isolate treatment effects and make reliable inferences. However, when wanting to understand behavior in specific situations, designing the experiment to provide relevant context to the participants is essential. Experiments outside the laboratory setting, known as "field experiments," may provide valuable insights about a decision-maker population of interest. 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). Additionally, by having participants make repeated lottery choices, researchers can estimate risk preferences at the individual-level in addition to the group-level.

We conduct in-person interviews with Michigan corn and soybean farmers to understand farmer risk perceptions and their future crop yield risk mitigation adoption decisions. This work contributes to the agricultural risk literature in three ways. First, we measure farmer perceptions of risk in a context-free versus an agricultural context using the random lottery pair method in a framed field experiment. To our knowledge, this is the first paper to frame risk preference elicitation in the context of climate change conditions that impact crop yields. Next, we estimate risk aversion under three different forms of utility function: i) the negative exponential function to model constant absolute risk aversion (CARA), ii) the power function to model constant relative risk aversion (CRRA), and iii) the expo-power function that nests CARA and CRRA while also allowing for non-constant risk preferences. We evaluate which utility model best fits our lottery data based on conceptual criteria and empirical goodness-of-fit tests. Lastly, we estimate risk preferences at both the sample- and individual-level, given that subjects repeatedly selected their preferred lottery from randomly presented lottery pairs.

We present participants with 25 lottery pairs in a general context and 18 lottery pairs in an agricultural context related to investments to mitigate weather risks related to drought or excess rain. The general lottery pairs offer a choice between two risky gambles, each with a pair of stated payoffs and associated probabilities. These lottery questions do not provide background information on the source of uncertainty relating to the lottery outcomes. In contrast, the second set of lottery choices frames the lottery outcomes in the context of agricultural investments in crop insurance, drought-tolerant seed, drainage tile, or irrigation investments, given a stated probability of adverse weather. We denote the set of these additional lottery choices as the agricultural lottery experiment since we provide the participants with information relating to corresponding payoffs and probabilities in terms of the agricultural investments to mitigate crop yield risk.

Using the data from these two experimental settings, we estimate the degree of risk aversion of Michigan field crop farmers and test whether elicited risk attitudes differ between the general and the agricultural lottery experiments relating to risk-reducing climate adaptation decisions. We find that the CRRA model provides the best model fit, so we focus on the estimates from this model. Although the overall sample-level estimates of CRRA are indistinguishable between lottery settings, a comparison between lottery settings at the individual-level highlights greater variation in risk preferences in the agricultural lottery setting. In the general lottery, participants' age significantly impacts risk preferences, whereas wealth (measured by acres in operation) significantly impacts risk preferences in both lottery settings. Assessing farmers' risk preferences in a context-free setting underestimates the heterogeneity in preferences and the specific factors influencing this variability. If agricultural producers' risk preferences estimated from a context-free setting are applied to model their production decisions, the estimates could lead to a flawed decision model.

We structure the remainder of this paper as follows. In Section 1.2, we provide an overview of the literature on different risk preference elicitation methods and the use of field experiments in the agricultural sector. We present our conceptual and empirical framework in Section 1.3, which offers an overview of utility theory, specifies the utility functional forms our study estimates, and explains the estimation method. Section 1.4 explains our data collection process, the structure of the in-person interviews, and the experimental design. We present our results in Section 1.5, comparing utility functional forms and lottery settings. Section 1.6 discusses the implications of our findings for consideration in future risk aversion elicitation under climate change scenarios and potential policy considerations. Lastly, Section 1.7 concludes and summarizes our findings.

1.2. Risk Preferences and Their Measurement

The theoretical work of Von Neumann and Morgenstern (1947), Pratt (1964), and Arrow (1965) set the stage for utility measurement and subsequent developments in experimental economics that have allowed for the empirical estimation of risk parameters. Von Neumann and Morgenstern (1947) proved that given certain axioms about decision-making, an expected utility function could exist. (EUT). Pratt (1964) and Arrow (1965) provided the Arrow-Pratt indexes of absolute and relative risk aversion that allow for the calculation of risk aversion measures. The past 30 years have witnessed significant advances in risk preference elicitation methods, with a shift from direct elicitation of certainty equivalents to choice experiments used to map underlying utility functions.

Harrison and Rutström (2008) review five categories of elicitation procedures: multiple price lists, ordered lottery selection, Becker-DeGroot-Marschak auction, tradeoff design, and random lottery pairs. The first criterion for selecting the best elicitation method for our study is whether it suits production risk scenarios, and the second is incentive compatibility. A method is incentive compatible if it incentivizes research subjects to respond truthfully. The multiple price list approach allows for the identification of a "switch point," which directly corresponds to a range of the CRRA or CARA parameter depending upon the list's construction and is best suited for single parameter utility functions. While the multiple price list method is incentive-compatible, its format does not allow for the elicitation of production risk preferences, given the focus on prices (Anderson et al., 2007). The ordered lottery selection method asks subjects to pick one lottery from an ordered set. This incentive-compatible method allows researchers to frame the lottery questions as production risk scenarios. There has been criticism about how the order in which the lotteries are presented can impact behavior with both the multiple price list and ordered lottery selection methods (Harrison & Rutström, 2008).

Similar to the multiple price list method, the Becker-DeGroot-Marschak auction is incentive-compatible but fails to meet the production risk criterion given the price framing. The Becker-DeGroot-Marschak auction for risk preference elicitation involves asking the subjects to provide a certainty equivalent representing the selling price of a lottery they have been endowed with. Previous studies have also shown that with the Becker-DeGroot-Marschak auction method, the elicited preferences depend on the underlying price distribution (Banerji & Gupta, 2014; Horowitz, 2006; Vassilopoulos et al., 2018). Additionally, the tradeoff design asks subjects to pick a lottery payoff value that makes them indifferent between two lotteries. While the tradeoff design can be framed as production risks, it is not incentive compatible as respondents are incentivized to inflate their responses as one of the lotteries will be chosen for a payout (Harrison & Rutström, 2008). Lastly, the random lottery pair method is easy to explain to participants, applicable to production risk, and incentive-compatible (Charness et al., 2016; Harrison & Rutström, 2008).

The random lottery pair method presents subjects with one pair of lotteries at a time, and the participants must choose between multiple pairs in a random sequence. Hey and Orme (1994) is the primary example highlighted in the literature. Their subjects chose from a pair of lotteries, repeated over 100 lottery pairs to estimate individual utility functions for each subject. Unlike the multiple price list method, one cannot directly infer risk preferences from the responses. Researchers must use estimation methods, such as maximum likelihood estimation (MLE), to calculate risk attitudes from random lottery pairs (Harrison & Rutström, 2008). The random lottery pair method allows us to estimate risk preferences in the context of production risk and to overcome the shortcomings of the aforementioned alternative methods.

Thus far, we have focused on risk preference elicitation using experimental methods. Other important aspects to consider with risk preference elicitation are the experimental setting, the experimental framework, and the target population, which can provide additional external validity (Roe & Just, 2009). Field experiments recruit subjects with particular expertise, provide context to the tasks and stakes involved, and occur outside of a lab setting (Harrison & List, 2004). This paper focuses on agricultural decisions relating to climate change adaptation, so relevant studies include field experiments focusing on farmers' risk preferences.

Previous studies have tailored their risk elicitation questions to create agricultural field experiments by selecting subjects from a specific agricultural producer group. Focusing on agricultural producers in Mississippi, Hudson et al. (2005) find differences in risk preferences between agricultural and general experiments with evidence of risk aversion in the context of yield and crop prices and risk-seeking behavior in the context-free auction. Menapace et al. (2016) find that Italian apple producers' risk preferences elicited from lotteries in the context of farm income explain farmer crop insurance purchases better than risk preferences from lotteries with no agricultural framing. Risk preferences can directly affect farmer decisions and how they perceive yield probability distributions. In an earlier study of apple farmers, Menapace et al. (2013) found a positive and meaningful relationship between the farmers' level of risk aversion and what they perceived to be the probability of crop losses. While the researchers framed the payoffs for the ordered lottery selection as the percentage of farm income the participants would receive, they did not provide additional context regarding the source of risk.

To identify how farmers will adapt to climate risk, it is crucial to understand how farmers perceive and respond to risk. Measuring risk preferences is essential for understanding farmer decisions, and researchers must be mindful when deciding how to estimate risk measurements. The empirical measurement of risk attitudes is shaped by both the elicitation method and the subsequent modeling choices. With choice experiment data, the parameters of the underlying utility function are generally estimated via MLE, given subject characteristics and other conditioning variables (Harrison & Rutström, 2008). The choice of the utility function can impact the interpretation of the estimated risk preferences, with simpler, one-parameter models generally assuming constant relative or absolute risk aversion behavior. More complex models can characterize different risk preference structures but may be more challenging to estimate.

1.3. Conceptual and Empirical Framework

1.3.1. Conceptual Framework

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, advancements 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 (*A[w]*) (Eq. 2) and relative risk aversion (*R[w]*) (Eq. 3) (Arrow, 1965; Pratt, 1964).

$$A(w) = \frac{-U"(w)}{U'(w)} \tag{2}$$

$$R(w) = \frac{-U"(w)w}{U'(w)} \tag{3}$$

The Arrow-Pratt indexes require assumptions regarding the functional form of utility. Two standard functions to model risk preferences compatible with EUT are the constant absolute risk aversion (CARA) and constant relative risk aversion (CRRA) functions. Pratt (1964) offers multiple examples of functions representing CARA or CRRA behavior. CARA implies preference equivalence sets for lottery pairs that differ by an additive context 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 context 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.

Researchers often use the negative exponential function to model CARA preferences with the risk preference parameter represented by α, as shown in Eq. (4). Alternatively, studies commonly utilize the power function to model CRRA preferences with the risk aversion parameter, represented by r in

Eq. (5). Eq. (4) and Eq (5) were explicitly derived to display constant parameters for CARA and CRRA, respectively.

$$U(w) = -e^{-\alpha w} \quad (4)$$

$$U(w) = \frac{w^{1-r}}{1-r} \quad (5)$$

When calculating A(w), shown by Eq. (2), for the negative exponential function defined by Eq. (4), we have that the Arrow-Pratt index of absolute risk aversion reduces to the constant term of α. Similarly, when calculating R(w), shown by Eq. (3), for the power function defined by Eq. (5), the Arrow-Pratt index of relative risk aversion reduces to the constant term of r. Under both CARA and CRRA, a negative risk parameter represents risk-loving behavior, a positive risk parameter represents risk-averse behavior, and a risk parameter of zero causes the equations to reduce to risk neutrality.

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. 4) and CRRA (Eq. 5) preferences. Saha (1993) introduced the expo-power utility function, a flexible form that can model relative and absolute risk aversion. Holt and Laury (2002) developed the expo-power function shown by Eq. (6) to modify Saha's (1993) original expo-power function that demonstrates alternative risk preferences based on the parameter signs and values. Eq. (6) allows for a nested test, considering that it represents CARA as $r \to 0$ and CRRA as $\alpha \to 0$.

$$U(w) = \frac{1 - \exp\left(-\alpha w^{1-r}\right)}{\alpha} \quad (6)$$

These reductions can be shown by the Arrow-Pratt indexes. The index of absolute risk aversion is represented by

$$A(w) = \frac{-U''(w)}{U'(w)} = \frac{r + \alpha(1-r)w^{1-r}}{w}. \quad (7)$$

When $r = 0$, Eq. (7) reduces to the CARA coefficient, α, with A'(w) = 0.

The index of relative risk aversion is represented by

$$R(w) = \frac{-U''(w)w}{U'(w)} = r + \alpha(1-r)w^{1-r}. \tag{8}$$

When $\alpha = 0$, Eq. (8) reduces to the CRRA coefficient, r, and R'(w) = 0.

Because the expo-power function encompasses relative and absolute risk aversion, its first derivative with respect to the outcome variable can capture how risk preferences vary with the stakes of risky gambles, as shown in Eq. (9) and (10).

$$A'(w) = \frac{-r[\alpha(1-r)w^{1-r} + 1]}{w^2} \tag{9}$$

$$R'(w) = \alpha(1-r)^2 w^{-r} \tag{10}$$

In these cases, risk preferences are not reduced to CARA or CRRA. Instead, we have decreasing relative risk aversion (DRRA) when R'(w) < 0, increasing relative risk aversion (IRRA) when R'(w) > 0, decreasing absolute risk aversion (DARA) when A'(w) < 0, and increasing absolute risk aversion (IARA) when A'(w) > 0. The alternative risk preference structures of the expo-power utility function depend on the values of α and r. Table 1.1 summarizes how risk aversion under the expo-power function varies over the ranges of α and r.

Table 1.1: Risk Preference Structures of the Expo-Power Function

	Decreasing Relative Risk Aversion (DRRA)	Increasing Relative Risk Aversion (IRRA)
Decreasing Absolute Risk Aversion (DARA)	$\alpha < 0, 0 < r < 1$	$\alpha > 0, 0 < r < 1$
Increasing Absolute Risk Aversion (IARA)	not feasible	$\alpha > 0, r > 1$

While the literature on DARA and IARA explores how preferences change with respect to changes in wealth, this research initially uses the stakes of risky gambles as a proxy for wealth. Under CARA and CRRA, the assumption is that risk preferences are constant across all levels of wealth. However, if an individual experiences an increase in wealth, they may change how they invest their money. In the case of DARA, when a person experiences an increase in wealth, they will be comfortable with decreasing the *absolute* amount of money they invest in safe assets and/or increasing the absolute amount of money they invest in risky assets. With IARA, an increase in wealth will lead someone to increase their investments in safe assets and/or decrease their investments in risky assets. Relative risk preferences are sometimes referred to as proportional risk preferences, given that they relate to the proportion of wealth invested in assets. DRRA describes behavior in which a person is willing to invest a smaller proportion, or *relative* amount, of their wealth in safe assets and more in risky assets as their wealth increases. Conversely, IRRA leads individuals to increase the proportion of their wealth invested in safe options while the proportion invested in risky assets may decrease (Levy, 1994).

Utility allows us to conceptualize and quantify an individual's welfare derived from consuming goods and services. This concept allows us to measure the subjective value of a person's consumption and investment decisions. The construction of utility functions allows us to measure risk preferences based on the assumption that each individual seeks to maximize their utility or well-being. Therefore, utility can be used to explain and predict individual choices and behaviors in various decision-making settings.

1.3.2. Empirical Framework

A fundamental challenge in measuring risk attitudes is that we cannot directly observe an individual's utility function. However, we can make statistical inferences from the preferences revealed by how a decision-maker n makes choices. The lottery choice method enables the econometric estimation of functions $U_n(w_{ij})$ based on the risk preference parameters in Eq. (4-6) from lottery 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 between lottery pairs where each lottery has two payoffs, each with a designated probability. The second set of lottery pairs involves choices in an agricultural context in which participants make decisions regarding investment payoffs to manage crop yield risk.

The random utility framework 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.

$$P(y_i = 1 | w_{ij}, p_{ij}, w_{kj}, p_{kj}) = Prob[EU_{ni} > EU_{nk}] \ \forall \ \mathrm{i} \neq \mathrm{k} \tag{11}$$

The underlying utility functions are latent variables that shape decision-maker choices and can be influenced by the decision-maker's personal characteristics. Because utility is not directly observable, one can only predict the probability that a decision-maker selects a given lottery. Using a choice probability equation, we can apply MLE to a binary response model. We can 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. (11) as

$$P(y = 1 | w_{ij}, p_{ij}, w_{kj}, p_{kj}) = Prob[EU_{ni} - EU_{nk} > 0] \ \forall \ \mathrm{i} \neq \mathrm{k}. \tag{12}$$

The utility functions of Eq. (4-6) 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. 13) 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:

$$LL(U_n(w);\ w_{ij}, p_{ij}, w_{kj}, p_{kj}) = \qquad (13)$$

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

where $\mathbf{I}(.)$ is the indicator function and y indicates the lottery choice. Through MLE, we can estimate either the $\hat{\alpha}$ from Eq. (4), $\hat{r}$ from Eq. (5), or $\hat{\alpha}$ and $\hat{r}$ from Eq. (6), depending on which utility function is used for the latent index that maximizes the probability that the lottery choices the individual selected provide them with greater expected utility than the lottery alternatives that they did not choose.

Once we have parameterized Eq. (4-6), we can evaluate which utility model best suits each lottery setting. Selection criteria for econometric models should include both theoretical and empirical aspects. From a conceptual perspective, we can evaluate the functional form selection based on Lau (1986), which defines the selection criteria as theoretical consistency, factual conformity, computational facility, flexibility, and domain of applicability. The exponential function (Eq. 4) that represents CARA, the power function (Eq. 5) that represents CRRA, and the nested expo-power function (Eq. 6) that provides a flexible form were all constructed to provide theoretical consistency and factual conformity in terms of rational economic behavior under the framework of utility theory. For the computational facility criterion, the single-parameter exponential (Eq. 4) and power (Eq. 5) functions allow for straightforward model estimation. However, the complexity of the expo-power function (Eq. 6) allows for greater flexibility and risk preferences outside of solely CARA or CRRA, which expands the domain of applicability. While the expo-power function is the preferred model according to the selection criteria based on Lau (1986), we also consider parsimony of parameters and readily interpreted parameters (Frank et al., 1990). With these additional criteria, there is a tradeoff between the flexibility of the two-parameter expo-power function (Eq. 6) and the single-parameter exponential (Eq. 4) and power (Eq. 5) functions.

We will evaluate the three utility models using the criteria for choice-of-functional-form listed above. In addition to these conceptual criteria, nested choice-of-model tests provide an empirical measure of goodness-of-fit. For the goodness-of-fit criterion, we use the Wald Test to evaluate whether the more complex expo-power model has added explanatory power that justifies its use over the simpler CARA or CRRA models nested inside it. The expo-power function (Eq. 6) allows for a nested test that indicates CARA preferences if $r = 0$ and CRRA preferences if $\alpha = 0$. Given that the expo-power function (Eq. 6) nests the exponential function (Eq. 4) and the power function (Eq. 5), we can perform a Wald Test to select the best-fitting utility model (Wald, 1943). The first null hypothesis to test is that all three utility functions are equally valid for both the general and agricultural lottery data. The Wald Test can test whether the expo-power function (Eq. 6) collapses to the exponential function (Eq. 4) or the power function (Eq. 5) by testing the restriction that $\hat{r}$ of $\hat{\alpha}$ are equal to zero. This can be done with the aggregate sample to capture behavior on average and at the individual-level to capture heterogeneity across the participants.

The second null hypothesis is that there is no difference between the degree of risk aversion between the general and agricultural lottery contexts. We can test this by comparing the confidence intervals for the risk aversion coefficients to see if an overlap prevents us from distinguishing between the parameter estimates. This is most easily done when comparing estimated risk preference parameters of the same utility function, such as comparing the estimated $\hat{\alpha}$ from the general lottery data to the $\hat{\alpha}$ estimated from the agricultural lottery data. Nevertheless, we can also compare $\hat{\alpha}$ from the exponential function (Eq. 4) that represents CARA or $\hat{r}$ from the power function (Eq. 5) that represents CRRA to the nested expo-power function (Eq. 6) that provides a flexible form containing both $\hat{\alpha}$ and $\hat{r}$. However, we cannot straightforwardly compare the parameter estimates since the $\hat{\alpha}$ of the nested expo-power function (Eq. 6) does not directly represent the Arrow Pratt Index of Absolute Risk Aversion, nor does the $\hat{r}$ from Eq. (6) represent the Arrow Pratt Index of Relative Risk Aversion. The $\hat{\alpha}$ and $\hat{r}$ estimated for the expo-power function must be plugged into Eq. (7) and Eq. (8), respectively, to calculate the corresponding Arrow Pratt Indexes of Absolute and Relative Risk Aversion.

Our third null hypothesis is that covariates do not affect the risk aversion coefficient estimate(s). We can test this hypothesis by estimating the best-fitting model with different combinations of independent variables to identify those that have statistically significant effects on risk aversion. To estimate the effects of decision-maker traits on decisions, we can regress estimates of risk aversion coefficients on a vector of such traits, $\boldsymbol{X'} = [X_1 \cdots X_j]$. To do so, we include covariates in the MLE process to allow the risk preference coefficient to be determined by individual coefficients. For the CARA risk aversion coefficient, this would look like,

$$\hat{\alpha} = \hat{\beta}_0 + \hat{\beta}_j \boldsymbol{X} \tag{14}$$

Given the stated choices from the lottery experiments and information on personal and farm characteristics from our survey, we can estimate risk preferences under model specifications that assume different utility functional forms and pertinent covariates.

There is evidence in the economic literature that age (Holt & Laury, 2002; Meissner et al., 2023; Tanaka et al., 2010), income (Holt & Laury, 2002; Meissner et al., 2023), and education (Harrison et al., 2007; Von Gaudecker et al., 2011) affect risk aversion. As individuals age, they are less likely to be impulsive and take unnecessary risks. However, their risk aversion level may decrease after reaching a certain age and being less concerned about long-term outcomes. With higher income and wealth, people are willing to take on more risk, given that they have a safety net. Our study uses income intervals, acres operated, and debt-to-asset ratio intervals to proxy for wealth. Although studies have found that education level impacts risk aversion, some research has found education to be positively associated with risk preferences (Vieider et al., 2019; Von Gaudecker et al., 2011), while others have found a negative association (Donkers et al., 2001; Gächter et al., 2022; Harrison et al., 2007) Identifying which characteristics impact risk aversion in the agricultural lottery setting could be of interest for targeting public policy related to farming decisions under climate risk.

By testing each of these hypotheses, we can characterize the type of risk preference behavior, detect potential differences in risk preference behavior between each lottery setting, and identify the farm and farmer characteristics that impact risk preference behavior. We hypothesize that risk aversion will be higher in the agricultural context, considering that these lotteries are framed as directly impacting participants' income. Additionally, we predict that age will positively affect risk aversion and that higher education levels will have a negative effect. We also predict that risk aversion will decrease with increases in wealth, with our potential measures of wealth being acres in operation, income level, and debt-to-asset ratio.

1.4. Data

1.4.1. Data Collection and Survey Framework

We implemented a framed field experiment by interviewing Michigan corn and soybean farmers at county-level meeting places, including restaurants and Michigan State University County Extension Offices. 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 experiment. The first section contained 25 binary lottery choices in an abstract setting, while the second section presented 18 lottery choices in the context of farm investment decisions.

We presented the 25 general lottery pairs in random order to prevent ordering effects, and they included payoffs that are 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 1.1 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. 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 chapter appendix includes the complete set of general lotteries, the experimental procedures, and example questions for each payoff type.

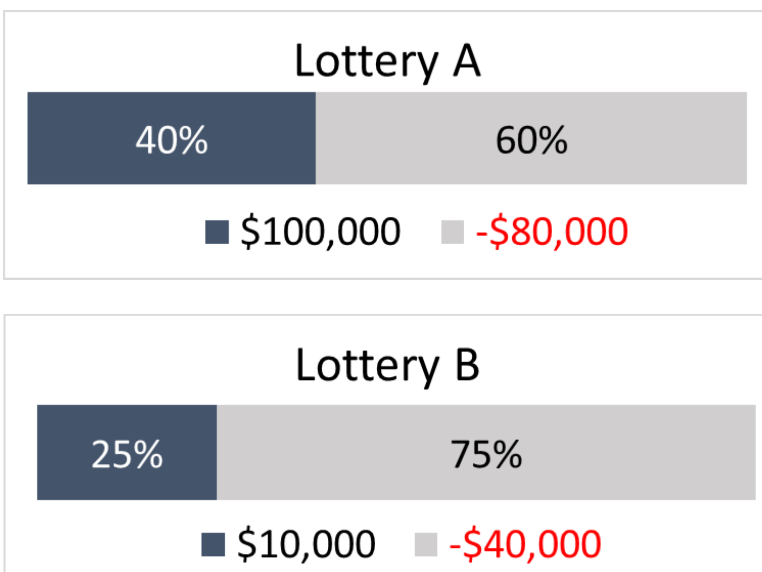


Figure 1.1: Example of visual representation of lottery bar graphs.

The agricultural lottery experiment framed the 18 lottery choices to mitigate revenue loss due to excessive moisture or drought. We informed the participants that payoffs are based on revenue of $24,000 for the hypothetical 40-acre field. The payoffs in our agricultural lottery setting are 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 relating 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 crop revenue assumption. Previous discussions with Michigan State Extension Agents informed us that significant investments such as irrigation mainly occur following years of high crop revenue. While the investment costs remained the same, the higher baseline of an assumed $48,000 crop revenue provided a more compelling tradeoff when deciding whether to invest.

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 (Table 1.2). 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 result 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. 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).

Table 1.2: Agricultural Lottery Experimental Design

	Probability of Adverse Weather	
Cost of Investment	High	Low
High	A	B
Low	C	D

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 see 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 Appendix, along with example questions for each investment type.

Given that the subject sample includes 44 farmers completing 25 general lottery questions and 18 agricultural lotteries, we have a panel data structure with 1,100 and 792 observations under each lottery type. With these responses, we can estimate risk preferences under different utility model assumptions and compare behavior across settings. Once we have our risk preference estimates, we can model these estimates as being dependent on farm and farmer characteristics to capture what factors drive risk preferences.

1.4.2. Descriptive Statistics and Representativity of the Sample

This sample broadly represents Michigan corn-soybean farms that rely heavily on farming for household income. While the sample was selected purposively with aid from Michigan State University Extension, the farms are spread across the southern half of Lower Michigan, where corn and soybean are cash crops, and the sample traits largely align with the 2022 Michigan Census of Agriculture (USDA-NASS, 2024a). Table A1.3 in the Appendix provides a detailed comparison of our sample characteristics to the 2022 Michigan Census of Agriculture data. 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. A number of 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, yet 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 1.3 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. Additionally, income and debt-to-asset ratio are defined as categorical variables in Appendix Table A1.3, 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.

Table 1.3: Summary Statistics for Main Covariates

	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 1.2 depicts the counties where our 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.

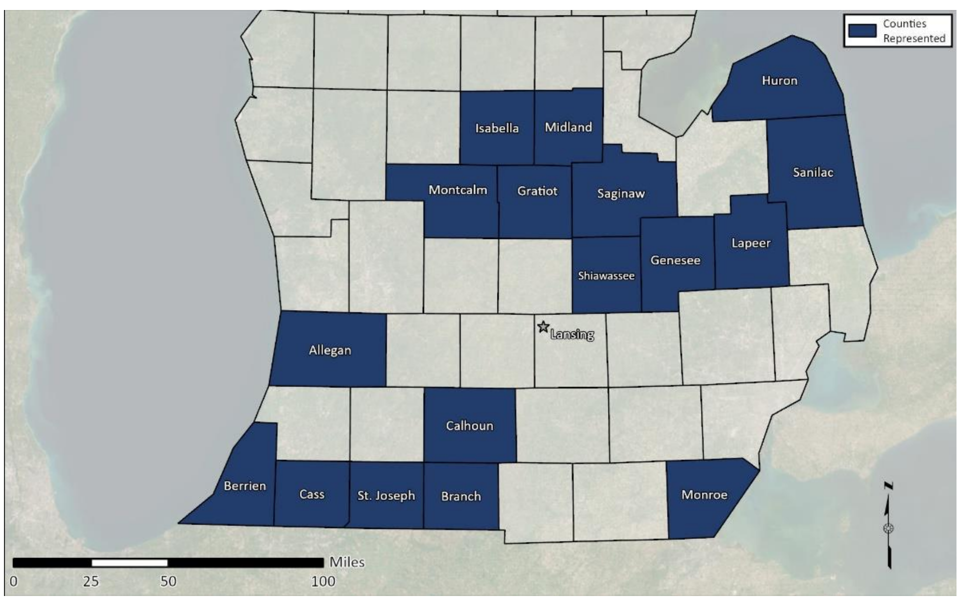


Figure 1.2: Counties represented in our sample indicated by our participants as the county where they operate most of their acres. (Map created by Justin Anderson.)

1.5. Results

First, we report results and choice of model tests for the aggregate sample and compare the CARA exponential, CRRA power, and nested RRA and ARA expo-power utility functions across the general and agricultural lottery settings. This allows us to understand how the average farmer in our sample behaves. Given the number of repeated choices in our lottery experiment, we are able to estimate utility functions for the individuals in our sample. Therefore, we also report the results and choice of model tests for the three utility functions at the individual-level. We identify the preferred utility functional form with these empirical results and our selection criteria. Lastly, we proceed to the hypothesis tests and report the results from the preferred utility model.

Table 1.4 shows the whole-sample probit model parameter estimates that maximize the likelihood of the lottery choices given the CARA exponential (Eq. 4), CRRA power (Eq. 5), and the nested expo-power (Eq.6) functions from standard, general lotteries, and lotteries based on agricultural investments. Both risk preference coefficients display risk aversion for CARA, but the general lottery CARA coefficient, α, is nearly risk neutral. In the context of agricultural investments, α is an order of magnitude larger, implying that farmers display higher risk aversion when making decisions specific to farming. While both of the CARA model α estimates are quite small, these magnitudes are typical for this model (Raskin & Cochran, 1986). In the case of CRRA, results indicate risk aversion for both lottery settings. However, we cannot reject the possibility that the risk coefficients, r, are equal, given the overlap in the 95% confidence intervals. At the 25% level, we can reject the null hypothesis that the CRRA parameters are equal across lottery contexts. Specifically, there is weak evidence of the CRRA risk preference parameter being larger in the agricultural lottery setting. The magnitude of CRRA r estimates also matches estimates in the literature (Lilleholt, 2019).

Table 1.4: 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	
	α	r	α	r
General	7.67e-6***	0.862***	-0.295***	0.852***
	(7.67e-6)	(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	
Wald chi-square				
General			19,767.06***	71,208.82***
Agricultural			34.21***	484.36***

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

The expo-power functional form provides flexibility that enables testing for changes in risk aversion with respect to the payoff level (Table 1.1). It also enables nested model tests to see if risk preferences can be characterized more parsimoniously as CARA or CRRA, depending on the values of α and r. The whole-sample results in Table 1.4 indicate that participants display both relative and absolute risk aversion. Upon performing Wald tests for α and r in each lottery setting, we reject the null hypothesis that the additional risk preference parameter provides no more explanatory power. Instead, we find that the expo-power function (Eq. 6) is preferred at the whole sample level, suggesting that risk preferences are not constant over wealth levels.[1] By modeling the absolute (Eq. 7) and relative (Eq. 8) risk aversion indexes, we can see how risk preferences change overall as a function of the estimated α and r values and the lottery payoff levels.

Figure 1.3 displays estimates and 95% confidence intervals (CIs) for the absolute risk aversion index under the general and agricultural lottery settings in the first row and for the relative risk

[1] The interpretations of the coefficient values of the expo-power utility function are not equivalent to those of the exponential or power utility functions. The conceptual framework describes the relationships between the Arrow-Pratt indexes of absolute (Eq. 2) and relative risk aversion (Eq. 3) and our utility functions. Both α and r impact the Arrow-Pratt indexes for the nested expo-power model (Eq. 6) as depicted by Eq. (7) and (8).

aversion index under each setting in the second row. Comparing the y-axis of panel B to panel A and the y-axis of panel D to panel C, we now see comparable values measuring absolute and relative risk aversion. The horizontal lines depict the corresponding CARA and CRRA results from Table 1.4 for comparison to the expo-power RRA and ARA estimates. The confidence intervals reveal that the agricultural context lotteries (panels B and D) had more heterogeneous results than the general ones (panels A and C). The absolute risk aversion measures in Panels A and B display DARA behavior, with the index decreasing as the lottery payoff amounts increase. Looking at the relative risk aversion index estimates for panels C and D, the change in magnitude is smaller as the payoffs increase. In the general lottery setting (panel C), there is a slight decrease in relative risk aversion, and while panel D suggests IRRA behavior in the agricultural lottery case, we cannot rule out CRRA. 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. This illustrates that in the context of agricultural yield risk, respondents are more risk averse than in a general (context-free) lottery.

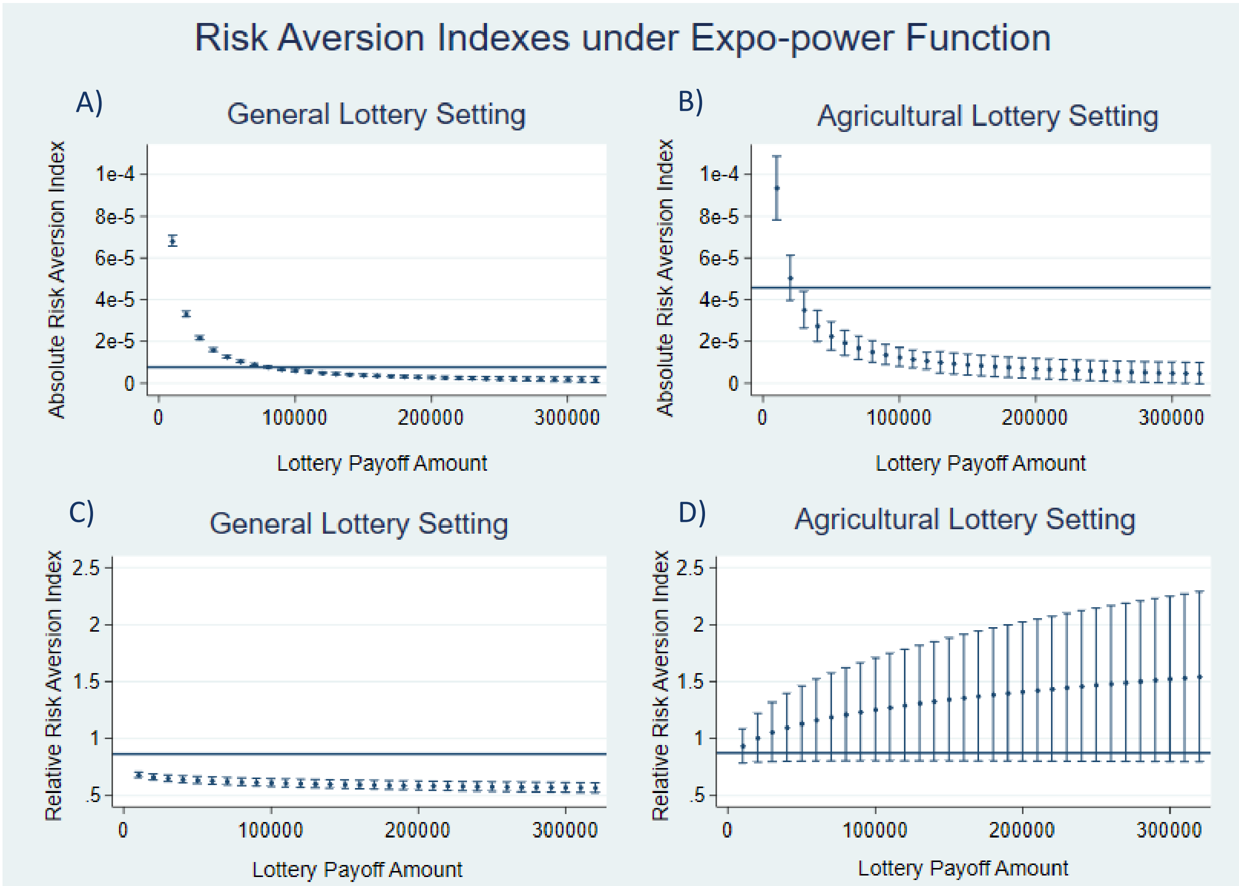


Figure 1.3: Risk aversion index estimates under the expo-power function and their 95% confidence intervals for a) absolute risk aversion under the general lottery setting, b) absolute risk aversion in the agricultural lottery setting, c) relative risk aversion in the general lottery setting, and d) relative risk aversion in the agricultural lottery setting. The solid horizantal lines represent the corresponding risk aversion estimates for the CRRA and CARA functions for comparison.

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 1.5 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 with the more parsimonious utility models. As noted above, rejection of the null hypothesis (Eq. 6) can provide evidence of CARA (if $\hat{r}_n$ = 0) or CRRA (if $\hat{\alpha}_n$= 0). Table A1.4 in the Appendix 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 Tabel 1.5 provide strong empirical evidence of CRRA preferences in both lottery settings. Specifically, 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 41 cases that converged. By contrast the CARA model fit only 2 of 44 cases that converged and was never preferred to the negative exponential. For the agricultural lottery data, the CRRA model fit in 35 of the 42 cases that converged and in 17 of the 32 negative exponential cases that converged. The CARA model fit in just 7 of 42 cases that converged and in 1 of the 32 negative exponential model cases that converged. No individual model with general lottery data and just four with negative exponential data failed to reject the null hypothesis that the negative exponential model was superior to both CARA and CRRA.

Table 1.5: 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

The nested choice-of-model tests provide empirical evidence supporting the expo-power model at the whole-sample level but the CRRA power model at the individual farmer level. We need to look beyond goodness-of-fit to evaluate a broader set of criteria for model selection. Our conceptual criteria include computational facility, flexibility, domain of applicability, parsimony of parameters, and readily interpreted parameters. Table 1.6 provides an overview of the choice of model criteria and which model performs best under each category. The CRRA model ranks first, followed by the expo-power model, and the CARA model places last. Therefore, given the evidence from the individual-level analyses, we focus the remainder of the Results section on estimates from the CRRA power (Eq. 5) utility model.

Table 1.6: 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***	Supported
General: Goodness-of-fit, Individual (Wald)	38 of 41 reject*	0 of 41 reject*	N/A
Agricultural: Goodness-of-fit, Aggregate (Wald)	Reject***	Reject***	Supported
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.

From the CRRA functions at the individual-level, we find greater variation in the estimated r values in the agricultural than in the general lottery setting. Figure 1.4 compares provides the individual r coefficient estimate distributions between the two for each lottery settings. We see a narrower distribution for the general lottery case with an average value of 0.843 and a standard deviation of 0.066. Meanwhile, the agricultural risk coefficients vary more, resulting in a wider distribution with an average value of 0.810 and a standard deviation of 0.125. While the averages of the risk preference coefficients in each lottery setting are similar, which is also reflected by the whole-sample estimates in Table 1.4, we see more variation in risk preferences within the agricultural lottery setting. This variation in risk preferences for the agricultural lottery case is also reflected in the larger 95% confidence interval reported in Table 1.4.

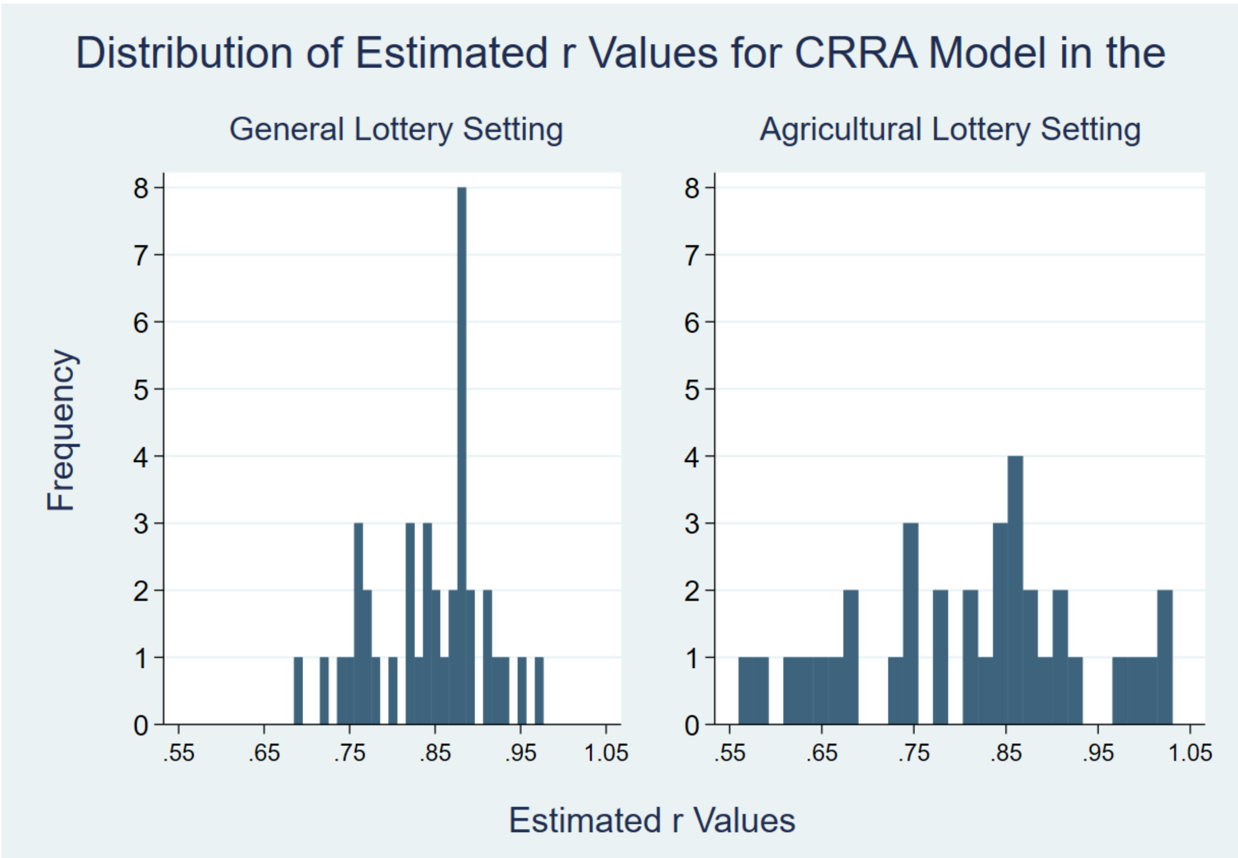


Figure 1.4: A comparison of estimated r values at the individual-level for both lottery settings.

To understand what is driving differences in participants' risk aversion measures, we estimate the risk preference parameters as functions of demographic and farm characteristics. The demographic variables of interest include age, age squared, and education. Since we do not have a direct measure of wealth, our three potential proxies for wealth are acres in operation, income, and debt-to-asset ratio. Income level and debt-to-asset ratio are categorical measures, whereas acres in operation is a continuous variable. The results for alternative demographic specifications under the

CRRA power (Eq. 5) utility function assumptions are provided in the Results section of the Appendix in Tables A1.5-A1.6 and are split by lottery setting for ease of viewing.

General lottery results showed evidence of a quadratic age effect across all specifications and evidence of acres operated having a negative effect in one of the three specifications. The agricultural lottery results showed no age effect for any of the specifications, but there is a significant negative effect of acres operated in two of the three specifications. The preferred specification shown in Table 1.7 was the most parsimonious that was directly comparable across general and agricultural lottery samples. We use acres in operation and income as proxies for wealth, since this model resulted in a medium estimated risk parameter value and a higher log-likelihood value. With and without demographic variables included the results in Table 1.7 indicate that we cannot reject the possibility that the risk coefficients, *r*, are equal across lottery types, given the overlap in the 95% confidence intervals. This is consistent with the results of Table 1.4 and the distributions shown in Figure 1.3, which demonstrate that the risk coefficient estimates for the general case fall within the wider range of estimates for the agricultural lottery setting. In the general lottery setting when we evaluate the CRRA model at the average values of the covariates, the average value of the CRRA parameter is 0.855 with a minimum value of 0.765 and a maximum of 0.899. For the agricultural lottery setting we have an average CRRA parameter value of 0.894 when we evaluate the model at the average covariate values. These with the constant coefficient value for the CRRA parameter of 0.862 for the general lottery setting and 0.890 for the agricultural lottery setting as shown in Table 1.7.

Table 1.7: 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-5)
education level	---	-0.003 (0.005)	---	0.032 (0.019)
acres operating	---	-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

The results for the general lottery setting indicate that as the age of our participants increases, so does their degree of risk aversion on average. While the coefficients for age and age squared are relatively small, Table 1.3 indicates that the average age of our participants is 56. On average, risk aversion increases by about 7% when someone increases age from 50 to 60 years old. However, the risk aversion is increasing at a decreasing rate given the negative coefficient on age squared. With the risk aversion estimate reaching its maximum at 70 years old, an increase in age from 70 to 80 years old results in a 2% decrease in risk aversion on average. Our findings also indicate that risk aversion decreases as the participants' acres in operation increase for both the general and agricultural lottery setting. Our sample's average acreage in operation is 2,420 acres, and the median is 1,650 acres. An increase in the size of the operation by 1,000 acres is associated with a 25% decrease in risk aversion in the general lottery setting and a 47% decrease in the agricultural lottery setting, on average. For both lottery settings, the levels of education and income do not impact risk aversion estimates.

1.6. Discussion and Conclusion

As climate variability increases, agricultural producers must adjust production systems and make investment decisions to adapt to increasing precipitation variability that will increase drought and flood conditions (Chen & Ford, 2023; Ford et al., 2021). Given the uncertainty surrounding weather patterns annually, agricultural producers may perceive crop yield risk and how best to manage it differently based on their experience and ground conditions. This research empirically estimates the risk aversion of Michigan corn-soybean farmers through in-person, lottery-based experiments. Consistent with the risk preference literature, we find that Michigan corn and soybean farmers display risk aversion in both the general and the agricultural lottery settings (Iyer et al., 2020).

Our findings suggest that risk aversion increases with age at a decreasing rate in the general lottery setting, which is supported in the literature (Ackert et al., 2009; Picazo-Tadeo & Wall, 2011). While we do not find an impact of income on risk aversion, we find evidence that those operating more acres have lower risk aversion in both lottery settings. This provides evidence of DRRA for individual farmers, though we found CRRA to be the preferred model based on lottery payoffs. Our results highlight the differences in the characteristics driving the variation of risk preferences in each lottery setting.

Our results highlight the importance of researchers considering the framing of their experimental design. While whole sample estimates of the CRRA in the general and agricultural lottery settings are indistinguishable, closer inspection highlights critical differences. First, we find greater heterogeneity of risk preferences in the agricultural lottery setting with an individual-level analysis of CRRA preferences. Second, our results identify key factors that influence farmers' risk preferences. In the general lottery setting, risk preferences increase quadratically with age up to 70 years old. In both lottery settings, risk aversion decreases with acres in operation, illustrating that farmers with larger operations are more willing to take on risk. Although Michigan's average oilseed and grain farm is relatively small, decision-makers with more extensive operations control a large percentage of overall cropland and can significantly impact policy outcomes. Oilseed and grain farmers operate approximately 67% of farmland in Michigan and 66% across the United States, so their management decisions can have widespread implications (USDA-NASS, 2024a, 2024b).

By using framed field experiments to explore farmer risk attitudes in the context of changing weather risks, we can identify drivers of risk preferences. We find that farmers who operate more acres are less risk averse. This supports targeting larger farms with climate adaptation messages based on threats to mean profitability and down-side risk. It also highlights the value of targeting smaller operations for risk-reduction policies such as subsidized climate insurance. The heterogeneity of risk preferences related to agricultural decisions implies a need to target different types of farmers with different messages. We find that some farmers are much more risk averse than average and therefore could be more receptive to policies that mitigate the effects of climate risk.

While we have a relatively small sample size, smaller sample sizes are common when conducting in-person interviews with specialized groups. We recruited farmers from across the lower half of Michigan to represent corn and soybean farmers. However, we were limited in the feasible number of interviews due to time and monetary constraints. Using Michigan State Extension educators to facilitate our recruitment, we gained the trust of the farmers we contacted. While this helped with our response rate, it did not allow us to sample the target population randomly. We are confident in the internal validity of our experiments, given the one-on-one interview style that enabled us to answer questions as they arose. However, although purposively selected, our sample aligns well with traits of Michigan corn & soybean farmers as reported by the 2022 Census of Agriculture.

Additional research will be needed to explore other drivers of farmer investment decisions in the face of climate change. Farmers are the primary land managers, and their preferences and beliefs about future outcomes drive their management decisions. While risk preferences are an essential piece of the puzzle, additional factors influence adoption decisions. While meteorologists predict higher variability in precipitation across Michigan, it is necessary to understand farmers' beliefs about future weather patterns and their impacts on subjective crop yield distributions. 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). Menapace et al. (2013) linked risk preferences to subjective probability assessments, though there is a gap in the literature regarding the link between risk preferences and climate change adaptations. Further research on farmer concerns regarding future crop yield distributions and beliefs about the efficacy of mitigation practices can provide a clearer picture.

Farming outcomes are dependent on climate conditions. While certain practices can mitigate weather-related risk, it is difficult to predict which practices will be most effective given climate variability. Understanding risk attitudes is vital for identifying the most desirable management avenues for farmers' responses to changing weather and associated crop yields. By quantifying farmer risk preferences in related to weather-related risk, we lay the foundation for modeling climate change adaptation decisions. Policymakers should carefully consider risk aversion measurements from studies that estimate risk preferences in a context relevant to the policy's topic area. Effective and efficient policies, government programs, and insurance plans should account for how agricultural producers will respond to risk.

REFERENCES

Abendroth, L. J., Miguez, F. E., Castellano, M. J., & Hatfield, J. L. (2019). Climate Warming Trends in the US Midwest Using Four Thermal Models. *Agronomy Journal*, *111*(6), 3230-3243.

Ackert, L. F., Gillette, A. B., Martinez-Vazquez, J., & Rider, M. (2009). Risk Tolerance, Self-Interest, and Social Preferences. *Andrew Young School of Policy Studies Research Paper Series*(11-03).

Anderson, S., Harrison, G. W., Lau, M. I., & Elisabet, R. E. (2007). Valuation Using Multiple Price List Formats. *Applied Economics*, *39*(6), 675-682.

Arrow, K. J. (1965). *Aspects of the Theory of Risk-Bearing*. Yrjö Jahnssonin Säätiö.

Banerji, A., & Gupta, N. (2014). Detection, Identification, and Estimation of Loss Aversion: Evidence from an Auction Experiment. *American Economic Journal: Microeconomics*, *6*(1), 91-133.

Barham, B. L., Chavas, J.-P., Fitz, D., Salas, V. R., & Schechter, L. (2014). The Roles of Risk and Ambiguity in Technology Adoption. *Journal of Economic Behavior & Organization*, *97*, 204-218.

Binswanger, H. P. (1980). Attitudes Toward Risk: Experimental Measurement in Rural India. *American Journal of Agricultural Economics*, *62*(3), 395-407.

Canales, E., Bergtold, J. S., & Williams, J. R. (2024). Conservation Intensification Under Risk: An Assessment of Adoption, Additionality, and Farmer Preferences. *American Journal of Agricultural Economics*, *106*(1), 45-75.

Challinor, A. J., Watson, J., Lobell, D. B., Howden, S., Smith, D., & Chhetri, N. (2014). A Meta-Analysis of Crop Yield Under Climate Change and Adaptation. *Nature Climate Change*, *4*(4), 287-291.

Charness, G., Gneezy, U., & Halladay, B. (2016). Experimental Methods: Pay One or Pay All. *Journal of Economic Behavior & Organization*, *131*, 141-150.

Chen, L., & Ford, T. W. (2023). Future Changes in the Transitions of Monthly-to-Seasonal Precipitation Extremes over the Midwest in Coupled Model Intercomparison Project Phase 6 Models. *International Journal of Climatology*, *43*(1), 255-274.

Dillon, J. L., & Scandizzo, P. L. (1978). Risk Attitudes of Subsistence Farmers in Northeast Brazil: A Sampling Approach. *American Journal of Agricultural Economics*, *60*(3), 425-435.

Donkers, B., Melenberg, B., & Van Soest, A. (2001). Estimating Risk Attitudes Using Lotteries: A Large Sample Approach. *Journal of Risk and Uncertainty*, *22*, 165-195.

Easterling, D. R., Arnold, J., Knutson, T., Kunkel, K., LeGrande, A., Leung, L. R., Vose, R., Waliser, D., & Wehner, M. (2017). Precipitation Change in the United States. In *Climate Science Special Report: Fourth National Climate Assessment* (Vol. 1, pp. 207-230). U.S. Global Change Research Program.

Edwards, W. (1953). Probability-Preferences in Gambling. *The American Journal of Psychology*, *66*(3), 349-364.

Edwards, W. (1961). Behavioral Decision Theory. *Annual Review of Psychology*, *12*(1), 473-498.

Eeckhoudt, L., Gollier, C., & Schlesinger, H. (1996). Changes in Background Risk and Risk Taking Behavior. *Econometrica*, 683-689.

Ford, T. W., Chen, L., & Schoof, J. T. (2021). Variability and Transitions in Precipitation Extremes in the Midwest United States. *Journal of Hydrometeorology*, *22*(3), 533-545.

Frank, M. D., Beattie, B. R., & Embleton, M. E. (1990). A Comparison of Alternative Crop Response Models. *American Journal of Agricultural Economics*, *72*(3), 597-603.

Gächter, S., Johnson, E. J., & Herrmann, A. (2022). Individual-Level Loss Aversion in Riskless and Risky Choices. *Theory and Decision*, *92*(3), 599-624.

Gilboa, I., Postlewaite, A. W., & Schmeidler, D. (2008). Probability and Uncertainty in Economic Modeling. *Journal of Economic Perspectives*, *22*(3), 173-188.

Halter, A. N., & Beringer, C. (1960). Cardinal Utility Functions and Managerial Behavior. *Journal of Farm Economics*, *42*(1), 118-132.

Harrison, G. W., Lau, M. I., & Rutström, E. E. (2007). Estimating Risk Attitudes in Denmark: A Field Experiment. *Scandinavian Journal of Economics*, *109*(2), 341-368.

Harrison, G. W., & List, J. A. (2004). Field Experiments. *Journal of Economic Literature*, *42*(4), 1009-1055.

Harrison, G. W., & Rutström, E. E. (2008). Risk Aversion in the Laboratory. In *Risk Aversion in Experiments* (pp. 41-196). Emerald Group Publishing Limited.

Hey, J. D., & Orme, C. (1994). Investigating Generalizations of Expected Utility Theory Using Experimental Data. *Econometrica*, 1291-1326.

Holden, S. T., & Quiggin, J. (2017). Climate Risk and State-Contingent Technology Adoption: Shocks, Drought Tolerance and Preferences. *European Review of Agricultural Economics*, *44*(2), 285-308.

Holt, C. A., & Laury, S. K. (2002). Risk Aversion and Incentive Effects. *American Economic Review*, *92*(5), 1644-1655.

Horowitz, J. K. (2006). The Becker-DeGroot-Marschak Mechanism is not Necessarily Incentive Compatible, even for Non-Random Goods. *Economics Letters*, *93*(1), 6-11.

Hudson, D., Coble, K., & Lusk, J. (2005). Consistency of Risk Premium Measures. *Agricultural Economics*, *33*(1), 41-49.

Iyer, P., Bozzola, M., Hirsch, S., Meraner, M., & Finger, R. (2020). Measuring Farmer Risk Preferences in Europe: a Systematic Review. *Journal of Agricultural Economics*, *71*(1), 3-26.

Jin, Z., Zhuang, Q., Wang, J., Archontoulis, S. V., Zobel, Z., & Kotamarthi, V. R. (2017). The Combined and Separate Impacts of Climate Extremes on the Current and Future US Rainfed Maize and Soybean Production Under Elevated CO2. *Global Change Biology*, *23*(7), 2687-2704.

Kaylen, M. S., Preckel, P. V., & Loehman, E. T. (1987). Risk Modeling via Direct Utility Maximization Using Numerical Quadrature. *American Journal of Agricultural Economics*, *69*(3), 701-706.

Kimm, H., Guan, K., Gentine, P., Wu, J., Bernacchi, C. J., Sulman, B. N., Griffis, T. J., & Lin, C. (2020). Redefining Droughts for the US Corn Belt: The Dominant Role of Atmospheric Vapor Pressure Deficit over Soil Moisture in Regulating Stomatal Behavior of Maize and Soybean. *Agricultural and Forest Meteorology*, *287*, 107930.

Lambert, D. K., & McCarl, B. A. (1985). Risk Modeling Using Direct Solution of Nonlinear Approximations of the Utility Function. *American Journal of Agricultural Economics*, *67*(4), 846-852.

Lau, L. J. (1986). Functional Forms in Econometric Model Building. *Handbook of econometrics*, *3*, 1515-1566.

Levy, H. (1994). Absolute and Relative Risk Aversion: An Experimental Study. *Journal of Risk and Uncertainty*, *8*, 289-307.

Li, Y., Guan, K., Schnitkey, G. D., DeLucia, E., & Peng, B. (2019). Excessive Rainfall Leads to Maize Yield Loss of a Comparable Magnitude to Extreme Drought in the United States. *Global Change Biology*, *25*(7), 2325-2337.

Lilleholt, L. (2019). Cognitive Ability and Risk Aversion: A Systematic Review and Meta Analysis. *Judgment and Decision Making*, *14*(3), 234-279.

Marra, M., Pannell, D. J., & Ghadim, A. A. (2003). The Economics of Risk, Uncertainty and Learning in the Adoption of New Agricultural Technologies: Where are We on the Learning Curve? *Agricultural Systems*, *75*(2-3), 215-234.

Marra, M. C., & Carlson, G. A. (2002). Agricultural Technology and Risk. In *A Comprehensive Assessment of the Role of Risk in U.S. Agriculture* (pp. 325-352). Springer Group.

McFadden, D. (1973). Conditional Logit Analysis of Qualitative Choice Behavior. *Frontiers in Econometrics*.

Meissner, T., Gassmann, X., Faure, C., & Schleich, J. (2023). Individual Characteristics Associated with Risk and Time Preferences: A Multi Country Representative Survey. *Journal of Risk and Uncertainty*, *66*(1), 77-107.

Menapace, L., Colson, G., & Raffaelli, R. (2013). Risk Aversion, Subjective Beliefs, and Farmer Risk Management Strategies. *American Journal of Agricultural Economics*, *95*(2), 384-389.

Menapace, L., Colson, G., & Raffaelli, R. (2016). A Comparison of Hypothetical Risk Attitude Elicitation Instruments for Explaining Farmer Crop Insurance Purchases. *European Review of Agricultural Economics*, *43*(1), 113-135.

Officer, R. R., & Halter, A. N. (1968). Utility Analysis in a Practical Setting. *American Journal of Agricultural Economics*, *50*, 257-277.

Ortiz-Bobea, A., Wang, H., Carrillo, C. M., & Ault, T. R. (2019). Unpacking the Climatic Drivers of US Agricultural Yields. *Environmental Research Letters*, *14*(6), 064003.

Pedroni, A., Frey, R., Bruhin, A., Dutilh, G., Hertwig, R., & Rieskamp, J. (2017). The Risk Elicitation Puzzle. *Nature Human Behaviour*, *1*(11), 803-809.

Picazo-Tadeo, A. J., & Wall, A. (2011). Production Risk, Risk Aversion and the Determination of Risk Attitudes Among Spanish Rice Producers. *Agricultural Economics*, *42*(4), 451-464.

Polasky, A. D., Evans, J. L., Fuentes, J. D., & Hamilton, H. L. (2022). Statistical Climate Model Downscaling for Impact Projections in the Midwest United States. *International Journal of Climatology*, *42*(5), 3038-3055.

Pratt, J. W. (1964). Risk Aversion in the Small and in the Large. *Econometrica*, *32*, 12-36.

Ramsey, A. F. (2020). Probability Distributions of Crop Yields: A Bayesian Spatial Quantile Regression Approach. *American Journal of Agricultural Economics*, *102*(1), 220-239.

Raskin, R., & Cochran, M. J. (1986). Interpretations and Transformations of Scale for the Pratt-Arrow Absolute Risk Aversion Coefficient: Implications for Generalized Stochastic Dominance. *Western Journal of Agricultural Economics*, *11*, 204-210.

Roberts, M. J., Schlenker, W., & Eyer, J. (2013). Agronomic Weather Measures in Econometric Models of Crop Yield with Implications for Climate Change. *American Journal of Agricultural Economics*, *95*(2), 236-243.

Roe, B. E., & Just, D. R. (2009). Internal and External Validity in Economics Research: Tradeoffs Between Experiments, Field Experiments, Natural Experiments, and Field Data. *American Journal of Agricultural Economics*, *91*(5), 1266-1271.

Saha, A. (1993). Expo-Power Utility: A 'Flexible' Form for Absolute and Relative Risk Aversion. *American Journal of Agricultural Economics*, *75*(4), 905-913.

Shrestha, D., Masarik, K., & Kucharik, C. (2023). Nitrate Losses from Midwest US Agroecosystems: Impacts of Varied Management and Precipitation. *Journal of Soil and Water Conservation*, *78*(2), 141-153.

Tack, J., Harri, A., & Coble, K. (2012). More than Mean Effects: Modeling the Effect of Climate on the Higher Order Moments of Crop Yields. *American Journal of Agricultural Economics*, *94*(5), 1037-1054.

Tanaka, T., Camerer, C. F., & Nguyen, Q. (2010). Risk and Time Preferences: Linking Experimental and Household Survey Data from Vietnam. *American Economic Review*, *100*(1), 557-571.

Tversky, A. (1967). Additivity, Utility, and Subjective Probability. *Journal of Mathematical Psychology*, *4*(2), 175-201.

USDA-NASS. (2022). *Farms and Land in Farms, 2021 Summary*. Retrieved from https://www.nass.usda.gov/Publications/Todays_Reports/reports/fnlo0222.pdf

USDA-NASS. (2024a). *Michigan, Table 75. Summary by North American Industry Classification System: 2022* (2022 Census of Agriculture State Level Data, Issue. https://www.nass.usda.gov/Publications/AgCensus/2022/Full_Report/Volume_1,_Chapter_1_State_Level/Michigan/st26_1_075_075.pdf

USDA-NASS. (2024b). *Table 75. Summary by North American Industry Classification System: 2022* (2022 Census of Agriculture, Issue. https://www.nass.usda.gov/Publications/AgCensus/2022/Full_Report/Volume_1,_Chapter_1_US/st99_1_075_075.pdf

Van Klompenburg, T., Kassahun, A., & Catal, C. (2020). Crop Yield Prediction Using Machine Learning: A Systematic Literature Review. *Computers and Electronics in Agriculture*, *177*, 105709.

Vassilopoulos, A., Drichoutis, A. C., & Nayga, R. (2018). Loss Aversion, Expectations and Anchoring in the BDM Mechanism. *Munich Personal RePEc Archive*.

Vieider, F. M., Martinsson, P., Nam, P. K., & Truong, N. (2019). Risk Preferences and Development Revisited. *Theory and Decision*, *86*, 1-21.

Von Gaudecker, H.-M., Van Soest, A., & Wengström, E. (2011). Heterogeneity in Risky Choice Behavior in a Broad Population. *American Economic Review*, *101*(2), 664-694.

Von Neumann, J., & Morgenstern, O. (1947). *Theory of Games and Economic Behavior* (2nd ed.). Princeton University Press.

Vuong, Q. H. (1989). Likelihood Ratio Tests for Model Selection and Non-Nested Hypotheses. *Econometrica*, 307-333.

Wald, A. (1943). Tests of Statistical Hypotheses Concerning Several Parameters when the Number of Observations is Large. *Transactions of the American Mathematical society*, *54*(3), 426-482.

Wilcox, N. T. (2008). Stochastic Models for Binary Discrete Choice Under Risk: A Critical Primer and Econometric Comparison. In *Risk Aversion in Experiments*. Emerald Group Publishing Limited.

APPENDIX 1

A1.1: General Lotteries

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.

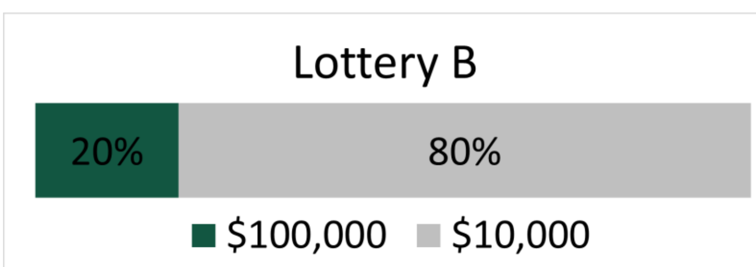


Figure A1.1: Example of general lottery outcome.

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 A1.1: General Lottery Set

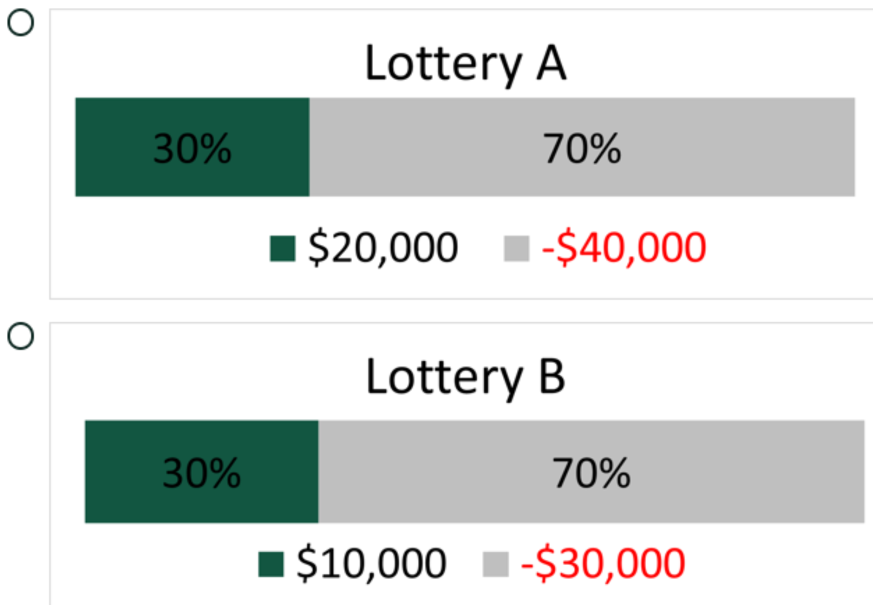
Lottery A				Lottery B			
Payoff	Probability	Payoff	Probability	Payoff	Probability	Payoff	Probability
$10,000	35%	$90,000	65%	$20,000	30%	$50,000	70%
$160,000	15%	$60,000	85%	$110,000	70%	$70,000	30%
$80,000	20%	$20,000	80%	$50,000	75%	$10,000	25%
$120,000	80%	$40,000	20%	$150,000	20%	$80,000	80%
$40,000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

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 A1.2: Survey instructions and an example for general lottery questions.

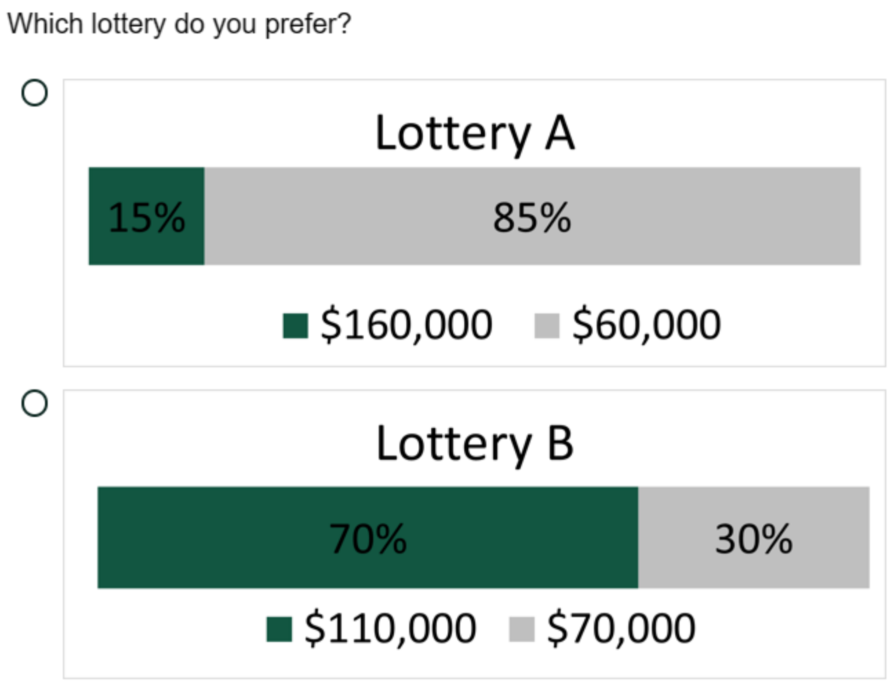


Figure A1.3: Example of a general lottery question with all positive payoffs.

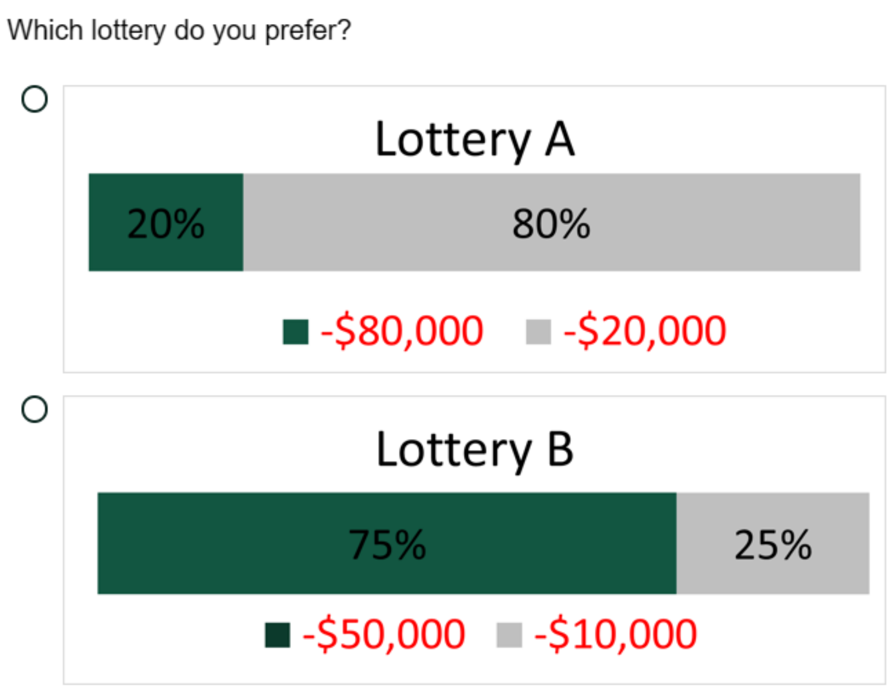


Figure A1.4: Example of a general lottery question with all negative payoffs.

Which lottery do you prefer?

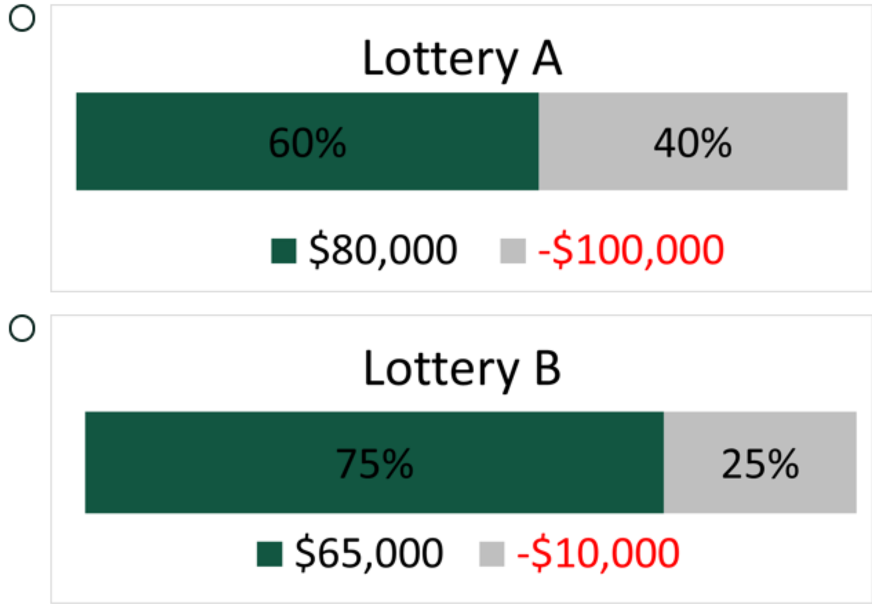


Figure A1.5: Example of a general lottery question with all mixed payoffs.

Table A1.2: 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 A1.6: Survey instructions for agricultural lottery section with explanation of lottery framing.

Agricultural Lottery Example Questions

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

You can invest in tile drainage at 60ft spacing. This costs $726 per acre which is an annual cost of $1,600 for the 40-acre field. These annualized costs are based on the full lifetime of the investment.

Would you

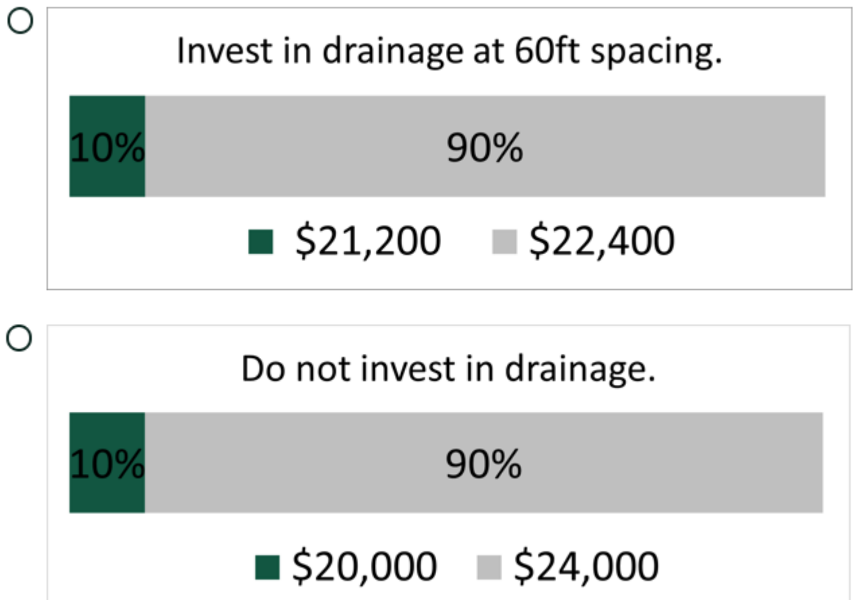
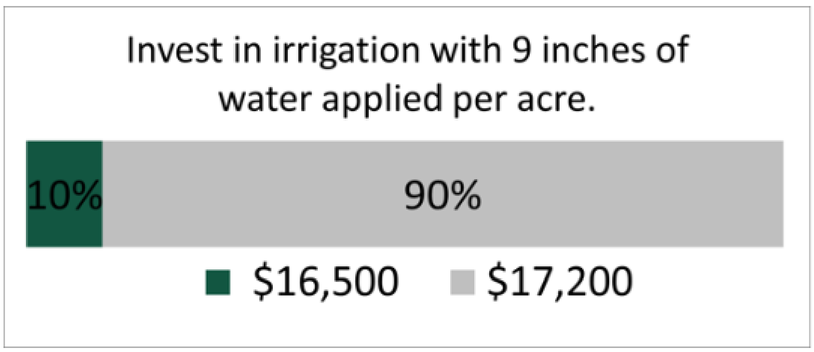


Figure A1.7: Example of drainage investment question in agricultural lottery experiment.

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



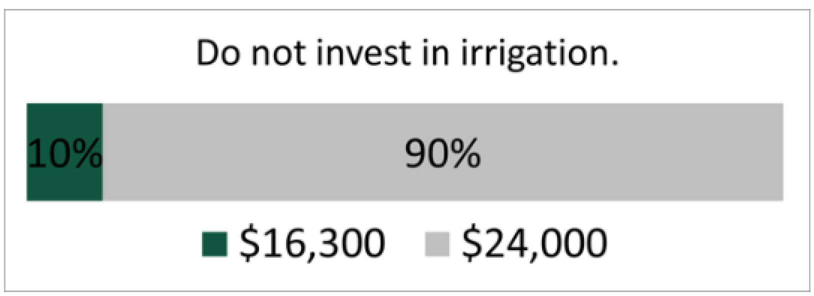


Figure A1.8: Example of irrigation investment question in agricultural lottery experiment.

Please note that the base revenue in the case of investing in irrigation was increased 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.

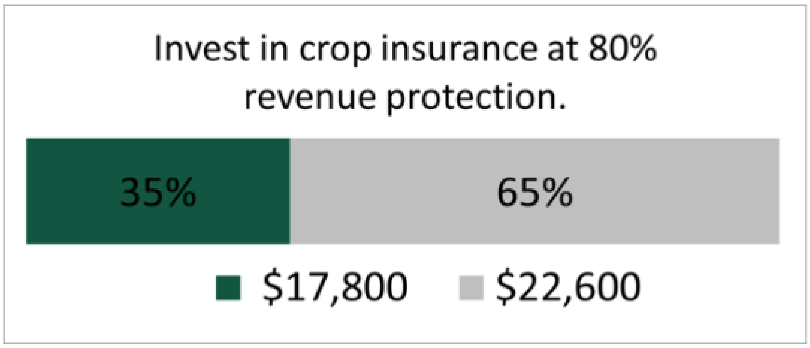
In the event of no severe drought (90% chance), you will earn $17,200 in gross crop revenue.

$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

○ 

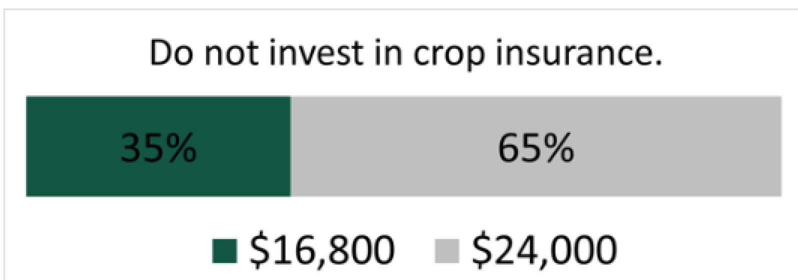
○ 

Figure A1.9: Example of crop insurance investment question in agricultural lottery experiment.

Suppose there is a 15% chance that your field experiences a drought next season and an 85% chance your field does not.

You can invest in drought tolerant corn seeds. This has a price premium of $4 per acre for an added annual cost of $160 for the 40-acre field.

Would you

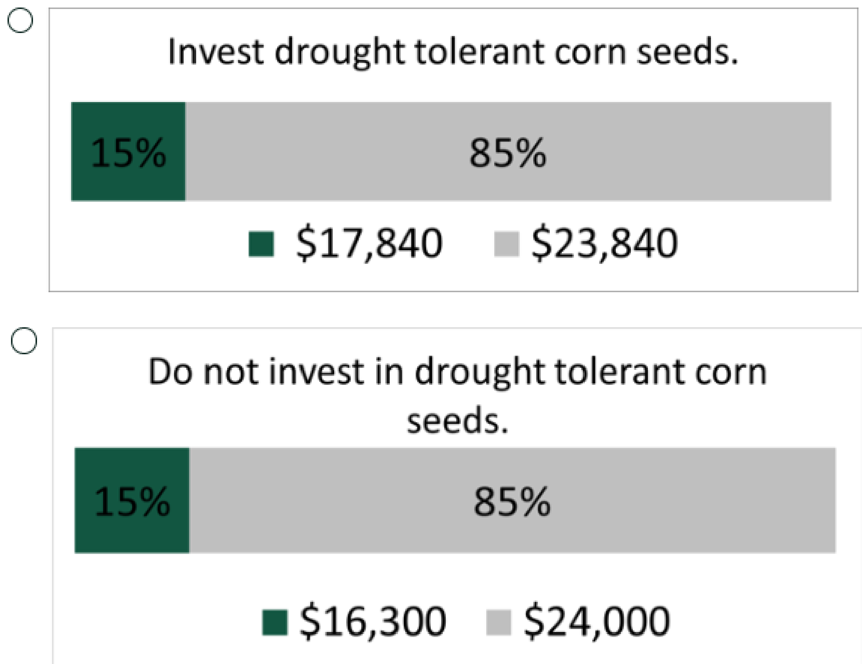


Figure A1.10: Example of drought tolerant seed investment question in agricultural lottery experiment.

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.

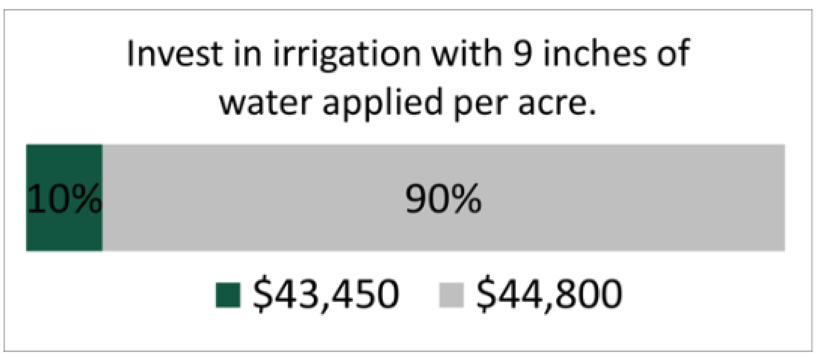
Apart from the fact that the crop is worth twice as much, these decisions are just like the ones you just saw.

Figure A1.11: 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



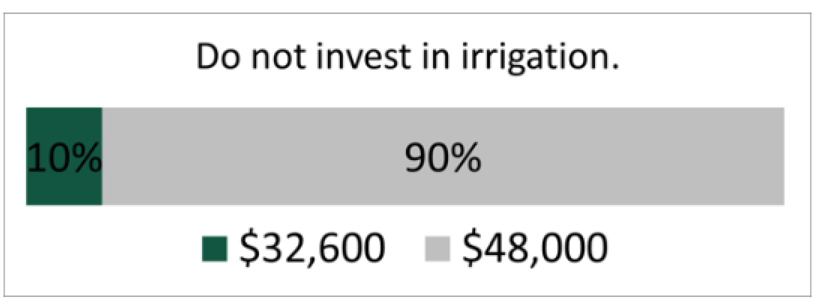


Figure A1.12: Example of a higher corn price irrigation investment question in agricultural lottery experiment.

A1.3: Results

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, 2024a). We compare the characteristics of our sample population and that of the 2022 Michigan Census of Agriculture in Table A1.3.

Table A1.3 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

Table A1.4: 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***	---
26	0.14	---	40.09***	---

Table A1.4 (cont'd):

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, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$

Table A1.5: 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 A1.6: 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, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$

CHAPTER 2: THE INFLUENCE OF FARMERS' RISK PREFERENCES AND CROP YIELD BELIEFS ON CLIMATE CHANGE ADAPTATION DECISIONS

Anticipated Coauthor: Scott M. Swinton

Abstract: Agricultural producers' risk preferences and perceptions of climate change risks play a significant role in shaping their adaptation decisions. This research delves into the relationship between farmer risk preferences, perceived crop yield distributions, and climate change adaptation decisions among Michigan corn and soybean growers. Based on interviews with 44 farmers, we discover that participants anticipate future crop yield distributions to shift upwards with increased variances. Participants with higher levels of risk aversion perceive higher crop yield variances and have an increased likelihood of intending to adopt irrigation technology in future. Overall, participants prefer to adopt adaptive technologies that they perceive as increasing expected crop yield or decreasing the variance of crop yield. These findings illuminate the complex interplay between risk preferences, subjective probabilities, and the perceived efficacy of adaptive inputs, providing policymakers and stakeholders with valuable insights into the drivers of climate change adaptation decisions.

2.1. Introduction

Understanding farmers' beliefs about future climate and how it could change crop yields can inform researchers, policymakers, and technology suppliers about the types of climate change adaptations that producers will likely adopt. Adaptation technologies can reduce farmers' vulnerability to weather-related risk and enhance their resilience to climate change conditions. For example, adaptations to drought conditions can include minor changes like growing drought-tolerant seed varieties or larger investments such as installing center pivot irrigation. How farmers choose to adapt to climate change depends on their risk preferences and perceptions of how climate change will affect the risks they face. Their subjective perceptions of future crop yield distributions are related to but distinct from observed probabilities in the past. Agricultural producers form their perceptions of crop yield distributions from their experience and expectations of future conditions.

Previous research has predicted future crop yield to quantify the implications of different climate change scenarios (Ortiz-Bobea et al., 2019; Ramsey, 2020; Van Klompenburg et al., 2020). Additional work has modeled the potential shifts in probability distributions of crop yield to inform crop insurance ratings (Liu & Ramsey, 2023; Ramsey, 2020). These studies utilize objective crop yield distributions as opposed to the subjective crop yield distributions that govern farmer decisions. Subjective beliefs or probabilities are based on an individual's judgement as opposed to objective probabilities formed from historical data or other scientific sources. Decision makers form subjective probabilities through experience or by analyzing the relative frequency of past occurrences and projecting future probabilities based on facts and opinions.

Researchers have applied the theory of subjective probability in statistics, economics, political science, and psychology (Kyburg, 1978). It allows us to capture beliefs about outcomes to better understand decision-making under uncertainty. Farmers base climate change adaptation adoption decisions on their subjective crop yield distributions and how comfortable they are with uncertainty in their yield outcome (Di Falco & Chavas, 2009; Emerick et al., 2016; Foster & Rosenzweig, 2010). By measuring farmers' subjective crop yield distributions, we capture their predictions of crop yields based on their professional experience. This allows us to measure and compare their perceived expected values and standard deviations of crop yields under different technologies and weather scenarios.

With their sensitivity to risk, farmers consider the expected return from adopting a practice and the variability in returns. Risk preferences directly impact producer choices based on their perception of tradeoffs between investments in risk-reducing inputs and the probability of adverse yield outcomes. One can measure the riskiness of a new technology by the perceived variation and downside risk, or lower proportion, of the crop yield distribution corresponding to the practice. Both standard deviations and lower proportions have been found to play a role in farmer decision-making regarding technological changes (Di Falco & Chavas, 2009; Emerick et al., 2016; Foster & Rosenzweig, 2010). Previous studies have used lottery-based experiments to elicit risk preferences and linked these preferences to technology adoption decisions and subjective crop yield beliefs. Menapace et al. (2013) used the multiple-price list to estimate risk preferences and find that farmers with higher risk preferences perceive greater crop yield losses. Meraner and Finger (2019) elicited risk preferences using the multiple-price list method and discover that more risk averse individuals are more likely to use on-farm risk management strategies. Liu (2013) estimated risk preference parameters of corn farmers in China using pair-wise lottery choices to understand what drives the adoption of Bt corn and pesticide use. The results indicated that even after adopting Bt corn, which requires less pesticide use, the more risk averse farmers use inefficiently high levels of pesticide.

Farmers with higher risk aversion may perceive greater yield risk, resulting in larger reported crop yield standard deviations (Menapace et al., 2013). We hypothesize that risk aversion may also affect demand for a risk-reducing input directly due to risk tolerance and indirectly from the change in the crop yield distribution. To decompose these different drivers of adoption, we develop a conceptual model of farmer demand for an input that reduces susceptibility to climate change risk. Based on that model, we proposed to test whether and how risk preferences impact the perceived probability distributions of past crop yields as well as how those yield distributions would respond to the adoption of climate change mitigation technology. We identify what drives an individual's decisions by measuring their risk preferences and the subjective probabilities associated with crop yield outcomes. In particular, we elicit subjective triangular distributions of past and future crop yield under the separate scenarios of no technology, center pivot irrigation, tile drainage at 40ft spacing, and drought-tolerant seeds. We provide three contributions to the literature by investigating how farmer risk preferences, their subjective perceptions of past and future crop yield distributions, and their perception of how risk-reducing practices change crop yields impact adoption decisions.

First, we elicit perceived crop yield distributions, or subjective probability distributions, under different technology investment scenarios to identify the perceived efficacy of various practices. Results indicate that while farmers believe that crop yield distributions under each scenario will rise in the future, the standard deviations of the future crop yield PDFs increase as well. The without technology cases under past and future weather conditions are left-skewed, meaning there is a higher perceived probability of receiving a crop yield below the most likely value. This highlights a concern of downside risk when there is no risk-reducing adaptation. Compared to the without-investment scenario, subjective crop yield distributions under the center pivot irrigation scenario have the most dramatic increases. While participants do not believe center pivot irrigation decreases the crop yield variance, they think it effectively reduces downside risk and increases yield potential. Participants do believe that adopting drought-tolerant seeds under past and future weather will decrease the crop yield variance.

Next, we test whether risk preferences affect subjective crop yield distributions and adoption decisions related to crop water needs. This allows us to identify risk preferences' direct impact on adoption decisions and the indirect effect via changes to the crop yield distributions. When investigating how farmers' risk attitudes impact subjective crop yield distributions, we find that more risk-averse individuals report higher perceived crop yield variances associated with investments in center pivot irrigation and tile drainage. Our findings suggest that more risk-averse individuals were less likely to have adopted irrigation in the past but are more likely to adopt it in the future.

Lastly, we examine how perceived changes in mean and variance of yield affect current use and potential future adoption of these technologies. Individuals who perceive a larger increase in expected crop yield due to irrigation are more likely already to have adopted center pivot irrigation or be considering adopting irrigation. Meanwhile, participants who believe that tile drainage will increase their variance of crop yield are less likely to adopt drainage. By developing tests for risk aversion, its potential role in subjective probability assessment of future crop yield, and the perceived efficacy of specific adaptive inputs, we set the stage for empirical research to predict how farmers will adapt in the face of climate change.

We structure the remainder of this paper as follows. Section 2.2 provides an overview of the literature on subjective probabilities and their elicitation in agricultural contexts. Section 2.3 presents our conceptual and empirical framework, which outlines our producer decision model, provides our testable hypotheses, and discusses the measurement of risk preferences and triangular distributions. Section 2.4 explains our data collection processes for eliciting risk preferences and subjective yield distributions. We provide our results and how they relate to our main hypotheses in Section 2.5. Section 2.6 discusses the implications of our findings, and Section 2.7 concludes and summarizes.

2.2. Subjective Probabilities and Their Measurement

Research in psychology and behavioral economics has extensively studied probabilistic sensitivity, heuristics, and subjective probabilities. Subjective probabilities represent a subject's belief that an event will occur based on available information (De Finetti, 1937). Researchers often elicit experimental data related to subjective probabilities via an interview process to allow the interviewer to aid the interviewee in quantifying their subjective probabilities. Direct elicitation methods for subjective probabilities include judgment fractals, scoring rules, and PDFs (Chesley, 1975). The process for judgment fractals often involves asking the interviewee to think of an upper and lower bound for potential values of the event in question, such as crop yield. The researcher then divides the range into quantiles to construct a discrete probability distribution. Once the researcher and participant decide on the quantiles, they can use a visual representation of the corresponding probabilities to verify the weight of each quantile. The researcher can then convert the discrete probability distribution into a continuous PDF and CDF. While graphing the elicited quantiles can help participants visualize the constructed distribution, judgment fractals can be time-consuming to implement and difficult for subjects to understand.

Scoring rules incentivize truthful probability reports and allow participants to report predictions in a lottery framework for the outcomes of some event. The linear and quadratic scoring rules calculate a score based on the forecast provided and the actual outcome. Scoring rules can undergo calibrating adjustments by having identical lotteries for the subjective probability elicitation and calibration tasks. A limitation of the quadratic scoring rule is that the participants are assumed to be risk neutral when much of the literature has provided evidence of risk-averse behavior (Iyer et al., 2020). Our goal is not to compare subjective beliefs to an actual outcome but rather to compare subjective beliefs across our hypothetical scenarios, so scoring rules are unsuited to our research objective.

Studies eliciting subjective probabilities commonly use PDF estimations of beta or triangular distributions that are easy for participants to understand. Eliciting PDFs fits our research objectives because we need not compare subjective beliefs to experimental outcomes. To fit a unique beta distribution, the participants must assign probabilities to at least three intervals in the distribution. A study can directly elicit triangular distributions by asking subjects to identify the maximum, minimum, and mode of the distribution in question. This distribution is easy to conceptualize for subjects and allows researchers to calculate the corresponding PDF directly. Given the length of our survey, we wanted to ensure we did not cause fatigue by including a judgment fractal exercise or multiple intervals for each of our eight crop yield distributions of interest. The triangle distribution elicitation method limits fatigue and avoids bias if the participants do not have risk-neutral preferences (Cerroni, 2020; Chesley, 1975; Hardaker et al., 2004). Carlson (1970) elicited triangular probability distributions for anticipated harvest loss due to peach brown-rot to model optimal pesticide use while others have used triangular probability distributions to measure subjective crop yield distributions (Clop-Gallart & Juárez-Rubio, 2007; Rejesus et al., 2013; Torkamani, 2006; Young, 1983).

In behavioral economics, and more specifically, agricultural economics related to production decisions and technology adoption, researchers have explored the roles of risk and ambiguity in decision-making. Risk preferences in the agricultural production setting can also be elicited in experimental studies using methods such as multiple price lists, random lottery pairs, ordered lottery selection, and tradeoff design (Harrison & Rutström, 2008). We utilize random lottery pairs for our risk preference elicitation method with further discussion in Loduca (In Progress). By measuring risk preferences and subjective crop yield probability distributions, we can create a decision model to understand the significant components of technology adoption decisions.

Previous work has analyzed risk and uncertainty aversion in decision making and technology adoption (Barham et al., 2014; Gilboa et al., 2008; Marra et al., 2003; Marra & Carlson, 2002). Studies have found that risk-seeking behavior is linked to optimism (Weinstock & Sonsino, 2014), while risk-averse behavior is correlated with pessimism (Ben Mansour et al., 2008). Zhao and Yue (2020) compared the risk preferences of commodity and specialty crop producers and linked these practices to beliefs about crop insurance adoption. They find that older specialty crop producers that rent their land to have higher aversion to losses. While their work evaluates how risk preferences influence the adoption of crop insurance, they do not investigate technology adoption and its influence on crop yields.

Menapace et al. (2013) conducted an experiment to assess the relationship between risk aversion and subjective probabilities with apple farmers in Italy. They asked farmers to assign probabilities to six primary damage intervals based on their beliefs about crop losses due to adverse weather for the upcoming season. The study elicited the participants' risk preferences using a multiple price list with payoffs framed as farm income. The results indicate a positive and significant relationship between farmer's risk aversion and their subjective probability assessment of crop losses. Furthermore, farmers who are older, have lower crop values, and have been exposed to more outreach materials perceive higher loss probabilities. These findings illustrate that risk preferences, past experiences, and farmer and farm characteristics can influence probabilistic beliefs.

2.3. Conceptual and Empirical Framework

To investigate how risk preferences and perceptions of crop yield distributions impact adoption decisions, we must build a farmer decision model that incorporates these factors. We want to understand how risk preferences affect the producers' subjective crop yield distributions, the perceived efficacy of various adaptation technologies in improving the crop yield distributions, and how risk preferences and the moments of the crop yield distributions related to those technologies impact their adoption. We first define the producer optimization problem given a production function based on crop yields to achieve these goals. Based on individual-level predicted risk preference parameters estimated in Loduca (In Progress), we assume that farmers aim to maximize a constant relative risk aversion (CRRA) utility function. We then transform the CRRA optimization problem into a mean-variance (EV) utility function based on CRRA preferences. With this transformation, we can make direct inferences about how decision makers with CRRA preferences view the mean and variance of subjective probability distributions of crop yield.

Assuming a representative crop farmer has mean-variance (EV) risk preferences and subjectively assesses the probability density function (PDF) for future crop yield distributions, the model supports testing the following null hypotheses: 1) risk aversion does not impact the perceived variance of crop yield, 2) an increase in risk aversion does not impact the perceived mean or variance of the subjective crop yield distributions related to adopting the risk-reducing input, 3) risk aversion does not impact the probability of adopting an adaptation technology, 4) a larger perceived increase in expected crop yield due to a risk-reducing input does not affect the probability of adopting that input, 5) a larger perceived decrease in crop yield variance due to a risk-reducing input does not affect the probability of adopting that input, 6) a larger predicted crop price does not affect the probability of adopting that input, and 7) A larger perceived decrease in the crop yield lower proportion due to a risk-reducing input does not affect the probability of adopting that input.

2.3.1. Conceptual Framework

We define *U(.)* as the utility function of a risk-sensitive agricultural producer, where r represents risk preferences, and H denotes household income. Specifically, we want to understand how agricultural producers make decisions regarding investing a portion of their income in practices that reduce crop yield variability due to climate risks. We assume the producer chooses agricultural production inputs to maximize risk-adjusted, income-based utility. Our producer produces a scale-neutral single output, crop yield, defined as $y = f(\boldsymbol{x})$ with $\boldsymbol{x}$ being a vector of *n* production inputs. We write our producer's optimization problem as

$$\max_{x_A} U(H, r)$$

$$s.t. H = pf(\boldsymbol{x}) - \boldsymbol{cx} + \bar{N} \tag{1}$$

where p is the market output price, $\boldsymbol{c}$ is a vector of the variable input costs, and $\bar{N}$ is off-farm income. We assume that output price and input prices are exogenously set. When making decisions regarding a risk-reducing input, x_A, producers must consider how the input will impact the crop yield distribution. We define x_A as a risk-reducing input that narrows the future yield distribution by reducing the variance, σ_y^2, and may also impact the expected yield, μ_y. Given that x_A is a risk-reducing input, we assume $\frac{\partial \sigma_y^2}{\partial x_A} < 0$. The effect of x_A on the expected yield can be neutral, positive, or negative, $\frac{\partial \mu_y}{\partial x_A} => < 0$.

With the mean-variance (EV) model, we can create a framework to develop expectations regarding how risk aversion affects the producer's subjective crop yield distributions. We then investigate how risk aversion and changes in the subjective crop yield distributions affect how farmers adapt to climate change. Such expectations can be developed tractably with an EV model. Nelson and Escalante (2004) have developed an EV model for decision makers characterized by constant relative risk aversion (CRRA). Given the evidence of farmer CRRA preferences found in Loduca (In Progress), we utilize the CRRA power utility function.

The EV model derived by Nelson and Escalante (2004) for the CRRA power utility function expresses that as a function of the mean and variance of a normally-distributed random variable. To do so, the expected utility model must satisfy the location-scale, or linear distribution, condition. This requires the utility function to be written as a location and scale transformation of a random variable, that is $E[U(H,r)] = E[U(\mu + \sigma x\phi)]$ where $U(\cdot)$ is random variable, ϕ is a centered and scaled random variable independent of choice, and (μ, σ) are deterministic functions of choice. With this condition satisfied, we rewrite the expected utility function as a

$$\max_{\boldsymbol{x}} E[U(H,r)] = \max_{\boldsymbol{x}} V(\mu_H, \sigma_H)$$

$$s.t. V(\mu_H, \sigma_H) = \mu_H^2 - r\sigma_H^2 \tag{2}$$

where

$$\mu_H = \bar{N} + \bar{p}\,\mu_y - \boldsymbol{cx} \tag{3}$$

$$\sigma_H^2 = \sigma_y^2 \bar{p}^{\,2}. \tag{4}$$

Taking the first order condition of the EV model (Eq. 2) given Eq. (3) and (4) to maximize utility given the risk-reducing input, we have

$$\frac{\partial V(\mu_H, \sigma_H)}{\partial x_A} = 2\frac{\partial \mu_H}{\partial x_A} - r\frac{\partial \sigma_H^2}{\partial x_A} = 0$$

$$\therefore \frac{\partial V(\mu_H, \sigma_H)}{\partial x_A} = 2\left[\bar{p}\,\frac{\partial \mu_y}{\partial x_A} - c_A\right] - r\left[\frac{\partial \sigma_y^2}{\partial x_A}\bar{p}^2\right] = 0 \tag{5}$$

For a risk-averse decision maker with $r > 0$, the optimality condition for the adoption of the risk-reducing input is determined by the expected output price, $\bar{p}$, the change in expected yield due to the risk-reducing input, $\frac{\partial \mu_y}{\partial x_A}$, and the change in crop yield variation, $\frac{\partial \sigma_y^2}{\partial x_A}$. Thus, these parameters jointly drive how much the producer is willing to pay for the risk-reducing input x_A. As a result, we have that the risk premium (RP) is equal to one half multiplied by the risk aversion parameter, r, the expected output price squared, $\bar{p}^2$, and the change in the farmers' exposure to risk with respect to the adaptation, $\frac{\partial \sigma_y^2}{\partial x_A}$. This is a measure of the combined impacts of risk in the form of a change in the variance of the future yield distribution and risk aversion. The value of $\frac{\partial \mu_y}{\partial x_A}$ represents the expected marginal physical product of the risk-reducing input with $\bar{p}\ \frac{\partial \mu_y}{\partial x_A}$ denoting the marginal value product (MVP).

$$\underbrace{\bar{p}\ \frac{\partial \mu_y}{\partial x_A}}_{MVP_{x_A}} - \underbrace{\frac{1}{2} r \frac{\partial \sigma_y^2}{\partial x_A} \bar{p}^2}_{RP} = c_A \tag{5'}$$

The marginal expected physical product, $\frac{\partial \mu_y}{\partial x_A}$, can be represented by three cases, given that the effect of x_A on the expected yield can be neutral, positive, or negative, $\frac{\partial \mu_y}{\partial x_A} =>< 0$. We illustrate the three cases below with the willingness-to-pay for the risk-reducing input, c_A, compared to the RP. In the yield-neutral case the input decreases the variance of crop yield but does not impact the overall expected yield. Given that the risk-reducing input's impact on the expected yield can be neutral, positive, or negative, we use the yield-neutral case as a base case to compare the three cases. We define the optimal adaptation input amounts in yield-positive and yield-negative case in reference to the yield-neutral case.

For the yield-neutral case, a producer will adopt the adaptation technology if the risk premium, which comprises one half multiplied by the risk aversion parameter, the change in the variance of the yield distribution from the technology, and the expected output price, is equal to or greater than the cost of the adaptation. With the yield-positive case, we have the addition of the marginal value product, which allows for adopting the technology at a higher cost. Lastly, adoption in yield-negative case depends on the relative change in the expected yield and yield variance compared to the adoption cost.

Yield-neutral Case: Yield-neutral, risk-reducing input: $\frac{\partial \mu_y}{\partial x_A} = 0$ given $r > 0$ and $\frac{\partial \sigma_y^2}{\partial x_A} < 0$.

$$\underbrace{\bar{p}\ \frac{\partial \mu_y}{\partial x_A}}_{=0} \underbrace{-\frac{1}{2} r \left[\frac{\partial \sigma_y^2}{\partial x_A} \bar{p}^2\right]}_{(+)} = c_A \rightarrow -\frac{1}{2} r \left[\frac{\partial \sigma_y^2}{\partial x_A} \bar{p}^2\right] = c_A$$

$\therefore RP = c_A$

Base case of $MVP_{x_A} = 0$ and $\bar{x}_A = x_A^*(\cdot)$

Yield-positive Case: Yield-increasing, risk-reducing input: $\frac{\partial \mu_y}{\partial x_A} > 0$ given $r > 0$ and $\frac{\partial \sigma_y^2}{\partial x_A} < 0$.

$$\underbrace{\bar{p}\ \frac{\partial \mu_y}{\partial x_A}}_{(+)} \underbrace{-\frac{1}{2} r \left[\frac{\partial \sigma_y^2}{\partial x_A} \bar{p}^2\right]}_{(+)} = c_A$$

$\therefore MVP_{x_A} + RP = c_A$

$x_A^*(\cdot) = MVP_{x_A} + RP > \bar{x}_A$ of Yield-neutral case

Yield-negative Case: Yield-decreasing, risk-reducing input: $\frac{\partial \mu_y}{\partial x_A} < 0$ given $r > 0$ and $\frac{\partial \sigma_y^2}{\partial x_A} < 0$.

$$\underbrace{\bar{p}\ \frac{\partial \mu_y}{\partial x_A}}_{(-)} \underbrace{-\frac{1}{2} r \left[\frac{\partial \sigma_y^2}{\partial x_A} \bar{p}^2\right]}_{(+)} = c_A$$

$\therefore RP - MVP_{x_A} = c_A$

$x_A^*(\cdot) = RP - MVP_{x_A} < \bar{x}_A$ of Yield-neutral case

Up to this point, we have a standard EV model to describe the demand for a risk-reducing input where risk preferences enter the input-use optimization decision. However, we assume yield expectations to be unaffected by risk attitude. However, empirical evidence suggests that risk attitudes can shape subjective expectations of a stochastic production output like crop yield (Menapace et al., 2013). We reframe the problem with yield, y, being dependent upon the expected yield based on past observed yields, the response of the yield distribution due to climate adaptation inputs, and individual risk preferences, r. With the incorporation of risk preferences into the subjective expectation of yield, μ_{y_s}, and the variance of subjective yield, $\sigma_{y_s}^2$, into Eq. (6'), we can predict the relationship between risk preferences and the first two moments of the distributions under different technology scenarios. Additionally, we can measure how risk preferences impact these expectations, conditional on the type of adopted adaptation. Risk preferences enter the partial derivative of utility with respect to adaptation explicitly and implicitly through μ_{y_s} and $\sigma^2_{y_s}$.

$$\bar{p}\,\frac{\partial \mu_{y_s}}{\partial x_A} - \frac{1}{2} r \frac{\partial \sigma^2_{y_s}}{\partial x_A} \bar{p}^2 = c_A \qquad (6'')$$

Based on Eq. (6'') written above and given $r > 0$, we have the following testable null hypotheses:

Hypothesis 1: An increase in risk aversion, *r*, does not impact perceived variation in crop yield, $\sigma^2_{y_s}$.

$$\frac{\partial \sigma^2_{y_s}}{\partial r} = 0$$

For the remaining hypotheses, we define x_A as a binary variable that equals one if the participant has implemented the corresponding adaptation. We focus on binary adoption decisions, with producers deciding whether to adopt the practice. With this assumption, we modify the notation to measure how adopting the risk-reducing input, x_A, changes the distribution compared to the without technology case. We denote the change in the expected yield of the distribution as a percentage change

$$\Delta \mu_{y_s} = \frac{\mu_{y_A} - \mu_{y_0}}{\mu_{y_0}} * 100$$

where μ_{y_A} represents the new expected crop yield with adopting the risk-reducing input, and μ_{y_0} represents the expected crop yield in the without technology case. Similarly, the percentage change in the crop yield variance associated with adopting the risk-reducing input, x_A, as

$$\Delta \sigma^2_{y_s} = \frac{\sigma^2_{y_A} - \sigma^2_{y_0}}{\sigma^2_{y_0}} * 100$$

where $\sigma^2_{y_A}$ represents the new crop yield variance with adopting the risk-reducing input and $\sigma^2_{y_0}$ represents the crop yield variance in the without technology case.

Hypothesis 2: An increase in risk aversion does not impact the a) change in the subjective expected crop yield, $\Delta \mu_{y_s}$, or b) change in the subjective crop yield variance, $\Delta \sigma^2_{y_s}$, from the risk-reducing input.

$$\text{a) } \frac{\partial \Delta\mu_{y_s}}{\partial r} = 0;\ \text{b) } \frac{\partial \Delta\sigma^2_{y_s}}{\partial r} = 0$$

Moreover, we are interested in how the changes in the probability distributions relating to the risk-reducing input and the expected output price impact adoption decisions. We denote the probability of adopting a risk-reducing input as $P(A = 1)$, meaning that $x_A = 1$. Thus, we have four additional hypotheses:

Hypothesis 3: A larger predicted risk aversion coefficient, $\hat{r}$, does not affect the probability of adoption.

$$\frac{\partial P(A = 1)}{\partial \ln(\hat{r})} = 0$$

Hypothesis 4: A larger perceived increase in expected yield due to the risk-reducing input, $\Delta\mu_{y_s}$, does not affect the probability of adopting that input.

$$\frac{\partial P(A = 1)}{\partial \Delta\mu_{y_s}} = 0$$

Hypothesis 5: A larger perceived decrease in the crop yield variance due to the risk-reducing input, $\Delta\sigma^2_{y_s}$, does not affect the probability of adopting that input.

$$\frac{\partial P(A = 1)}{\partial \Delta\sigma^2_{y_s}} = 0$$

Hypothesis 6: A larger predicted average output price (e.g., price per bushel of corn over the next ten years), $\bar{p}$, does not affect the probability of adopting that input.

$$\frac{\partial P(A = 1)}{\partial \bar{p}} = 0$$

2.3.2. Empirical Framework

To parameterize Eq. (6''), we need measurements for risk preferences, changes in the first two moments of the subjective crop yield distributions related to adopting the risk-reducing adaptation, and the predicted future crop prices. For risk preferences, we use individual-level predicted CRRA risk preference parameters estimated in Loduca (In Progress). To understand the perceived efficacy of different risk-reducing practices, we need to measure changes in the first two moments of the subjective crop yield distributions related to adopting the risk-reducing adaptation. Triangular distributions are widely used to assess probability distributions, given that they can be fully characterized by the distribution's highest, lowest, and most likely values (Caldwell et al., 2023; Engelberg et al., 2009; Falck-Zepeda et al., 2000; Hareau et al., 2006; Recktenwald & Deinert, 2012; Theurer et al., 2015). If we define the lowest possible crop yield as a, the highest as b, and the mode as m, the PDF is

$$f(y) = \begin{cases} \dfrac{2(y-a)}{(b-a)(m-a)}, y \leq m \\ \dfrac{2(b-y)}{(b-a)(b-m)}, y > m. \end{cases} \tag{7}$$

Additionally, the first two moments of the triangular distributions are:

$$\mu_y = \frac{a+m+b}{3} \tag{8}$$

$$\sigma_y^2 = \frac{\{(b-a)^2 + (m-a)(m-b)\}}{18}. \tag{9}$$

While variance measures the overall spread of the crop yield distributions, we can calculate the area of the triangle below the mode to measure the downside risk. Downside risk refers to the probability that yield falls below the mode. To calculate the corresponding area, we need the cumulative distribution function, $F(y)$.

$$F(y) = \begin{cases} \dfrac{(y-a)^2}{(b-a)(m-a)}, y \leq m \\ 1 - \dfrac{(b-y)^2}{(b-a)(b-m)}, y > m \end{cases} \tag{10}$$

We denote the area of the triangle below the mode as the lower proportion, lp. To calculate the area, we transform the CDF by setting $y = m$.

$$lp_{y_s} = \frac{(m-a)}{(b-a)} \tag{11}$$

Adaptations can shrink the lower proportion of the crop yield distribution and thus increase the probability of receiving a crop yield higher than the most likely yield value. Given that this could be an attractive quality for a risk-reducing input, we propose an additional hypothesis.

Hypothesis 7: A larger perceived decrease in the crop yield lower proportion due to the risk-reducing input, Δlp_{y_s}, does not affect the probability of adopting that input

$$\Delta lp_{y_s} = \frac{lp_{y_A} - lp_{y_0}}{lp_{y_0}} * 100$$

where lp_{y_A} represents the new lower proportion of crop yield with adopting the risk-reducing input and lp_{y_0} represents the lower proportion of crop yield in the without technology case.

Now that we have defined how we measure the first two moments and the lower proportion of a triangle distribution, we can use these calculations to test our hypotheses. To test Hypothesis 1, we model the variance of the subjective crop yield distributions, $\sigma_{y_s}^2$, as dependent on the participants' predicted risk preferences, $\hat{r}$. By taking the log transformations of the subjective crop yield variances and predicted risk aversion coefficients from Loduca (In Progress), we can model how a percentage change in risk aversion translates to a percentage change in the variance. Through the double log transformation of the data, the estimated coefficient is the elasticity of the variance with respect to the individual level predicted risk preference estimates or $\frac{\partial \sigma_{y_s}^2 / \sigma_{y_s}^2}{\partial \hat{r} / \hat{r}}$. This allows us to interpret β_1 as $\% \Delta \sigma_{y_s}^2 = \beta_1 \% \Delta \hat{r}$.

Measurement: $$\ln(\sigma_{y_s}^2) = \beta_0 + \beta_1 ln(\hat{r}); \tag{12}$$

Hypothesis 1: $$\frac{\partial \sigma_{y_s}^2}{\partial r} = 0 \rightarrow H_0: \beta_1 = 0$$

Similarly, to test Hypotheses 2, we model the perceived change in the crop yield expected values and variances due to adopting one of the three practices as being dependent on $\hat{r}$. To do so, we calculate the change in subjective crop yield distribution moments from the without technology case compared to the cases of center pivot irrigation, tile drainage at 40ft spacing, and drought-tolerant seeds.

Measurement: (13)

$$\Delta\mu_{y_s} = \beta_0 + \beta_1 ln(\hat{r})$$

$$\Delta\sigma_{y_s}^2 = \beta_0 + \beta_1 ln(\hat{r});$$

(14)

Hypotheses 2a & 2b:

a) $\frac{\partial\Delta\mu_{y_s}}{\partial r} = 0 \rightarrow H_0: \beta_1 = 0$

b) $\frac{\partial\Delta\sigma_{y_s}^2}{\partial r} = 0 \rightarrow H_0: \beta_1 = 0$

Unlike Eq. (12), Eq. (13) and (14) measure the semi-elasticity with respect to the risk aversion coefficient instead of the elasticity. We are now measuring $\frac{\partial\Delta\mu_{y_s}}{\frac{\partial\hat{r}}{\hat{r}}} = \beta_1$ and $\frac{\partial\Delta\sigma_{y_s}^2}{\frac{\partial\hat{r}}{\hat{r}}} = \beta_1$ for Eq. (13) and (14), respectively. To express this as how a percentage change in the risk aversion coefficient affects the perceived changes in the first and second moments of the distribution, we have $\partial\Delta\mu_{y_s} = \%\Delta\hat{r}\,\frac{\beta_1}{100}$ and $\partial\Delta\sigma_{y_s}^2 = \%\Delta\hat{r}\,\frac{\beta_1}{100}$.

We use revealed and stated preferences for adopting center pivot irrigation, tile drainage at 40ft spacing, or drought-tolerant seeds to understand practice preferences. We asked participants if they are currently implementing (revealed preference) center pivot irrigation, tile drainage at 40ft spacing, and drought-tolerant seeds and if they are planning (stated preference) to adopt these practices in the future. For Hypotheses 3-7, we model the adoption decision ($x_A = 1$) as a function of risk preferences and the perceived changes in the expected values and variances of crop yield due to the corresponding adopted adaptation technology. We would expect that adopting center pivot irrigation increases the expected yield and reduces the variance of crop yield (Grassini et al., 2011; Sorensen et al., 2022), while drought-resistant seed varieties could decrease the variance of crop yield (Adee et al., 2016; McFadden et al., 2019). For stated preferences about plans to adopt technologies that help adapt to anticipated climate change, we include the participants' predicted average price per bushel of corn over the next ten years. We omit the average price per bushel of corn over the past ten years, given that this does not vary by individual.

Measurement:

Probability of past (revealed) adoption using the logistic function:

$$P(x_A = 1) = \frac{1}{1 + e^{-(\beta_0 + \beta_1 ln(\hat{r}) + \beta_2 \Delta\mu_{y_s} + \beta_3 \Delta\sigma^2_{y_s} + \beta_4 \Delta lp_{y_s})}} \tag{15}$$

With the

Probability of future (stated) adoption using the logistic function:

$$P(x_A = 1) = \frac{1}{1 + e^{-(\beta_0 + \beta_1 ln(\hat{r}) + \beta_2 \Delta\mu_{y_s} + \beta_3 \Delta\sigma^2_{y_s} + \beta_4 \Delta lp_{y_s} + \beta_5 \bar{p})}} \tag{16}$$

Hypothesis 3: $$\frac{\partial P(A = 1)}{\partial ln(\hat{r})} = 0 \rightarrow H_0 \colon \beta_1 = 0$$

Hypothesis 4: $$\frac{\partial P(A = 1)}{\partial \Delta\mu_{y_s}} = 0 \rightarrow H_0 \colon \beta_2 = 0$$

Hypothesis 5: $$\frac{\partial P(A = 1)}{\partial \Delta\sigma^2_{y_s}} = 0 \rightarrow H_0 \colon \beta_3 = 0$$

Hypothesis 6: $$\frac{\partial P(A = 1)}{\partial \bar{p}} = 0 \rightarrow H_0 \colon \beta_5 = 0$$

(for stated preferences only)

Hypothesis 7: $$\frac{\partial P(A = 1)}{\partial \Delta lp_{y_s}} = 0 \rightarrow H_0 \colon \beta_4 = 0$$

2.4. Data

We interviewed 44 Michigan corn and soybean farmers at county-level meeting places, including restaurants and Michigan State University County Extension Offices. Our recruitment criteria required that the interviewee be a primary decision-maker for crops on their farm, have at least 300 acres in operation, and have a portion of this land devoted to growing corn for grain. With the help of Michigan State University County Extension Educators and the Michigan Corn Growers

Association, we recruited 44 farmers. We conducted in-person interviews between September 2022 and April 2023 with the help of graduate students from Michigan State University. The survey contained five main sections: 1) a general lottery experiment where no context was given, 2) an agricultural lottery experiment where the payoffs were framed as changes in income based on investment decisions and the probabilities related to the chance of adverse weather conditions, 3) the elicitation of subjective crop yield distributions, 4) current and future farm practices and how they relate to weather perceptions, and 5) farm and farmer characteristics.

Our risk preference estimation is based on the agricultural lottery experiment from the survey's second section. The agricultural lottery experiment framed 18 lottery choices as investment decisions to mitigate income loss due to excess moisture or drought. These lottery questions offered choices between taking no action to mitigate crop yield loss or investing in 1) tile drainage at 40ft spacing, 2) center pivot irrigation, 3) drought-tolerant seeds, or 4) crop insurance. We use these stated choices to estimate the risk preference parameter in our conceptual framework and hypotheses. Further analysis of both the general and the agricultural lottery experiments is provided in Loduca (In Progress). The third section of the survey examines how participants perceive the probability of past and future corn yields under different management scenarios. Instead of having participants make decisions based on the specifications we give them, this section asks them to think about their fields and experiences. Because this paper focuses on understanding the relationship between risk preferences and changes in crop yield from technology adaptation, we do not include results related to crop insurance.

In eliciting how the participants believed crop yield distributions would respond to new technology investments, we asked them to picture a field representative of their current fields but without any irrigation, drainage tile, or drought-resistant seed varieties. Next, we asked participants to think back over the past ten years and picture what corn yields would have been on this field with current corn hybrids but under past weather conditions. The participants then indicated what they believe would be the lowest, most likely, and highest likely yield without and with center pivot irrigation, tile drainage at 40ft spacing, or drought-tolerant seeds. Subjects then repeated this thought exercise but under the weather they expect over the next ten years. The survey presents their stated crop yield distributions for the past scenarios as a reference. These eight triangular distributions of crop yields allow us to observe how these practices affect the shape of the subjective probability distributions of crop yield payoffs. We can then calculate the first two moments of distributions and measure the perceived efficacy of the practices by comparing the technology cases to the no technology case.

2.5. Results

2.5.1. Crop Yield Probability Density Functions

We elicited triangular distributions for past and future crop yield distributions without technology and with only center pivot irrigation, tile drainage at 40ft spacing, or drought-tolerant seeds. Given these four technological assumptions under past and future weather conditions, we have eight distributions for crop yield, y, following Eq. (7). From these distributions, we calculated the mean, μ_{y_s}, and variance, $\sigma_{y_s}^2$, of crop yield in each scenario using Eq. (8) and (9). Another measure of interest is the downside risk of the crop yield PDF or the lower proportion (Eq. 11). The lower proportion represents the area of the portion of the triangle distribution that falls below the expected value. At the same time, the standard deviation characterizes the overall spread of the distribution. Table 2.1 provides the sample averages for the crop yield distributions' expected values or means, μ_{y_s}, standard deviations, σ_{y_s}, and lower proportion areas, lp_{y_s}, under the past and future scenarios.

Table 2.1: Sample Averages for Moments of the Subjective Corn Yield Distributions (n=44)

	Expected Value			Standard Deviation			Lower Proportions		
Scenarios	Past	Future	%Δ	Past	Future	%Δ	Past	Future	%Δ
	bushels/acre			bushels/acre			bushels/acre		
Without technology	141	148	5.55	15.78	17.09	8.26	0.54	0.54	0.63
With center pivot irrigation	191	203	5.88	15.92	16.32	2.52	0.47	0.44	-7.02
With tile drainage at 40ft spacing	171	180	4.86	15.74	15.92	1.13	0.51	0.52	1.06
With drought-tolerant seeds	156	165	5.73	13.70	14.10	2.96	0.53	0.51	-3.92

Figure 2.1 illustrates the average perceived crop yield probability distributions, with grey representing the past distributions and blue representing the future distributions. On average, participants expect all future crop yield distributions to shift upwards, though the standard deviations also increase. Compared to the without investments scenarios shown in Panel A), subjective PDFs under the center pivot irrigation scenarios in Panel B) have the most dramatic increases. The change in the expected values from the without technology case to the with center pivot irrigation case are 35% and 47% increases for the past and future weather conditions, respectively. In comparison, the changes for the expected values from the without investments scenario to the with tile drainage at 40ft spacing scenarios in Panel C) are 21% and 22% increases for the past and future weather conditions, respectively. The least drastic change from the without investment scenario is with drought-tolerant seeds shown in Panel D), resulting in an increase in the expected values under past and future weather conditions of 11%. While the standard deviations with drought-tolerant seed investment decrease compared to without investments, they improve the largest possible values by only 6%. Respondents perceive center pivot irrigation as the most effective in improving yields compared to the without technology case and drought-tolerant seeds as the least effective. Participants commented that while they believed center pivot irrigation would benefit their operation, it was the most expensive practice.

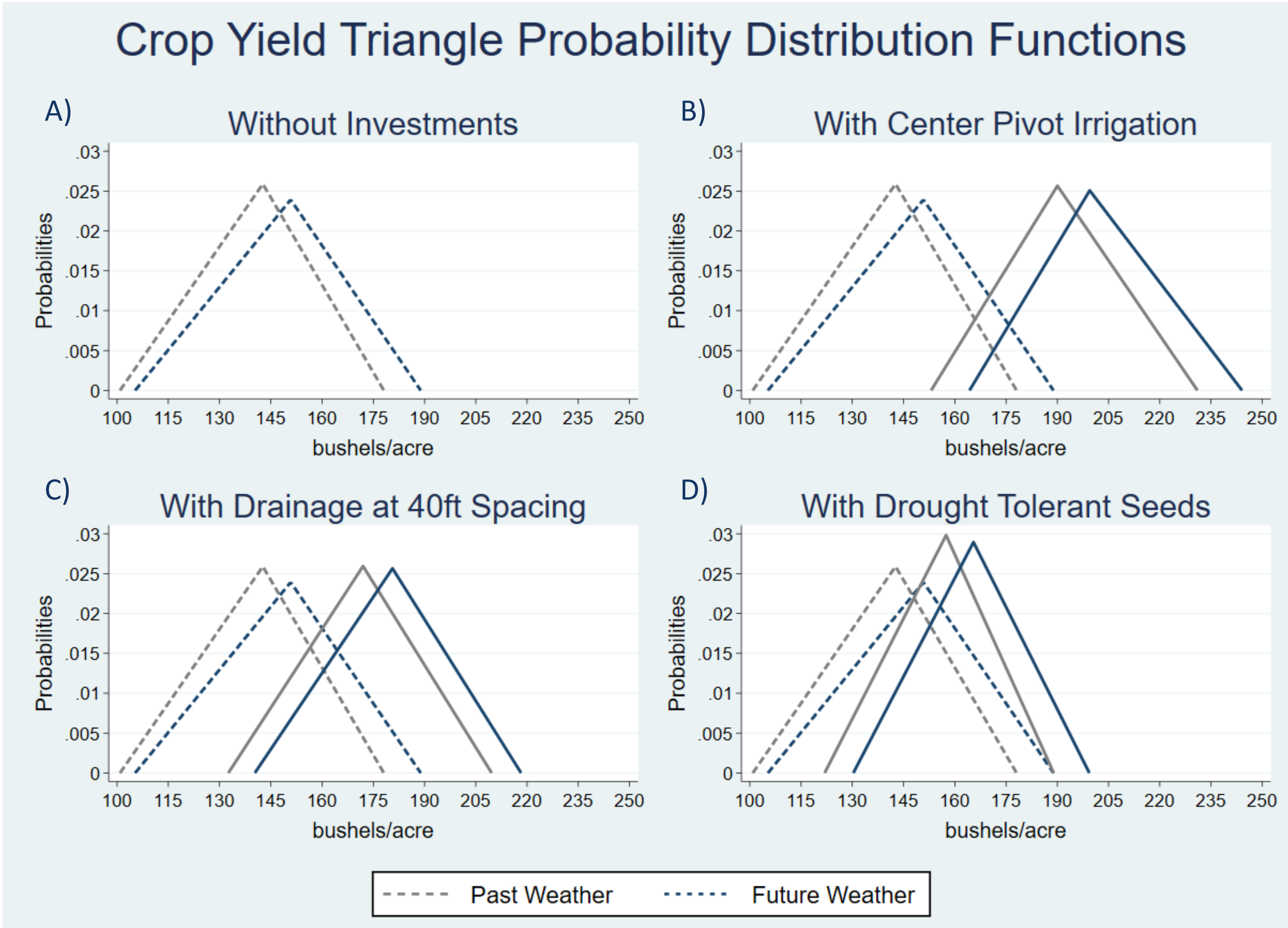


Figure 2.1: Perceived crop yield triangle PDFs with grey representing past distributions and blue representing future distributions. The dashed lines in A) illustrate the PDFs in the without investments cases, and we include them in the technology cases with B) center pivot irrigation, C) tile drainage at 40ft spacing, and D) drought-tolerant seeds for comparison (n=44).

The EV model in Eq. (3) assumes CRRA preferences and a normal distribution for the random variable, y. However, the triangle distributions can be skewed depending on the proportion of yield that falls below or above the most likely value or the peak of the distribution. The shape or skewness of the triangular distributions can provide information on the perceived downside risk for each technology scenario. The downside risk refers to the proportion of the crop yield distribution below the most likely value represented by the left side of the triangle (Eq. 11). Table 2.1 provides the lower proportions for the scenarios without technology, with center pivot irrigation, with tile drainage at 40ft spacing, and with drought-tolerant seeds under past and future weather conditions. At the sample level, each triangle is roughly symmetrical, with a lower proportion between 0.47 and 0.54.

We perform paired t-tests to test hypotheses related to the shape of the crop yield distributions at the individual level. By comparing moments of the distributions within and across the crop yield scenarios, we can test for symmetry of each distribution and how each technology scenario changes the distribution compared to the without technology case. When testing the symmetry of the distributions at the individual level by comparing the expected value and the most likely value of the crop yield distributions, we fail to reject the hypothesis that the expected value and mode are equal for seven of the eight triangular distributions with evidence provided in Table A2.1 of the Appendix. In the eighth instance, the crop yield distribution is right-skewed for adopting center pivot irrigation under future weather conditions. In this case, participants predict a higher probability of receiving a crop yield above the most likely value than below the most likely value, meaning participants see irrigation as reducing downside risk and increasing yield potential. We cannot reject the normality assumption for the great majority of the distributions.

Next, we compare measures of the distributions under each technology scenario to the ones without technology to test how the adaptations change the crop yield distribution. We find that participants perceive all adaptations as increasing the expected value compared to the without technology case, as shown in Table A2.2 of the Appendix. We also test the assumption that each adaptation reduces perceived crop yield risk by decreasing the crop yield variance and the lower proportion of the density function compared to the without technology case. Table A2.3 illustrates that participants perceive adopting drought-tolerant seeds both under past and future weather as decreasing the crop yield variance. However, we do not find evidence of this for adopting center pivot irrigation or tile drainage at 40ft spacing. Table A2.4 provides evidence that participants perceive adopting center pivot irrigation under past and future weather as decreasing the lower proportion of the crop yield distribution. These results illustrate that while participants do not see center pivot irrigation as decreasing the crop yield variance, it does decrease the probability of receiving a crop yield below the most likely crop yield value. Center pivot irrigation does not meet our risk-reducing assumption of decreasing subjective crop yield variance, because participants perceive irrigation to increase the upper proportion area of the yield distribution.

To illustrate the heterogeneity of the triangular distributions at the individual level, Figure 2.2 depicts the frequency of the individual values for the lower proportions of the crop yield distributions under past and future scenarios. The smaller the lower proportion, the smaller the perceived downside risk or area of the triangle below the most likely value. A lower proportion equal to 0.5 represents an isosceles triangle with equal left and right sides, above 0.5 represents a left-skewed distribution with a larger left side of the triangle, and below 0.5 indicates a right-skewed distribution with a larger right side of the triangle. A left-skewed triangle with a larger left side of the triangle illustrates more downside risk or a higher probability of crop yield falling below the most likely value of crop yield. The individual values for the lower proportions of the crop yield distributions provide a sense of the heterogeneity in the shape of the triangles that is not captured by the sample-level distributions of Figure 2.1. Specifically, Figure 2.2 illustrates that while some participants reported symmetric triangle distribution PDFs, others perceived skewed distributions.

In the without investment case illustrated by Panel A) of Figure 2.2, 43% of participants perceived a left-skewed crop yield distribution under past weather conditions and 52% under future weather conditions. Moreover, the paired t-tests comparing the most likely value to the expected value of the distribution in the without technology cases under past weather provided weak evidence of a left-skewed distribution, while we have strong evidence of a left-skewed distribution with predicted future weather.[2] By reporting a larger left side of the triangular distribution, participants indicate that they perceive a higher downside risk for crop yields under future weather conditions.

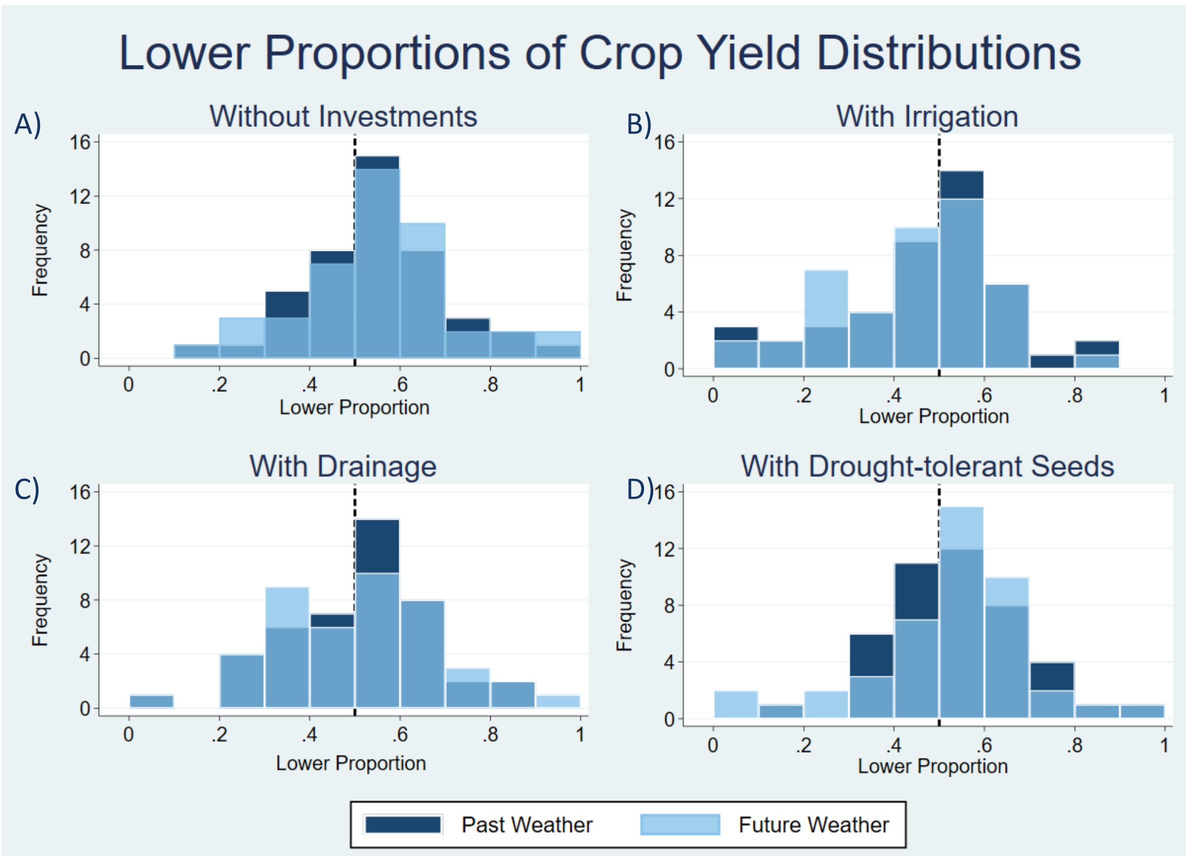


Figure 2.2: Lower proportions of the crop yield triangular distributions under past weather versus predicted future weather conditions for A) without investments, B) center pivot irrigation, C) tile drainage at 40ft spacing, and D) drought-tolerant seeds A lower proportion equal to 0.5 represents an isosceles triangle, above 0.5 represents a left-skewed distribution, and below 0.5 indicates a right-skewed distribution (n=44).

Panel B) of Figure 2.2 displays the lower proportions of the perceived crop yield distributions from adopting center pivot irrigation. With investment in center pivot irrigation, 34% of participants

[2] Please refer to Table A2.1 in the Appendix.

perceived a left-skewed crop yield distribution under past weather conditions and 25% under future weather conditions. This shift suggests that participants believe center pivot irrigation will be more effective at reducing the probability of lower yields in the future. Indeed, this was the one case where the paired t-tests comparing the most likely value to the expected value of the distribution provided evidence that the crop yield distribution from adopting center pivot irrigation under future weather conditions is right-skewed. Additionally, participants view center pivot irrigation as decreasing the lower proportion of crop yields compared to the without technology case. They see irrigation as a way to decrease downside risk and increase yield potential, with this effect being more pronounced under predicted future weather.

With investment in tile drainage at 40ft spacing, 48% of participants perceived a left-skewed crop yield distribution under past weather conditions and 45% under future weather conditions. Under past weather conditions, the lower proportions are concentrated around 0.5, with 48% of participants indicating a lower proportion between 0.4 and 0.6, as shown in Panel C) of Figure 2.2. While there is still a relatively even split amongst participants perceiving a left- or right-skewed distribution with future weather, we see more variation in the predicted lower proportion, with 36% of participants indicating a lower proportion between 0.4 and 0.6.

Panel D) of Figure 2.2 depicts that 43% of participants perceived a left-skewed crop yield distribution with drought-tolerant seeds under past and future weather conditions. Although participants do not see drought-tolerant seeds as a means to reduce the downside risk of crop yields, they view them as an overall risk-reducing adaptation. According to the paired t-tests reported in Table A2.2 of the Appendix, participants expect drought-tolerant seeds to reduce crop yield variances compared to the without technology case under past and future weather conditions.

Table 2.2 summarizes the percentage of participants who indicated whether 1) they are currently implementing center pivot irrigation, tile drainage at 40ft spacing, and drought-tolerant seeds and 2) if they plan to adopt these practices in future. Note that a respondent who has already adopted a practice on some fields may plan to adopt it on other fields in future. Moreover, adopters of tile drainage may also opt to increase the density of tile lines on fields that already have tile drainage (e.g., by "splitting" tile lines to double the number). We find that 52% of participants currently have center pivot irrigation while 86% have tile drainage and drought-tolerant seeds. Additionally, 50% of participants are considering the future adoption of center pivot irrigation and tile drainage, while 68% are considering planting drought-tolerant seeds. Lastly, we see that most current tile drainage users are considering installing additional drainage systems on their other fields (58%) and increasing the density of their current systems (63%) while 47% are also considering installing center pivot irrigation.

Table 2.2: Past and Intended Future Adoption Rates for the Adaptation Technologies (n=44)

Percentage of	Center Pivot Irrigation	Install Tile Drainage	Increase Tile Drainage	Drought-Tolerant Seeds
Past Adoption Rate	52%	86%	---	86%
Future Adoption Rate	50%	50%	---	68%
Future Adoption Rate of Current Tile Drainage Users	47%	58%	63%	33%

The results above describe the shape and changes to the subjective yield distributions related to the adaptation technologies and summarize revealed and stated preferences for these technologies. To understand what drives the shapes of these distributions, we test our seven hypotheses below.

2.5.2. Results for Hypotheses 1-7

Loduca (In Progress) estimates CRRA risk aversion coefficients at the individual and sample levels. For the individual participants with converging models (n=35), the average estimate is 0.810 with a minimum of 0.560 and a maximum of 1.030. Given these predicted values, the assumption of risk aversion ($r > 0$) holds. We utilize the individual level estimated risk coefficients (n=35) for the following analyses. We are testing multiple hypotheses, given that we have four crop yield distributions, which can increase the likelihood of incorrectly rejecting a null hypothesis. Therefore, we apply the Bonferroni adjustment ($\alpha_{new} = \alpha_{old} * \#\, of\ tests$) to the coefficients' p-values to account for the familywise error rate. For example, if a coefficient had an original p-value of 0.07, we multiply the p-value of 0.07 by the number of tests corresponding to the number of columns in Tables 2.3-2.7. Specifically, we multiply the coefficient p-values for Tables 2.3 and 2.7 by four (so 0.07 becomes 0.28) and the p-values for Tables 2.4-2.6 by three (so 0.07 become 0.21), given the corresponding number of tests. This means that coefficient estimates distinct from zero may not be reported as significant given their higher adjusted p-value. Below, we present our hypothesis results:

> *Hypothesis 1*: Increases in the predicted risk aversion coefficient, $\hat{r}$, does not impact the perceived variation in crop yield, $\sigma^2_{y_s}$.

Table 2.3 displays the results from estimating Eq. (12) to test Hypothesis 1 under past and future weather conditions. We reject the hypothesis that increases in the predicted risk aversion coefficient, $\hat{r}$, does not impact the perceived variation in crop yield, $\sigma^2_{y_s}$, for the crop yield distributions under center pivot irrigation. With Eq. (12) being a log-log model, the estimated coefficient is the elasticity of the crop yield variance with respect to the individual level predicted risk preference estimates. We find that under past weather conditions a 1% increase in the predicted risk aversion coefficient is associated with a 2.3% increase in the perceived crop yield variance with center pivot irrigation. Under future weather conditions, a 1% increase in the predicted risk aversion coefficient is associated with a 1.9% increase in the perceived crop yield variance with center pivot irrigation.[3]

[3] Table A2.5 in the Appendix includes current use as an additional explanatory variable for the technology cases. The results show a positive, significant effect of risk aversion on the perceived crop yield standard deviation for tile drainage under past weather. Meanwhile, the results do not show a weakly significant positive effect of risk aversion on the perceived standard deviation for irrigation under future weather.

Table 2.3: Elasticity of Subjective Crop Yield Variances with Respect to Risk Aversion Under Past and Future Weather (n=35)

	Past Weather		Future Weather	
$ln(\sigma^2_{y_s})$	$ln(\hat{r})$	R^2	$ln(\hat{r})$	R^2
Without Technology	0.690 (0.781)	0.016	0.798 (0.875)	0.017
Center Pivot Irrigation	2.269*** (0.675)	0.138	1.918* (0.809)	0.096
Tile Drainage at 40ft Spacing	1.944 (0.860)	0.115	1.367 (0.980)	0.052
Drought-Tolerant Seeds	1.305 (0 .838)	0.042	1.554 (0.959)	0.066

Note: Standard errors in parentheses, for Bonferroni adjusted p-values based on four tests * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Hypothesis 2: An increase in risk aversion does not impact the a) change in the subjective expected crop yield, $\Delta\mu_{y_s}$, or b) change in the subjective crop yield variance, $\Delta\sigma^2_{y_s}$, from the risk-reducing input.

Table 2.4 reports the marginal effects of the predicted risk aversion coefficients on the change in the subjective expected crop yield from the risk-reducing input (Eq. 13) under past and future weather. Similarly, Table 2.5 reports the marginal effects of the predicted risk aversion coefficients on the change in the subjective crop yield variance from the risk-reducing input (Eq. 14) under past and future weather. Given Eq. (13) and (14) are level-log equations, we have that when the risk aversion coefficient increases by 1%, the perceived percentage change in either the subjective expected crop yield or the subjective crop yield variance increases by $\frac{\beta_1}{100}$ percentage points. We fail to reject the null hypothesis that an increase in risk aversion does not impact the change in the subjective expected crop yield or the change in the subjective crop yield variance associated with adopting any of our adaptation strategies of interest. These results indicate that risk aversion levels do not impact the perceived effectiveness of the adaptation technologies.[4]

Table 2.4: Change in the Subjective Expected Crop Yield from No Technology to with Technology Scenarios with Respect to Risk Aversion Under Past and Future Weather. (n=35)

	Past Weather		Future Weather	
$\Delta\mu_{y_s}$	$ln(\hat{r})$	R^2	$ln(\hat{r})$	R^2
Center Pivot Irrigation	22.464 (32.651)	0.016	20.630 (34.865)	0.015
Tile Drainage at 40ft Spacing	59.428 (29.220)	0.131	60.682 (32.653)	0.126
Drought-Tolerant Seeds	-7.879 (17.394)	0.007	-4.705 (18.320)	0.002

Note: Standard errors in parentheses, for Bonferroni adjusted p-values based on three tests * p < 0.10, ** p < 0.05, *** p < 0.01

Table 2.5: Change in the Subjective Crop Yield Variance from No Technology to with Technology Scenarios with Respect to Risk Aversion Under Past and Future Weather. (n=35)

	Past Weather		Future Weather	
$\Delta\sigma^2_{y_s}$	$ln(\hat{r})$	R^2	$ln(\hat{r})$	R^2
Center Pivot Irrigation	123.320 (77.507)	0.049	83.744 (91.960)	0.014
Tile Drainage at 40ft Spacing	173.265 (83.773)	0.033	129.166 (100.487)	0.016
Drought-Tolerant Seeds	61.826 (53.679)	0.023	80.284 (66.082)	0.026

Note: Standard errors in parentheses, for Bonferroni adjusted p-values based on three tests * p < 0.10, ** p < 0.05, *** p < 0.01

For the following four hypotheses, we analyzed the impacts of risk aversion and perceived changes in the crop yield distributions resulting from adopting a practice on the probability of adopting that practice. For past adoption (Eq. 15), we use the perceived change under the average weather over the past ten years. For the stated future adoption of a practice (Eq. 16), we use the

[4] Tables A2.6 and A2.7 in the Appendix include current use as an additional explanatory variable. While risk aversion levels do not impact the perceived effectiveness of the adaptation technologies, current use does impact the perceived percentage change in the subjective expected crop yield under irrigation and drainage.

perceived changes under the average predicted weather over the next ten years and include the predicted average price per bushel of corn over the next ten years as an additional explanatory variable. Tables 2.6 and 2.7 report results for Eq. (15) and Eq. (16), respectively.

Hypothesis 3: A larger predicted risk aversion coefficient, $\hat{r}$, does not affect the probability of adoption.

We fail to reject Hypothesis 3 for past adoption of installing tile drainage and planting drought-tolerant seeds and future adoption of installing tile drainage, increasing tile drainage, and planting drought-tolerant seeds, as shown in Tables 2.6 and 2.7, respectively.[5] We reject Hypothesis 3 when considering adopting center pivot irrigation. By obtaining the elasticity of the probability of adopting each adaptation technology with respect to the risk aversion coefficients, we have that a 1% increase in risk aversion is associated with a -0.91 and 1.49 percentage point change in the probability of past and future adoption, respectively. Our findings suggest that more risk-averse individuals were less likely to have adopted irrigation in the past but are more likely to adopt it in the future. An important distinction between revealed preferences regarding realized past adoption and stated preferences related to future adoption is that participants may not adopt the practice.[6] Our participants indicate they are considering the future adoption of center pivot irrigation, and those with higher risk aversion coefficients are more likely to consider adopting irrigation. Conversely, more risk-averse participants are less likely to have center pivot irrigation installed on their farm currently. This could be because irrigation is a costly investment, and when considering costs and returns, it can significantly impact farm revenue. Previous work has found a positive correlation between production and financial risk preferences (Finger et al., 2023; Flaten et al., 2005).

[5] These findings are robust with the inclusion of an indicator variable for well-drained soil as shown in Tables A2.8 and A2.9.
[6] Research within the choice experiment literature has highlighted the issue of hypothetical bias (Penn & Hu, 2018).

Table 2.6: Drivers of the Probability of Past Adoption of Risk-Reducing Inputs

Probability of	$ln(\hat{r})$	$\Delta\mu_{y_s}$	$\Delta\sigma^2_{y_s}$	Δlp_{y_s}	R^2
Center Pivot Irrigation	-0.910 *** (0.300)	0.008*** (0.002)	-0.001 (0.001)	0.001 (0.002)	0.298
Tile Drainage at 40ft Spacing	0.221 (.308)	0.010 (0.005)	-0.000 (0.000)	-0.001 (0.002)	0.279
Drought-Tolerant Seeds	0.182 (0.447)	-0.001 (0.004)	-0.000 (0.001)	-0.002 (0.002)	0.090

Note: Standard errors in parentheses, for Bonferroni adjusted p-values based on three tests
* p < 0.10, ** p < 0.05, *** p < 0.01

Table 2.7: Drivers of the Probability of Future Adoption of Risk-Reducing Inputs

Probability of	$ln(\hat{r})$	$\Delta\mu_{y_s}$	$\Delta\sigma^2_{y_s}$	Δlp_{y_s}	$\bar{p}$	R^2
Center Pivot Irrigation	1.491*** (0.318)	0.008** (0.003)	-0.001 (0.000)	-0.001 (0.002)	-0.022 (0.053)	0.328
Install Tile Drainage	0.042 (0.422)	0.007 (0.004)	-0.002** (0.001)	-0.003 (0.001)	-0.078 (0.058)	0.346
Increase Tile Drainage	0.438 (0.478)	0.003 (0.005)	-0.000 (0.001)	0.002 (0.002)	-0.023 (0.059)	0.069
Drought-Tolerant Seeds	0.775 (0.402)	0.005 (0.006)	-0.001 (0.001)	-0.001 (0.002)	-0.037 (0.050)	0.082

Note: Standard errors in parentheses, for Bonferroni adjusted p-values based on three tests * p < 0.10,
** p < 0.05, *** p < 0.01

Hypothesis 4: A larger perceived increase in expected yield due to the risk-reducing input, $\Delta\mu_{y_s}$, does not affect the probability of adopting that input.

We fail to reject Hypothesis 4 for past adoption of installing tile drainage and planting drought-tolerant seeds (Table 2.6) and future adoption of installing tile drainage, increasing tile drainage, and planting drought-tolerant seeds (Table 2.7). However, we reject Hypothesis 4 when considering adopting center pivot irrigation. Tables 2.6 and 2.7 illustrate that a 1 unit increase in the expected yield due to the risk-reducing input is associated with a 0.80 percentage point increase in the probability of both current and future adoption. While participants perceive all adaptations as mean increasing, they see center pivot irrigation as providing the largest increase in crop yields compared to the other adaptation technologies. Intuitively, individuals who perceive a larger increase in expected crop yield due to irrigation are more likely to adopt irrigation. Installing a center pivot is expensive, and a larger marginal physical product translates to higher returns on investment. While there is some evidence that increased expected yield due to adopting drainage does increase the probability of past and future adoption, the significance of these effects did not withstand the Bonferroni adjustment.

Hypothesis 5: A larger perceived decrease in the crop yield variance due to the risk-reducing input, $\Delta\sigma^2_{y_s}$, does not affect the probability of adopting that input.

As the results in Tables 2.6 and 2.7 indicate, we fail to reject Hypothesis 5 for past adoption of installing tile drainage and planting drought-tolerant seeds and future adoption of increasing tile drainage and planting drought-tolerant seeds. We do find evidence that a perceived one percentage point increase in the change in crop yield variance under future weather conditions due to adopting tile drainage at 40ft spacing is associated with a 0.20 percentage point decrease in the probability of future adoption. This suggests that individuals who believe adopting tile drainage will increase the variation in their crop yield are less likely to consider adopting tile drainage in the future. When comparing the crop yield variances of the no technology case to the adaptation technology scenarios, we find that participants perceive a significant decrease in crop yield variance with adopting drought-tolerant seeds. However, this decrease does not translate to increased adoption of drought-tolerant seeds. Given the lower explanatory power of our models related to the adoption of drought-tolerant seeds, there appear to be other determining factors, such as relationships with seed dealers or extension agents.

Hypothesis 6: A larger predicted average price per bushel of corn over the next ten years, $\bar{p}$, does not affect the probability of adopting that input in the future.

We fail to reject the hypothesis that a larger predicted average price per bushel of corn does not impact the probability of adopting any of the adaptation practices.

Hypothesis 7: A larger perceived decrease in the crop yield lower proportion due to the risk-reducing input, Δlp_{y_s}, does not affect the probability of adopting that input.

We fail to reject the hypothesis that a larger perceived decrease in the crop yield lower proportion due to the risk-reducing input does not change the probability of adopting that input. When comparing the lower proportions of the no technology case to those of the adaptation technology scenarios, participants view adopting center pivot irrigation under past and future weather as decreasing the lower proportion of the crop yield distribution. While we find evidence that participants perceive a significant shift in the lower proportions related to irrigation, this shift is not driving their adoption decisions. There is evidence that decreases in the lower proportion due to adopting drainage do increase the probability of stated future adoption. However, the significance of this effect did not withstand the Bonferroni adjustment.

2.6. Discussion and Conclusion

Our results highlight that while the Michigan farmers in our sample are concerned about extreme weather events and predict higher crop yield variability in the future, they are also optimistic about future yield outcomes. Indeed, 11% of participants indicated having a high concern for extreme weather while 30% and 32% indicated medium-high and medium concern, respectively. Overall, center pivot irrigation is seen as the most effective adaptation, followed by tile drainage at 40ft spacing. While drought-tolerant seeds are not perceived as causing an overall positive shift, subjects perceive them as an effective means to decrease crop yield variance. Adopting drought-tolerant seeds is an inexpensive adaption with an 86% adoption rate in our sample. Additionally, 86% of our sample indicated having tile drainage, though the intensity ranges from 60ft to 40ft spacing.

We also found that of the participants who already have tile drainage in some of their fields, 58% are considering installing new drainage, and 63% are planning to decrease the spacing of current drainage systems. About 47% of these participants who already have tile drainage are also considering installing center pivot systems. Simultaneously considering adopting drainage and irrigation underscores the concern in extreme precipitation patterns. Although center pivot irrigation is believed to be the most effective at increasing expected crop yield and decreasing downside risk, it has the lowest adoption rate, at 52% of participants. Center pivot irrigation has high fixed costs for installation and equipment in addition to the energy and labor costs. This higher cost outweighed the perceived benefits of adoption for almost half of our sample. However, 29% of our sample is considering installing their first center pivot irrigation system, and 70% of participants who already have irrigation are considering installing an additional center pivot.

To our knowledge, this is the first study to link elicited risk preferences and subjective crop yield beliefs to technology adoption decisions. Risk perceptions are often elicited and defined in various manners, with some studies asking participants to indicate their beliefs about climate change (Niles & Mueller, 2016), how they rank in likelihood to take risks compared to their peers (Greiner et al., 2009), and their level of concerns related to production risks (Mase et al., 2017). While these studies captured measures of production risk preferences, they do not estimate risk parameters of utility functions. Meanwhile, we elcited our risk preferences using the random lottery pair method with the questions framed as agricultural investment decisions to mitigate weather-related risk. In Loduca (In Progress) we found the CRRA power function to be the best model fit and allowed this utility funtion to inform our decision-model. By estimating risk preference parameters at the individual-level, we were able to model how risk preferences impact crop yield perceptions and climate change adaptation adoption decisions. We find that risk preferences impact adoption decisions directly through intolerance of risk as well as indirectly by increasing perceived crop yield variances.

While previous work has linked risk preferences to either adoption decisions or subjective beliefs about crop yield, we model the relationships among all three. By incorporating the previously estimated risk preferences of the participants into our behavioral model, we can identify the various factors that impact crop yield beliefs and adaptation decisions. Our findings highlight that both risk aversion and perceptions of crop yield outcomes impact adaptation adoption decisions. Similar to

Menapace et al. (2013), we find that risk aversion does impact subjective crop yield beliefs. Specifically, our results indicate that more risk-averse individuals report higher crop yield variances under the center pivot irrigation and tile drainage at 40ft spacing scenarios. Akin to Meraner and Finger (2019), we also find that more risk averse participants have a higher probability of adopting center pivot irrigation.

Additionally, increases in the perceived change in crop yield expected value from adoption center pivot irrigation impact past and future adoption of the practice. Interestingly, lower risk aversion levels predict the past adoption of irrigation, while higher levels of risk aversion predict the future adoption of irrigation. This demonstrates a shift from producers believing irrigation to be a potentially risky investment to a risk-reducing technology under future climate variability. Moreover, participants who perceive center pivot irrigation as increasing their expected value of crop yield are more likely to adopt irrigation, while participants who believe tile drainage will increase their variance of crop yield are less likely to adopt drainage. These results are in line with Liu (2013) in that farmers want to implement practices that benefit both expected values and standard deviations of crop yields.

The findings from this study indicate that our participants are concerned about future crop yield variability and extreme weather conditions. While irrigation and drainage are potential methods for reducing downside risk, drought-tolerant seeds are believed to decrease overall crop yield variability. Ultimately, investing in a risk-reducing practice is a personal choice dependent on the producer's tolerance for risk, how they perceive changing yield probability distributions, how they perceive the efficacy of the practice at influencing mean and variance of yield, and, of course, product price and input cost. We illustrate how risk preferences derived from utility theory can be linked to a producer's decision model to predict climate change adaptation behavior. Measuring risk preferences and subjective crop yield distributions under different technology scenarios allows us to deconstruct the crop production decisions and evaluate the critical drivers of adoption decisions.

Participants who believe irrigation will increase their expected crop yield and drainage will decrease the standard deviation of their crop yield are more likely to adopt the corresponding practice. While corn and soybean operations in Michigan are primarily rainfed, we are likely to see increased irrigated production. Future research can examine the environmental and policy implications of increased irrigation in Michigan.

REFERENCES

Adee, E., Roozeboom, K., Balboa, G. R., Schlegel, A., & Ciampitti, I. A. (2016). Drought-Tolerant Corn Hybrids Yield More in Drought-Stressed Environments with no Penalty in Non-Stressed Environments. *Frontiers in Plant Science*, *7*, 210680.

Barham, B. L., Chavas, J.-P., Fitz, D., Salas, V. R., & Schechter, L. (2014). The Roles of Risk and Ambiguity in Technology Adoption. *Journal of Economic Behavior & Organization*, *97*, 204-218.

Ben Mansour, S., Jouini, E., Marin, J. M., Napp, C., & Robert, C. (2008). Are Risk-Averse Agents more Optimistic? A Bayesian Estimation Approach. *Journal of Applied Econometrics*, *23*(6), 843-860.

Caldwell, S., Nelson, S., & Waldinger, D. (2023). Tax Refund Uncertainty: Evidence and Welfare Implications. *American Economic Journal: Applied Economics*, *15*(2), 352-376.

Carlson, G. A. (1970). A Decision Dheoretic Approach to Crop Disease Prediction and Control. *American Journal of Agricultural Economics*, *52*(2), 216-223.

Cerroni, S. (2020). Eliciting Farmers' Subjective Probabilities, Risk and Uncertainty Preferences Using Contextualized Field Experiments. *Agricultural Economics*, *51*(5), 707-724. https://doi.org/10.1111/agec.12587

Chesley, G. (1975). Elicitation of Subjective Probabilities: A Review. *The Accounting Review*, *50*(2), 325-337.

Clop-Gallart, M., & Juárez-Rubio, F. (2007). Elicitation of Subjective Crop yield PDF [Probability Density Functions]. *Spanish Journal of Agricultural Research*, *5*(1), 16-24.

De Finetti, B. (1937). Foresight: Its Logical Laws, its Subjective Sources. In *Breakthroughs in Statistics* (pp. 134-174). Springer.

Di Falco, S., & Chavas, J.-P. (2009). On Crop Biodiversity, Risk Exposure, and Food Security in the Highlands of Ethiopia. *American Journal of Agricultural Economics*, *91*(3), 599-611.

Emerick, K., De Janvry, A., Sadoulet, E., & Dar, M. H. (2016). Technological Innovations, Downside Risk, and the Modernization of Agriculture. *American Economic Review*, *106*(6), 1537-1561.

Engelberg, J., Manski, C. F., & Williams, J. (2009). Comparing the Point Predictions and Subjective Probability Distributions of Professional Forecasters. *Journal of Business & Economic Statistics*, *27*(1), 30-41.

Falck-Zepeda, J. B., Traxler, G., & Nelson, R. G. (2000). Surplus Distribution from the Introduction of a Biotechnology Innovation. *American Journal of Agricultural Economics*, *82*(2), 360-369.

Finger, R., Wüpper, D., & McCallum, C. (2023). The (In)stability of Farmer Risk Preferences. *Journal of Agricultural Economics*, *74*(1), 155-167.

Flaten, O., Lien, G., Koesling, M., Valle, P. S., & Ebbesvik, M. (2005). Comparing Risk Perceptions and Risk Management in Organic and Conventional Dairy Farming: Empirical Results from Norway. *Livestock Production Science*, *95*(1-2), 11-25.

Foster, A. D., & Rosenzweig, M. R. (2010). Microeconomics of Technology Adoption. *Annu. Rev. Econ.*, *2*(1), 395-424.

Gilboa, I., Postlewaite, A. W., & Schmeidler, D. (2008). Probability and Uncertainty in Economic Modeling. *Journal of Economic Perspectives*, *22*(3), 173-188.

Grassini, P., Yang, H., Irmak, S., Thorburn, J., Burr, C., & Cassman, K. G. (2011). High-Yield Irrigated Maize in the Western US Corn Belt: II. Irrigation Management and Crop Water Productivity. *Field Crops Research*, *120*(1), 133-141.

Greiner, R., Patterson, L., & Miller, O. (2009). Motivations, Risk Perceptions and Adoption of Conservation Practices by Farmers. *Agricultural Systems*, *99*(2-3), 86-104.

Hardaker, J. B., Huirne, R. B. M., Anderson, J. R., & Lien, G. (2004). *Coping with Risk in Agriculture* (2nd ed.). CAB International.

Hareau, G. G., Mills, B. F., & Norton, G. W. (2006). The Potential Benefits of Herbicide-Resistant Transgenic Rice in Uruguay: Lessons for Small Developing Countries. *Food Policy*, *31*(2), 162-179.

Harrison, G. W., & Rutström, E. E. (2008). Risk Aversion in the Laboratory. In *Risk Aversion in Experiments* (pp. 41-196). Emerald Group Publishing Limited.

Iyer, P., Bozzola, M., Hirsch, S., Meraner, M., & Finger, R. (2020). Measuring Farmer Risk Preferences in Europe: a Systematic Review. *Journal of Agricultural Economics*, *71*(1), 3-26.

Kyburg, H. (1978). Subjective Probability: Criticisms, Reflections, and Problems. *Journal of Philosophical Logic*, 157-180.

Liu, E. M. (2013). Time to Change What to Sow: Risk Preferences and Technology Adoption Decisions of Cotton Farmers in China. *Review of Economics and Statistics*, *95*(4), 1386-1403.

Liu, Y., & Ramsey, A. F. (2023). Incorporating Historical Weather Information in Crop Insurance Rating. *American Journal of Agricultural Economics*, *105*(2), 546-575.

Loduca, N. R. (In Progress). *Farmer Risk Aversion in a General vs. Contextual Lottery Setting*.

Marra, M., Pannell, D. J., & Ghadim, A. A. (2003). The Economics of Risk, Uncertainty and Learning in the Adoption of New Agricultural Technologies: Where are We on the Learning Curve? *Agricultural Systems*, *75*(2-3), 215-234.

Marra, M. C., & Carlson, G. A. (2002). Agricultural Technology and Risk. In *A Comprehensive Assessment of the Role of Risk in U.S. Agriculture* (pp. 325-352). Springer Group.

Mase, A. S., Gramig, B. M., & Prokopy, L. S. (2017). Climate Change Beliefs, Risk Perceptions, and Adaptation Behavior among Midwestern US Crop Farmers. *Climate Risk Management*, *15*, 8-17.

McFadden, J., Smith, D., Wechsler, S., & Wallander, S. (2019). *Development, Adoption, and Management of Drought-Tolerant Corn in the United States*.

Menapace, L., Colson, G., & Raffaelli, R. (2013). Risk Aversion, Subjective Beliefs, and Farmer Risk Management Strategies. *American Journal of Agricultural Economics*, *95*(2), 384-389.

Meraner, M., & Finger, R. (2019). Risk Perceptions, Preferences and Management Strategies: Evidence from a Case Study Using German Livestock Farmers. *Journal of Risk Research*, *22*(1), 110-135.

Nelson, C. H., & Escalante, C. (2004). Toward Exploring the Location-Scale Condition: A Constant Relative Risk Aversion Location-Scale Objective Function. *European Review of Agricultural Economics*, *31*(3), 273-287.

Niles, M. T., & Mueller, N. D. (2016). Farmer Perceptions of Climate Change: Associations with Observed Temperature and Precipitation Trends, Irrigation, and Climate Beliefs. *Global Environmental Change*, *39*, 133-142.

Ortiz-Bobea, A., Wang, H., Carrillo, C. M., & Ault, T. R. (2019). Unpacking the Climatic Drivers of US Agricultural Yields. *Environmental Research Letters*, *14*(6), 064003.

Ramsey, A. F. (2020). Probability Distributions of Crop Yields: A Bayesian Spatial Quantile Regression Approach. *American Journal of Agricultural Economics*, *102*(1), 220-239.

Recktenwald, G., & Deinert, M. (2012). Cost Probability Analysis of Reprocessing Spent Nuclear Fuel in the US. *Energy Economics*, *34*(6), 1873-1881.

Rejesus, R. M., Marra, M. C., Roberts, R. K., English, B. C., Larson, J. A., & Paxton, K. W. (2013). Changes in Producers' Perceptions of Within-Field Yield Variability After Adoption of Cotton Yield Monitors. *Journal of Agricultural and Applied Economics*, *45*(2), 295-312.

Sorensen, R. B., Lamb, M. C., & Butts, C. L. (2022). Corn Yield Response to Irrigation Level, Crop Rotation, and Irrigation System. *Journal of Crop Improvement*, *36*(5), 701-716.

Theurer, M., White, B., Larson, R., & Schroeder, T. (2015). A Stochastic Model to Determine the Economic Value of Changing Diagnostic Test Characteristics for Identification of Cattle for Treatment of Bovine Respiratory Disease. *Journal of Animal Science*, *93*(3), 1398-1410.

Torkamani, J. (2006). Measuring and Incorporating Farmers' Personal Beliefs and Preferences About Uncertain Events in Decision Analysis: A Stochastic Programming Experiment. *Indian Journal of Agricultural Economics*, *61*(2).

Van Klompenburg, T., Kassahun, A., & Catal, C. (2020). Crop Yield Prediction Using Machine Learning: A Systematic Literature Review. *Computers and Electronics in Agriculture*, *177*, 105709.

Weinstock, E., & Sonsino, D. (2014). Are Risk-Seekers More Optimistic? Non-Parametric Approach. *Journal of Economic Behavior & Organization*, *108*, 236-251.

Young, D. (1983). A Practical Procedure for Eliciting Subjective Probability Distributions. Symposium" Introduction to Risk Measures from the Behavioral Sciences," American

Agricultural Economics Association Annual Meeting, Purdue University, West Lafayette, Indiana,

Zhao, S., & Yue, C. (2020). Risk Preferences of Commodity Crop Producers and Specialty Crop Producers: An Application of Prospect Theory. *Agricultural Economics*, *51*(3), 359-372. https://doi.org/10.1111/agec.12559

APPENDIX 2

Tables A2.1-A2.4 provide the p-values from paired t-test results from comparing moments of the crop yield distributions the individual level. Table A2.1 provides results from comparing the expected value and the most likely value of the crop yield distributions to test for symmetry. Next, we compare measures of the distributions under each technology scenario to the ones without technology to test how the adaptations change the crop yield distribution. Table A2.2 provides results from comparing the expected value of the without technology case to each of the technology cases. For all cases there is strong evidence that the technology increases the expected value of crop yield. Tables A2.3 and A2.4 provide results from testing the assumption that each adaptation reduces perceived crop yield risk by decreasing the crop yield variance and the lower proportion of the density function compared to the without technology case, respectively.

Table A2.1: Paired T-Test Results for Symmetry of Crop Yield Distributions (Ho: mean–mode = 0)

	Mean < mode (left-skewed)	Mean ≠ mode	Mean > mode (right-skewed)
Past w/o tech	0.288	0.576	1.000
Past w/ center pivot irrigation	1.000	1.000	0.701
Past w/ tile drainage at 40ft spacing	1.000	1.000	1.000
Past w/ DT seeds	0.488	0.975	1.000
Future w/o tech	0.197	0.396	1.000
Future w/ center pivot irrigation	1.000	0.132	**0.064**
Future w/ tile drainage at 40ft spacing	0.268	1.000	1.000
Future w/ DT seeds	0.365	1.000	1.000

Note: Values displayed are Bonferroni adjusted p-values based on three tests.

Table A2.2: Paired T-Test Results for Change in Expected Value of Crop Yield Related to Technology Adoption (Ho: mean without technology–mean with technology = 0)

	w/o < w/ tech Yield increasing	w/o ≠ w/ tech	w/o > w/ tech Yield decreasing
Past w/ center pivot irrigation	**0.000******	**0.000******	1.000
Past w/ tile drainage at 40ft spacing	**0.000******	**0.000******	1.000
Past w/ DT seeds	**0.000******	**0.000******	1.000
Future w/ center pivot irrigation	**0.000******	**0.000******	1.000
Future w/ tile drainage at 40ft spacing	**0.000******	**0.000******	1.000
Future w/ DT seeds	**0.000******	**0.000******	1.000

Note: Values displayed are Bonferroni adjusted p-values based on three tests.

Table A2.3: Paired T-Test Results for Change in Variance of Crop Yield Related to Technology Adoption (Ho: variance without technology – variance with technology = 0)

	w/o < w/ tech	w/o ≠ w/ tech	w/o > w/ tech (risk-reducing)
Past w/ center pivot irrigation	1.000	1.000	1.000
Past w/ tile drainage at 40ft spacing	1.000	1.000	1.000
Past w/ DT seeds	1.000	**0.049**	**0.024**
Future w/ center pivot irrigation	1.000	0.927	0.465
Future w/ tile drainage at 40ft spacing	1.000	0.822	0.411
Future w/ DT seeds	1.000	**0.051**	**0.026**

Note: Values displayed are Bonferroni adjusted p-values based on three tests.

Table A2.4: Paired T-Test Results for Change in Lower Proportion of Crop Yield Related to Technology Adoption (Ho: lower proportion without technology – lower proportion with technology = 0)

	w/o < w/ tech	w/o ≠ w/ tech	w/o > w/ tech (risk-reducing)
Past w/ center pivot irrigation	1.000	**0.081**	**0.042**
Past w/ tile drainage at 40ft spacing	1.000	0.593	0.297
Past w/ DT seeds	1.000	1.000	1.000
Future w/ center pivot irrigation	1.000	**0.012**	**0.006**
Future w/ tile drainage at 40ft spacing	1.000	0.672	0.336
Future w/ DT seeds	1.000	1.000	0.555

Note: Values displayed are Bonferroni adjusted p-values based on three tests.

Tables A2.5-A2.7 provide regression results for how risk aversion levels relate to the moments of the crop yield distributions. These regressions now include a binary variable that indicates the current use of the corresponding technology as a robustness check to Tables 2.3-2.5 of the main text.

Table A2.5: Elasticity of Subjective Crop Yield Variances with Respect to Risk Aversion Under Past and Future Weather (n=35)

	Past Weather			Future Weather		
$ln(\sigma^2_{y_s})$	$ln(\hat{r})$	Current Use	R^2	$ln(\hat{r})$	Current Use	R^2
Center Pivot Irrigation	2.180** (0.737)	-0.101 (0.325)	0.141	1.810 (0.827)	-0.122 (0.329)	0.010
Tile Drainage at 40ft Spacing	2.336** (0.757)	-0.615 (0.403)	0.166	1.719 (0.950)	-0.554 (0.502)	0.090
Drought-Tolerant Seeds	1.296 (0.878)	0.773 (0.624)	0.114	1.547 (1.008)	0.562 (0.676)	0.107

Note: Standard errors in parentheses, for Bonferroni adjusted p-values based on three tests * p < 0.10, ** p < 0.05, *** p < 0.01

Table A2.6: Change in the Subjective Expected Crop Yield from No Technology to with Technology Scenarios with Respect to Risk Aversion Under Past and Future Weather. (n=35)

	Past Weather			Future Weather		
$\Delta\mu_{y_s}$	$ln(\hat{r})$	Current Use	R^2	$ln(\hat{r})$	Current Use	R^2
Center Pivot Irrigation	48.611 (30.070)	29.678** (9.859)	0.274	46.818 (33.241)	29.726** (9.910)	0.291
Tile Drainage at 40ft Spacing	48.723 (30.391)	16.803** (6.126)	0.178	47.038 (34.129)	21.416** (7.708)	0.194
Drought-Tolerant Seeds	-7.830 (17.277)	-4.368 (7.504)	0.018	-4.588 (17.883)	-10.448 (9.208)	0.059

Note: Standard errors in parentheses, for Bonferroni adjusted p-values based on three tests * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A2.7: Change in the Subjective Crop Yield Variance from No Technology to with Technology Scenarios with Respect to Risk Aversion Under Past and Future Weather. (n=35)

	Past Weather			Future Weather		
$\Delta\sigma^2_{y_s}$	$ln(\hat{r})$	Current Use	R^2	$ln(\hat{r})$	Current Use	R^2
Center Pivot Irrigation	86.765 (79.838)	-41.491 (28.562)	0.099	23.395 (103.760)	-68.500 (39.087)	0.095
Tile Drainage at 40ft Spacing	178.142 (78.707)	-7.655 (41.131)	0.033	126.358 (96.751)	4.408 (64.258)	0.016
Drought-Tolerant Seeds	61.777 (54.081)	4.413 (28.076)	0.023	80.176 (67.284)	9.633 (41.074)	0.028

Note: Standard errors in parentheses, for Bonferroni adjusted p-values based on three tests * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Tables A2.8 and A2.9 provide regression results for the impacts of risk aversion and perceived changes in the crop yield distributions resulting from adopting a practice on the probability of adopting that practice. These regressions now include a binary variable that indicates if the primary soil type for the farm is well-draining as a robustness check to Tables 2.6 and 2.7 of the main text.

Table A2.8: Drivers of the Probability of Past Adoption of Risk-Reducing Inputs

Probability of	$ln(\hat{r})$	$\Delta\mu_{y_s}$	$\Delta\sigma^2_{y_s}$	Δlp_{y_s}	Well-drained soil indicator	R^2
Center Pivot Irrigation	-0.918*** (0.302)	0.007*** (0.002)	-0.001 (0.001)	0.001 (0.002)	0.035 (0.171)	0.296
Tile Drainage at 40ft Spacing	0.198 (0.551)	0.020*** (0.005)	-0.001 (0.000)	0.004** (0.001)	Not estimable	0.480
Drought-Tolerant Seeds	-0.259 (1.057)	0.001 (0.006)	0.001 (0.002)	-0.003 (0.003)	Not estimable	0.129

Note: Standard errors in parentheses, for Bonferroni adjusted p-values based on three tests * p < 0.10, ** p < 0.05, *** p < 0.01

Table A2.9: Drivers of the Probability of Future Adoption of Risk-Reducing Inputs

Probability of	$ln(\hat{r})$	$\Delta\mu_{y_s}$	$\Delta\sigma^2_{y_s}$	Δlp_{y_s}	$\bar{p}$	Well-drained soil indicator	R^2
Center Pivot Irrigation	1.572*** (0.393)	0.009** (0.003)	-0.001 (0.000)	-0.033 (0.054)	-0.001 (0.002)	-0.104 (0.129)	0.355
Install Tile Drainage	0.100 (0.453)	0.006* (0.003)	-0.002** (0.001)	-0.093 (0.075)	-0.002 (0.001)	-0.181 (0.141)	0.380
Increase Tile Drainage	0.533 (0.453)	0.003 (0.003)	-0.001 (0.000)	-0.040 (0.065)	0.003 (0.003)	-0.421** (0.142)	0.218
Drought-Tolerant Seeds	0.746 (0.411)	0.005 (0.006)	-0.000 (0.000)	-0.035 (0.047)	-0.001 (0.002)	0.108 (0.139)	0.083

Note: Standard errors in parentheses, for Bonferroni adjusted p-values based on three tests * p < 0.10, ** p < 0.05, *** p < 0.01

CHAPTER 3: EXPLORING THE INFLUENCE OF NRCS COST-SHARE PROGRAMS ON COVER CROP ADOPTION IN THE MIDWEST

Anticipated Coauthor: James Sears

Abstract: This paper investigates the role of Natural Resource Conservation Service (NRCS) cost-share programs in promoting cover crop adoption through various conservation programs. Cover crops offer multiple public ecological benefits, including reducing greenhouse gas emissions and improving water quality, and private benefits to farmers from improvements in soil health, weed suppression, and a reduction in soil erosion. The cost-share payments from NRCS allow farmers to bridge the gap between the public and private benefits of conservation practices. This study analyzes the impact of NRCS cover crop cost-share percentage level on adoption rates at the county-level in the Midwest, employing fixed effects and contract-type controls to understand drivers of cover crop adoption in agriculture. By decomposing the per-acre payments into cost-share proportions and per-acre costs, we isolate the marginal effect of increasing the cost-share generosity on enrolled cover crop acreage. The basic single species contract is the most popular contract type, and higher adoption corresponds to lower precipitation levels in the previous growing season. Both of these trends could have negative implications for potential environmental benefits. However, we find complementarity in adopting cover crops and conservation tillage practices using remote sensing data. By adopting a suite of regenerative practices, producers can increase benefits to ecosystem services. These findings contribute to a comprehensive understanding of the factors influencing the adoption of cover crops and offer insights into the role of government incentives in increasing sustainable agricultural practices.

3.1. Introduction

Agricultural best management practices, such as cover crops, are becoming a primary focus for conservation and climate-smart actions, given their potential to sequester soil organic carbon and mitigate nutrient runoff while still allowing the land to remain in production (Fargione et al., 2018). The Natural Resource Conservation Service (NRCS) is an agency within the United States Department of Agriculture (USDA) that delivers conservation improvements in agricultural settings. In particular, the NRCS provides technical and financial assistance to farmers for conservation practices that support natural resource concerns through various programs. Some of these are working land programs, including the Environmental Quality Incentive Program (EQIP), Conservation Stewardship Program (CSP), and other regional programs. EQIP and CSP help to support a variety of approved conservation practices. In addition to providing technical support related to the practices, the NRCS cost-share programs cover a proportion of the adoption costs.

For this study, we focus on cover crop enrollment in NRCS contracts. The 2022 Census of Agriculture reports that cover crops are planted on approximately 4.7% of total cropland, representing a 17% increase from the 2017 Census of Agriculture (USDA-NASS, 2024). Within the Midwest, cover crops were planted on approximately 7.2% of cropland in 2021 (Zhou et al., 2022). While these percentages are small, the NRCS is committed to increasing cover crop acreage. In 2022, the NRCS announced a partnership with Farmers for Soil Health with "a goal of doubling the number of corn and soybean acres using cover crops to 30 million acres by 2030" (USDA, 2022). Due to their wide-ranging soil and water quality benefits, the NRCS recognizes cover crops as a conservation practice standard that is eligible for payments.

The USDA defines cover crops, such as grasses, legumes, and forbs, as non-cash crops planted between rotations for seasonal vegetative cover (USDA-NRCS, 2020). Given that cover crops are non-cash crops, farmers may not harvest and sell them but use them for grazing if grazing does not compromise the conservation purpose. Cover cropping, specified as practice code 340 by the NRCS, has three key practice types: a basic cover crop contract with a single species that is chemically or mechanically terminated, a winter-kill basic cover crop contract with a single species that is terminated by frost conditions, and a multiple species contract that is chemically or mechanically terminated. Farmers can seed cover crops in the fall after harvesting their cash crop or in early spring, provided there is enough time for the cover crops to mature. Fall planting allows nonwinter-hardy cover crop varieties to be terminated by frost conditions, while spring-planted cover crops are generally terminated by chemical or mechanical methods (USDA-NRCS, 2019).

Cover crops provide multiple ecosystem benefits, including reducing greenhouse gas emissions by accumulating soil organic carbon and fixing nitrogen in the soil, improving water quality by decreasing soil erosion, nitrogen leaching, and phosphorous loss, and suppressing weeds and pests (Blesh, 2018; Snapp et al., 2005). Syntheses of ecological studies find significantly higher soil organic carbon levels in fields with cover crops in comparison to reference plots without cover crops, as well as increased resilience to climate vulnerability due to soil health benefits (Kaye & Quemada, 2017; Poeplau & Don, 2015). Additional studies highlight the differences in ecosystem benefits from cover crop practices depending on the ecoregion, soil type, cash crop species, and cover crop mixture (Abdalla et al., 2019). Benefits to farmers include reductions in soil erosion and the amount of nitrogen fertilizer needed for cash crops, as well as increased cash crop yields due to soil carbon accumulation. However, benefits from soil carbon and nitrogen mineralization can take years to materialize (Snapp et al., 2005).

Despite the environmental benefits related to cover cropping, adoption rates are lower than the levels desired by the NRCS. The USDA's Sustainable Agriculture Research and Education program conducts annual National Cover Crop Surveys with the 2022-2023 Report highlighting the main barriers to cover crop adoption: no measurable economic benefits, yield reduction in the following cash crop, increased production risk, and time or labor requirements (SARE, 2023). With some agricultural producers perceiving cover crops as having no measurable economic benefits, NRCS conservation cost-share payment programs incentivize cover crop adoption. By providing a subsidy payment, these cost-share programs essentially pay for the public benefits to climate change mitigation and emissions reductions that farmers cannot internalize.

Given the sum of money the federal government is allocating to expanding agricultural conservation practices, it is also essential to understand the behavioral response to EQIP and CSP payments. This is the first paper to use detailed NRCS cover crop practice-level data to identify the effectiveness of payment generosity on cover crop adoption. By quantifying the adoption response to cost-share payments, we can identify the effectiveness of these programs in achieving their goals of increasing cover crop adoption to improve ecosystem service and climate change mitigation potential. Previous work has calculated changes in cover crop acreage using remote-sensing data (Hively et al., 2015; Seifert et al., 2018), but little literature has attempted to link these changes to economic incentives. Zhou et al. (2022) employ multiple remote sensing datasets to synthesize estimates of cover crop adoption rates from 2000 to 2021 and illustrate a correlation between cover crop adoption trends and state funding in their supplemental material. Additional studies have examined the farm and farmer characteristics that influence cover crop adoption using survey data (Luther et al., 2020; Pathak et al., 2021; Plastina et al., 2020; Prokopy et al., 2019; Thompson et al., 2021). Some work has utilized the Agricultural Resource Management Survey (ARMS) data to obtain a larger sample size, though the analysis was confined to a single year (Claassen et al., 2018; Lee & McCann, 2019). Park et al. (2023) use aggregate county-level EQIP and CSP data for all conservation practices to measure how each program impacts cover crop adoption with 2006-2015 panel data.

We build upon these studies and contribute to the literature in three ways. First, we provide the first estimates of how contract characteristics impact cover crop contract payments. Given that our data provide specific information on cover crop specific contracts, we can shed new light on how differences in cover crop planting specifications and contract classification, such as priority watershed initiatives, impact payment levels. Second, we are the first to separately identify farmer responsiveness to cost-share proportions from their response to adoption costs. As program payments depend on the percentage level that the program covers and the private costs of adopting the practices, it is important to separate these values.

Lastly, we contribute to the literature on temporal and spatial spillover effects of NRCS-induced cover crop adoption and its complementarity with conservation tillage. Once a farmer has enrolled cover crop acres in a cost-share program, they can learn how to implement the practice and observe the benefits to their operation. These experiences can reduce the barriers to continuing cover crop practices after their contract payment has ended and promote adoption on nearby farms through peer effects. Additionally, the relationship between cover crop acres and conservation tillage can signify that farmers are adopting conservation practices to boost private and public benefits.

Using NRCS contract data at a previously unseen level of disaggregation, we capture variation in per-acre payments and adoption rates from 2008-2023 and across Midwestern counties. We can understand the factors that impact payment amounts by utilizing information on contract characteristics related to cover crop species, environmental initiatives, and historically underserved farmer status. We measure the drivers of NRCS cover crop payment levels and how the payments impact cover crop adoption at the county-level using a variety of model specifications. First, we model per-acre payments as a function of contract characteristics while controlling for county and time fixed effects. We find price premiums for historically underserved and priority initiative contract status, a price discount for contracts that do not require species termination, and a price premium for multispecies contracts. While these findings align with the cost structure, their magnitudes highlight that winter-kill and multispecies contract recipients are willing to accept payments about 25% lower than the published price difference from basic cover crop contracts.

Next, we estimate the relationships between enrolled cover crop acreage and cost-share proportions, computed per-acre costs, contract characteristics, and weather conditions from the previous growing season. We find a positive relationship between the magnitude of the cost-share proportion and cover crop acres enrolled, providing evidence that higher payments incentivize higher adoption. For practice implementation at the county-level, we find that winter-kill and multispecies contracts contain fewer cover crop acres on average than the basic single-species contract when controlling for time and county fixed effects. Producers plant winter-kill species in the fall and do not need to terminate the species with chemical or mechanical methods. While this translates to lower adoption costs, some benefits could diminish, given that cover crops are absent throughout winter and spring.

Multispecies contracts are more expensive than basic single-species or winter-kill species contracts due to seed costs, but species diversification can promote additional ecosystem services. Lower adoption of multispecies cover crop acreage provides evidence that despite the potential for increased cost-share payments, adoption of multispecies contracts still lags behind traditional cover crop approaches. This suggests that further premium increases are necessary to motivate the higher levels of adoption of practice variations with higher public and private benefits. Additionally, the weather controls indicate that increased enrolled cover crop acres are related to lower precipitation levels. With our quadratic specification of precipitation from the previous cash crop growing season, we find adoption increases at a decreasing rate in relationship to precipitation. Once precipitation reaches a level of approximately 5% higher than the mean level, the average enrolled cover crop acres in a contract begin to decrease.

Lastly, we employ remotely-sense data from OpTIS on total county-level cover crop adoption to estimate complementarity and spillover models. This dataset contains total county cover crop acreage, regardless of enrollment status and conservation tillage acreage from 2015 to 2021. This allows us to identify potential lagged effects from cover crop enrollment in NRCS programs that represent positive spillover related to learning and peer effects. Moreover, we measure the complementarity between cover crop acreage and conservation tillage, indicating that farmers adopt a suite of conservation practices. We do not find evidence of a lagged effect from cover crop enrollment, meaning we do not see evidence of learning or peer effects on total cover crop acreage. We find a positive relationship between cover crops and no tillage practices. By adopting multiple conservation practices, farmers can increase benefits to soil health and ecosystem services.

We structure the remainder of this paper as follows. Section 3.2 provides an overview of the policy background for NRCS conservation incentive programs and previous work on policy evaluation. Section 3.3 defines a behavioral model for an agricultural producer maximizing their utility based on production decisions as a basis for our analysis. Section 3.4 presents an overview of our NRCS administrative, weather-related, and remote-sensing data. Section 3.5 identifies our estimation methods, and 3.6 examines the corresponding results. Section 3.7 discusses the policy implications of our findings and summarizes.

3.2. Cover Crop Policy Background and Evaluation

In 1935, Congress directed the Secretary of Agriculture to establish the Soil Conservation Service as a permanent agency in the USDA in response to the Dust Bowl. The Soil Conservation and Domestic Allotment Act of 1936 created the Agricultural Conservation Program as the first conservation cost-sharing program. Congress renamed the Soil Conservation Service the NRCS in 1994 to mirror the breadth of the agency's concerns and responsibilities (USDA-NRCS, 2024a). The 1996 Farm Bill established EQIP and consolidated four conservation programs: the Agricultural Conservation Program, the Great Plains Conservation Program, the Water Quality Incentives Program, and the Colorado River Basin Salinity Control Program (Cain & Lovejoy, 2004). The 2018 Farm Bill reauthorized and amended EQIP, stating that conservation practices funded through EQIP will improve soil health, reduce erosion and nutrient loss, increase wildlife habitats, and provide other environmental benefits (USDA-NRCS-CCC, 2019). The 2002 Farm Bill established the Conservation Security Program, renamed the Conservation Stewardship Program (CSP) by the 2008 Farm Bill. CSP supports agricultural landowners in managing and continuing existing conservation activities while pursuing additional improvements in natural resource and land management.

To be eligible for an EQIP contract, land related to agricultural or forest management must be able to have natural resource concerns addressed by a USDA-approved conservation practice. The USDA defines a natural resource concern as "an expected degradation of the soil, water, air, plant, or animal resource base to an extent the sustainability or intended use of the resource is impaired" (USDA-NRCS). EQIP provides financial and technical assistance to agricultural producers to implement conservation practices on their farms, with applications accepted on a continual basis. Compared to EQIP, CSP requires farmers to have a suite of practices, and the contracts are for five years instead of three years. CSP helps agricultural producers expand their existing conservation practices with eligibility based on meeting or exceeding NRCS standards for at least two priority resource concerns and a goal of meeting or exceeding at least one additional priority resource concern by the end of the contract term (USDA-CCC, 2020). NRCS designates the priority resource concerns addressed by CSP contracts at a state or regional level, such as improving water quality, reducing soil erosion, and providing wildlife habitat. The Agriculture Improvement Act of 2018 also established provisions to support historically underserved individuals, defined as beginning, socially disadvantaged, veteran, and limited resources farmers and ranchers (USDA-NRCS, 2024b). Given the cost-share nature of EQIP and CSP, payments are based on a percentage of estimated adoption costs with priority goals or historically underserved farmer status, potentially increasing the covered cost.

Much of the cover crop adoption literature has used survey data at the farm level, generally obtained in one year for one state (Fleming, 2017; Fleming et al., 2018; Thompson et al., 2021). Analyses on drivers of conservation adoption have found that education, vulnerable land measures, and perceiving a positive influence on yield are positively associated with adoption, while age generally negatively correlates (Prokopy et al., 2019). Few studies have utilized large spatial datasets to understand cover crop adoption trends. The 2022-2023 National Cover Crop Survey found that 90% of the respondents who received payments for cover crops in 2022 indicated they plan to continue using them after their payments end (SARE, 2023). However, there could be selection bias, with longtime cover crop users more likely to respond to the survey. Lee and McCann (2019) employed the 2012 ARMS Soybean survey to obtain a nationally representative sample of U.S. soybean growers. They found that cover crop adoption positively correlates with the number of hired laborers and field crops planted, practicing no-till or conservation tillage, receiving NRCS payments, using renewable energy, and county-level precipitation.

While EQIP and CSP address pressing goals related to improving the management of natural resources and environmental conditions, it is crucial to evaluate the effectiveness of their efforts. Park et al. (2023) obtained total EQIP and CSP payments at the county-level as an aggregate of payments for all conservation practices. They divided these totals by all cropland acreage in the county to calculate a proxy for per-acre cover crop payments. Their results suggest that EQIP payments have a positive impact on cover crop adoption while CSP payments have a negative impact. This finding could be due to the use of aggregate EQIP and CSP data and using all cropland as a basis for per-acre enrollment payments rather than actual contracted acreage. This highlights the difficulty in capturing adoption behavior given data availability and the cost-share structure of the programs.

For our analysis, we have NRCS data that includes cover crop practice-specific per-acre payments and acreage. With this information, we can better capture cover crop specific enrollment behavior instead of conservation practice enrollment as a whole. Additionally, we can measure the determinants of per-acre payments, parse out the impact of the cost-share rate versus the estimated cost of adopting cover crops, and understand the dynamics of total county cover crop acreage.

3.3. Behavioral Model

We model the cover crop adoption decision as a utility maximization problem over farm-level profit. $U(C, E)$ is the utility function of the agricultural producer, C denotes the consumption bundle of market goods, $E(\cdot)$ denotes non-market ecosystem services, and F denotes heterogeneous farm and farmer characteristics. We assume concavity and separability in C and E: $\partial U/\partial C > 0$, $\partial U/\partial E > 0$, $\partial^2 U/\partial C^2 < 0$, and $\partial^2 U/\partial E^2 < 0$. The non-market ecosystem services are non-decreasing in the amount of land devoted to cover crops enrolled in a cost-share program, α, such that $E'(\alpha) \geq 0$. Within the budget constraint, π denotes the on-farm profits, while $\bar{N}$ denotes the exogenous constant of off-farm income.

$$\max_{C,\alpha} U(C, E(\alpha)|F)$$
$$s.t. C \leq \pi + \bar{N}$$

Field-level profit depends on the revenue from selling the produced agricultural goods, $Y(X, \alpha, \omega)$, as a function of field inputs X, such as water, crop seed, and pesticides, as well as potential effects from enrolling cover crop acreage, α, in a cost-share program, and nonmarket inputs, ω, such as weather conditions. We assume concavity in X: $\partial Y/\partial X > 0$, $\partial^2 Y/\partial X^2 < 0$. The total acreage of the field dedicated to cash crop production is denoted by A. The exogenous agricultural goods output price is defined as p_Y. For adopting cover crops, the farmer may receive a per-acre payment, δ, for α acres of cover crops enrolled. First, we consider field-level decisions regarding allocating acres to cover crops and input levels. Cover crop adoption also incurs variable costs for the inputs used in managing this conservation land, X_α, at prices p_{X_α}.

Given that the payment provided for cover crop adoption is from a cost-share program, we have that $\delta < p_{X_\alpha} X_\alpha$. Field-level variable costs unrelated to cover crops come from inputs, $X_{-\alpha}$, purchased for $p_{X_{-\alpha}}$ for crop production of A total acres. Therefore, the on-farm field-level profit function, π_n, is the sum of crop revenue net of variable costs from output $(p_Y Y_n(X_n, \alpha_n) - p_{X_{-\alpha}} X_{n.-\alpha})$ for A_n acres of the field during the regular growing season and the net revenue from managing conservation land $(\delta_n - p_{X_\alpha} X_{n,\alpha})$ for the enrolled cover crop acreage, α_n, minus fixed farming costs (θ_n). Rewriting farm profits as a sum of N field-level profits within the farmer's utility maximization problem yields:

$$\max_{C,\alpha} U(C, E(\alpha)|F) \tag{1}$$
$$s.t. C \leq \pi + \bar{N}$$
$$s.t. \pi = \sum_{n=1}^{N} \pi_n = \{A_n[p_Y Y_n(X_n, \alpha_n, \omega) - p_{X_{-\alpha}} X_{n.-\alpha}] + \alpha_n[\delta_n - p_{X_\alpha} X_{n,\alpha}] - [\theta_n]\}$$
$$= A[p_Y Y(X, \alpha, \omega) - p_{X_{-\alpha}} X_{-\alpha}] + \alpha[\delta - p_{X_\alpha} X_\alpha] - [\theta]$$

By deriving the first-order condition of the Lagrangian representing the utility maximization problem with respect to C, we find that the marginal utility from an additional unit of consumption is equal to the shadow price of relaxing the consumption bundle constraint shown by Eq. (2).

$$\frac{\partial \mathcal{L}}{\partial C} = \frac{\partial U(C, E(\alpha)|F)}{\partial C} - \lambda = 0$$

$$\therefore \; \frac{\partial U(C, E(\alpha)|F)}{\partial C} = \lambda \tag{2}$$

Similarly, at the privately-optimal choice of α, we find that the marginal utility from an additional acre of cover crops is equal to the marginal utility from an additional unit of consumption multiplied by the marginal profit related to cover crop acres.

$$\frac{\partial \mathcal{L}}{\partial \alpha} = \frac{\partial U(C, E(\alpha)|F)}{\partial \alpha} - \lambda[-Ap_Y \frac{\partial Y(X, \alpha, \omega)}{\partial \alpha} - \delta + p_{X_\alpha} X_\alpha] = 0$$

$$\therefore \frac{\partial U(C, E(\alpha)|F)}{\partial C} \frac{\partial C}{\partial \alpha} + \frac{\partial U(C, E(\alpha)|F)}{\partial E(\alpha)} \frac{\partial E(\alpha)}{\partial \alpha} = \frac{\partial U(C, E(\alpha)|F)}{\partial C} [-Ap_Y \frac{\partial Y(X, \alpha, \omega)}{\partial \alpha} - \delta + p_{X_\alpha} X_\alpha] \tag{3}$$

Combining both first-order conditions in Eq. (3) allows us to understand the dynamics of the optimization problem. The producer may value environmental quality and derive utility from nonmarket ecosystem services generated by cover crops that solely provide public benefits. If we normalize prices so that $\frac{\partial U(\cdot)}{\partial C} = 1$ and given that $\frac{\partial C}{\partial \alpha} = 0$, we have:

$$\underbrace{\frac{\partial U(C, E(\alpha)|F)}{\partial E(\alpha)} \frac{\partial E(\alpha)}{\partial \alpha}}_{\substack{marginal\ utility\ of\ ecosystem \\ services\ from\ cover\ crop\ acres}} + \underbrace{Ap_Y \frac{\partial Y(X, \alpha, \omega)}{\partial \alpha}}_{\substack{marginal\ value\ product\ of \\ cover\ crop\ acres}} = \underbrace{p_{X_\alpha} X_\alpha - \delta}_{\substack{net\ cost\ of\ adopting \\ cover\ crop\ acres}} \tag{4}$$

Eq. (4) demonstrates that the optimal level of enrolled cover crop acreage, α, is such that the marginal utility of ecosystem services and the marginal value product from cover crop acreage must equal the remaining cost of cover crop acreage incurred by the producer. As the marginal physical product of enrolled cover crop acreage, $\frac{\partial Y(X,\alpha,\omega)}{\partial \alpha}$, increases, the more cover crop acreage the producer is willing to adopt. The larger the magnitude of $\frac{\partial U(C,E(\alpha)|F)}{\partial E(\alpha)} \frac{\partial E(\alpha)}{\partial \alpha} > 0$, the lower the necessary subsidy rate or cost-share proportion to induce adoption. Additionally, the higher the per-acre payment, δ, the more the producer is willing to adopt and enroll cover crop acreage. Conversely, higher adoption costs for cover crops will decrease the adopted acreage. Our analysis focuses on how the per-acre payment, δ, impacts adoption.

However, the issue with identifying how the per-acre payment, δ, impacts enrolled acres is that with cost-share programs like EQIP and CSP, δ depends on the cost of adoption, as shown by Eq. (5):

$$\delta = (\sigma + \tau)p_{X_\alpha}X_\alpha. \tag{5}$$

The per-acre payment, δ, is based on a proportion of the cover crop adoption costs with $\sigma \leq 0.75$ in the baseline case. Under certain circumstances, such as a farm in a priority watershed or a farmer of a historically underserved group, there can be a higher payment rate with the addition of τ with $\sigma + \tau \leq 0.90$. The cost-share proportion provides a subsidy to pay a portion of the adoption cost of the practice, given that there are public benefits to address natural resource concerns that are not fully captured in the producer maximization problem. The key is to understand the impact of the proportion of σ and τ separate from the cost effects. Combining Eq. (4) and Eq. (5) into Eq. (6) highlights the importance of disentangling the cost-share proportion from the adoption costs.

$$\underbrace{\frac{\partial U(C,E(\alpha)|F)}{\partial E(\alpha)}\frac{\partial E(\alpha)}{\partial \alpha}}_{\substack{marginal\ utility\ of\ ecosystem \\ services\ from\ cover\ crop\ acres}} + \underbrace{Ap_Y\frac{\partial Y(X,\alpha,\omega)}{\partial \alpha}}_{\substack{marginal\ value\ product\ of \\ cover\ crop\ acres}} = \underbrace{(1-\sigma-\tau)p_{X_\alpha}X_\alpha}_{\substack{net\ cost\ of\ adopting \\ cover\ crop\ acres}} \tag{6}$$

If one were to model enrolled cover crop acres as a function of the cost-share payments, one could find a negative relationship (Park et al., 2023). This is because the cost-share payment is a function of cost, and the more something costs, the lower the willingness to adopt. While we do not have farm- or field-level data, we can use this behavioral model as a basis for our econometric methods. We assume that our county-level data aggregates this individual utility maximization problem.

3.4. Data

To understand drivers of cover crop adoption over time and across space, we analyze cover crop acreage and payment data from 2008 to 2023. In particular, we acquire NRCS data for cover crop contracts following corn or soybean production for the 12 Midwestern states[7] at the county-level from 2008 to 2023, obtained by a Freedom of Information Act (FOIA) request with USDA's Farm Production and Conservation Business Center. The Farm Production and Conservation Business Center processes FOIA requests for the USDA Farm Service Agency, NRCS, and Risk Management Agency. At the county level for a given year, we have component-level observations broken up by component names that specify key contract characteristics. The component names provide information on the cover crop species and termination method.

For our study, we focus on the three main practice types: a basic contract that contains a single species cover crop that is chemically or mechanically terminated, a winter-kill contract that contains a single species that is terminated by frost conditions, and a multiple species contract that is chemically or mechanically terminated. The component name can also specify a priority initiative program, such as a water quality initiative, or indicate a historically underserved contract recipient. Historically underserved farmers are defined as beginning, socially disadvantaged, veteran, and limited resources farmers and ranchers (USDA-NRCS, 2024b). We code the relevant binary variables that constitute our contract types by identifying unique component names within the data. Table 3.1 provides the definitions of our binary variables and their totals.

Table 3.1: Data Description and Totals for Binary Variables from NRCS Cover Crop County-Level Data (from 2008-2023, n=4,177)

Variable	Variable Description	Total	Mean	SD
Basic	Basic practice type indicator (baseline)	2,363	0.57	0.50
WK	Basic winter-kill practice type indicator	637	0.15	0.36
Multi	Multispecies practice type indicator	1,177	0.28	0.45
Init	Priority initiative area indicator	156	0.04	0.19
HU	Historically underserved farmer indicator	422	0.10	0.30

[7] The 12 Midwestern states include Illinois, Indiana, Iowa, Kansas, Michigan, Minnesota, Missouri, Nebraska, North Dakota, Ohio, South Dakota, and Wisconsin.

With the three primary practice types, priority initiative status, and historically underserved status, we have twelve possible contract types within a county for a given year.[8] We have an unbalanced panel because each county can have a different number of contract types in a given year. Each county has at least one contract type for a given year, with a maximum of seven contract types. While the county-level data provides more spatially disaggregated measures of program participation than a state-level dataset, counties with four or fewer contracts for a given component-year combination are omitted due to privacy concerns.[9] The county-level dataset consists of 4,177 contract type-county-year observations with 615 unique counties across the 16 years.

Each state publishes the estimated adoption costs and contract payments for NRCS practice scenarios (USDA-NRCS, 2024d). The scenario documents contain the estimated costs for adopting the different cover crop practice types along with other practice scenarios. Each state also provides the payment amount for the approved NRCS conservation practices within a separate document, with payments divided into baseline levels and levels for historically underserved and priority initiative statuses. While some states also publish the corresponding cost-share proportion, cost-share proportions can be calculated using the estimated costs and payment information. The published state estimated costs and payment levels provide an upper bound for potential adopters to reference. Our data provides the actual total payment amount and cover crop acreage provided by the NRCS for each contract type in a county in a given year. With this information, we can calculate the per-acre payments. To decompose the per-acre payments into the cost-share proportion and per-acre adoption cost, we divide the per-acre payments by the state-level cost-share to compute the per-acre adoption cost. Table 3.2 presents data descriptions for our continuous variables.

[8] Tables A3.1 and A3.2 in the Appendix provide summaries of the attributes and totals for the contract types.

[9] Figure A3.1 provides the distribution of the shares of total cover crop acreage represented in the county-level data out of the total in the state-level data for the corresponding state and year combination.

Table 3.2: Variable Descriptions for Continuous Variables from NRCS Cover Crop County-Level Data (from 2008-2023, n=4,177)

Variable	Variable Description
δ_{jit}	Per-acre payment ($) for contract type *j*, county *i*, time *t*
α_{jit}	Cover crop acreage for contract type *j*, county *i*, time *t*
$(\sigma + \tau)_{ji}$	State-level cost-share percentage contract type *j*, county *i*
$(p_{X_\alpha} X_\alpha)_{jit}$	Per-acre cost ($) for contract type *j*, county *i*, time *t*

Cost-share proportions are defined at the state-level, but cover crop acreage, payments, and costs depend on the three dimensions of contract type, county, and year. For our analysis, we multiplied the cost-share proportion by 100 so that a 1-unit change in the cost-share variable is equivalent to a one percentage point increase. Table 3.3 provides a summary of the state-level cost-share proportions. Most states employ a 75% cost-share percentage as a baseline and provide a 15-percentage point boost for historically underserved farmer and priority initiative contracts.

Table 3.3: NRCS State-Level Cost-Share Proportions

Cost-share	IL	IN	IA	KS	MI	MN	MO	NE	ND	OH	SD	WI
σ_{ji}	0.75	0.75	0.50	0.75	0.75	0.40	0.75	0.50	0.75	0.75	0.75	0.75
τ_{ji}	0.15	0.15	0.25	0.15	0.15	0.25	0.15	0.25	0.15	0.15	0.15	0.15

Table 3.4 provides summary statistics for the NRCS cover crop contract continuous variables by contract type.

Table 3.4: Summary Statistics for NRCS Cover Crop Contract Data by Contract Type, County, and Year (from 2008-2023, n=4,177)

	Per-acre payment ($) δ_{jit}		Enrolled cover crop acres α_{jit}		State-level cost-share (%) $(\sigma + \tau)_{ji}$		Per-acre adoption cost ($) $(p_{X_\alpha} X_\alpha)_{jit}$	
Contract Type	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**
Basic (n=2,040)	38.73	21.85	1,908.00	2,123.95	65.22	12.87	62.08	41.91
Basic, HU (n=224)	57.97	11.65	699.07	554.04	82.05	7.80	70.67	12.46
Basic, Init (n=90)	51.38	17.14	775.02	823.10	73.67	6.74	71.77	28.53
Basic, HU, Init (n=9)	63.96	48.74	587.62	201.20	75.00	0.00	85.27	15.34
WK (n=556)	31.71	10.65	1,947.07	2,140.96	68.91	11.06	45.79	14.28
WK, HU (n=65)	43.12	9.51	727.26	532.15	86.77	6.21	49.51	9.78
WK, Init (n=15)	39.85	5.60	658.08	307.97	75.00	0.00	53.13	7.47
WK, HU, Init (n=1)	35.98	---	468.20	---	75.00	---	47.97	---
Multi (n=1,015)	37.33	15.36	1,539.69	2,020.96	61.79	13.84	62.19	33.07
Multi, HU (n=121)	60.54	14.05	694.51	642.38	77.93	8.43	78.88	19.99
Multi, Init (n=39)	58.91	12.81	911.47	620.54	75.77	3.35	77.97	17.62
Multi, HU, Init (n=2)	72.49	14.02	694.85	320.25	75.00	0.00	96.65	18.70
Overall	39.72	19.42	1,663.37	2,004.37	67.83	13.53	61.81	35.37

In addition to the NRCS cover crop data that provides contract information, we define weather variables using the Parameter Regression Independent Slopes Model (PRISM) Climate Group measures. Weather can vary by county in a given year and may impact cover crop adoption decisions. Farmers may adopt cover crops to mitigate yield losses due to extreme weather, such as drought, extreme heat, and floods. By adopting cover crops, they could benefit from soil moisture retention as well as reductions in soil erosion and nutrient loss. Therefore, the included weather variables are the number of growing degree days and precipitation (in millimeters). We use the temperature averaging method to calculate growing degree days with a base of 50°F (Battel, 2017). We collect and aggregate the weather measures for the year from the growing season months of May to September. Table 3.5 provides the PRISM weather variable descriptions and summary statistics.

Table 3.5: Variable Descriptions and Summary Statistics for PRISM Variables from May to September (county, year data from 2007-2022 with n=4,177)

Variable	Variable Description	Mean	SD
GDD_{it-1}	Growing degree days for county *i,* growing season *t-1*	1,594.60	188.94
$Precip_{it-1}$	Total precipitation (mm) for county *i,* growing season *t-1*	544.09	148.28

Lastly, we want to test how total cover crop acres in a county for a given year relate to enrolled cover crop acreage and conservation tillage practices. To do so, we combine the NRCS program data with remote sensing data on conservation practices on agricultural land. The Conservation Technology Information Center partnered with Regrow and The Nature Conservancy to create the Operational Tillage Information System (OpTIS) using remote sensing data to provide total cover crop acreage data from 2015 to 2021. While the OpTIS satellite-based computations are performed at the field-level, the dataset provides aggregate soybean and corn acres and the related cover crop and tillage acreage at the county-level to protect privacy. The OpTIS data contain information for 1,045 counties over the seven years for the twelve Midwestern states included in our analysis. When merging these data, we aggregate the NRCS data across contract types to the county-level since we are interested in the dynamics of changes in acreage at the county-level as opposed to the component-level. Once the OpTIS and NRCS data are combined, the resulting dataset contains 520 counties and 2,051 county-year observations. Table 3.6 provides variable descriptions and summary statistics for the variables of interest in the combined NRCS and OpTIS datasets.

Table 3.6: Variable Descriptions and Summary Statistics for Continuous Variables (county, year data from 20015-2021 with n=2,051)

Variable	Variable Description	Mean	SD
φ_{it}	Total cover crop acreage for county *i*, time *t*	10,337.11	9,650.09
α_{it-1}	Enrolled cover crop acreage for county *i*, time *t-1*	1,548.79	1,962.74
$(p_{X_\alpha}X_\alpha)_{it-1}$	Per-acre cost ($) for county *i*, time *t-1*	66.59	24.34
$RdcTil_{it}$	Total reduced-tillage acreage for county *i*, time *t*	102,394.40	68,463.13
$NoTil_{it}$	Total no-tillage acreage for county *i*, time *t*	50,098.33	37,335.57

3.5. Estimation Methods

Based on our behavioral model, we know that cover crop contract payments are a driver of adoption. We first model payments as a function of contract attributes to understand what drives the differences in contract payments. Our dependent variable, δ_{jit}, in Eq. (7) is per acre cover crop contract payments for contract specification *j*, in county i at time t. We have a vector of binary variables, $\boldsymbol{Z}_{jit}$, that defines the twelve contract types with three primary practice types, the priority initiative, and historically underserved specifications, as in Table 3.1. We also control for county, c_i, and time, γ_t, fixed effects. With fixed effects, our identifying variation comes from the time variation within a county. The county fixed effect controls for time-constant unobservable heterogeneity across the counties, while the time fixed effects control for unobserved factors that impact all counties. We assume that the explanatory variables related to the contract types are strictly exogenous conditional on county fixed effects, c_i. However, we need not assume that c_i is independent of the explanatory variables. Theoretically, we assume the idiosyncratic errors, ε_{jit}, have a constant variance across time and are serially uncorrelated (Wooldridge, 2010).

$$\delta_{jit} = \beta_0 + \boldsymbol{\beta Z}_{jit} + c_i + \gamma_t + \varepsilon_{jit} \tag{7}$$

Based on Eq. (5), we know that per-acre cover crop contract payments can be partitioned into the state-level cost-share proportion and the adoption costs. We want to measure how the percentage level covered by the cost-share programs impacts cover crop adoption. Therefore, for Eq. (8), our dependent variable is cover crop acres enrolled in contracts, α_{jit}. We decompose the average contract per-acre payment for contract type *j* in county *i* at time *t*, δ_{jit}, into the cost-share proportion, $(\sigma + \tau)_{ji}$,, and the per-acre adoption costs, $(p_{X_\alpha}X_\alpha)_{jit}$. Given the correlation between the per-acre payment and cost, this separation allows us to overcome the identification issue.

Lastly, to understand how weather conditions from the previous cash crop growing season impact cover crop adoption, we include a vector of weather variables, $\boldsymbol{W}_{it-1}$. The weather variables in Eq. (8) include growing degree days (GDD), precipitation (Precip), and precipitation squared (Precip_sq). Given the benefits of reductions in soil erosion and nutrient loss, we anticipate a positive relationship between precipitation and cover crop acreage. This relates to $E(\cdot)$ of our behavioral model, which defines the non-market ecosystem services from cover cropping. The larger the magnitude of the perceived marginal change in non-market ecosystem services from cover crop acres, the lower the necessary cost-share proportion to induce adoption, as shown in Eq. (3).

Eq. (8) controls for county, c_i, and time, γ_t, fixed effects. We assume strict exogeneity of the cost-share percentage, per-acre costs, contract-type binary variables, and weather variables conditional on the fixed effects. For this specification, we define the idiosyncratic errors as μ_{jit}, and make the theoretical assumption that they have a constant variance across time and are serially uncorrelated.

$$\alpha_{jit} = \beta_0 + \beta_1(\sigma + \tau)_{ji} + \beta_2(p_{X_\alpha}X_\alpha)_{jit} + \boldsymbol{\beta Z}_{jit} + \boldsymbol{\beta W}_{it-1} + c_i + \gamma_t + \mu_{jit} \tag{8}$$

Our primary coefficients of interest are β_1 and β_2. We expect β_1 to be positive since this coefficient measures the relationship between the percentage covered by the cost-share program and the adopted cover crop acres. Given that the purpose of the EQIP and CSP cost-share programs is to encourage the adoption of conservation practices by covering a portion of the costs, β_1 measures how a one percentage point increase in the percentage of costs covered by the NRCS translates to adopted cover crop acreage. In contrast, we expect β_2 to be negative, as this captures how a \$1 increase in the per-acre cost impacts enrolled cover crop acreage. Eq. (6) of the behavioral model captures these relationships.

Our dependent variables of per-acre payments and enrolled cover crop acreage in Eq. (7) and (8) are censored, given that we are missing observations for counties with four or fewer contracts for a given component-year combination due to privacy concerns. Therefore, we implement the Heckman correction method to test and correct for potential selection bias (Wooldridge, 2010). We expanded the data to include all possible county-year-component combinations and generated a binary variable, O_{jit}, for the observations included in the NRCS equation. Our selection equation, defined by Eq. (9), includes the vector of binary variables, $\boldsymbol{Z}_{jit}$, that defines the twelve contract types with three primary practice types, the priority initiative, and historically underserved specifications, as in Table 3.1. We have a vector of unknown parameters, $\boldsymbol{U}_{jit}$, and Φ is the cumulative distribution function of the standard normal distribution. The second stage equations follow Eq. (7) and (8).

$$P\left(O_{jit} = 1 \middle| \boldsymbol{Z}_{jit}\right) = \Phi(\boldsymbol{Z}_{jit}\boldsymbol{U}_{jit}) \tag{9}$$

Finally, we want to test the impact of enrolled cover crop and conservation tillage acreage on total cover crop acres in county i for time t, φ_{it}, with Eq. (10). Findings from SARE's 2022-2023 National Cover Crop Survey suggest that participants previously enrolled in an NRCS cost-share program will continue to practice cover cropping after their contract period ends. Previous experience with cover cropping can allow program participants to learn the practice and recognize the benefits to their operation. In addition to the learning effect, there could be a peer effect with adopters encouraging their neighbors to adopt. Thus, we include the lag of enrolled cover crop acres, α_{it-1}, and adoption costs, $\left(p_{X_\alpha} X_\alpha\right)_{it-1}$. Based on the potential learning and peer effects, we predict a positive relationship between previously enrolled cover crop acres and total cover crop acres captured by β_1. Additionally, cover crop adopters could implement a suite of conservation practices, so there could be a positive relationship between cover crop acres and other conservation practices. Therefore, we include acres enrolled in conservation tillage practices, $\mathbf{\Gamma}_{it}$, and lagged conservation acres, $\mathbf{\Gamma}_{it-1,}$to control for potential complementarity and are interested in the sign of $\boldsymbol{\beta}$. As before, we control for county, c_i, and time, γ_t, fixed effects and have idiosyncratic errors, ξ_{it}.

$$\varphi_{it} = \beta_0 + \beta_1\alpha_{it-1} + \beta_2\left(p_{X_\alpha}X_\alpha\right)_{it-1} + \boldsymbol{\beta}\mathbf{\Gamma}_{it} + \boldsymbol{\beta}\mathbf{\Gamma}_{it-1} + c_i + \gamma_t + \xi_{it} \quad (10)$$

3.6. Results

Table 3.7 provides results for measuring how the contract characteristics affect per-acre payments. Results for alternative specifications for Eq. (7) are provided in Tables A3.5 and A3.8 to test for robustness. The first column provides results for the specification without the county and time fixed effects, the second column with county fixed effects, and the third column is our preferred specification with both county and time fixed effects (Eq. 7). The inverse Mills ratio of Model 4 is insignificant, meaning that we fail to reject the null hypothesis of that the errors are uncorrelated. With the inclusion of fixed effects, it is difficult to interpret the coefficient given that its value is relative to the omitted county and year with each included county and year having a binary variable and corresponding coefficient. Therefore, it is helpful to first examine Model 1 of Table 3.7. The results for Model 1 indicate that the basic contract has an average associated per-acre payment of $38.68, and there is an average price discount associated with winter-kill contracts of $7.92.

Table 3.7: Regression Results for Determinants of NRCS Per-Acre Payments for Enrolled Cover Crop Acres for Contract Types in a County (n=4,177)

Binary Variables ($/acre)	**(1)**	**(2)**	**Preferred (3)**	**(4)**
Constant	38.683*** (0.700)	37.243*** (0.417)	20.651*** (1.830)	27.160* (14.896)
Winter-kill	-7.917*** (1.009)	-5.769*** (1.323)	-4.996*** (1.300)	-5.990** (2.696)
Multi-Species	-0.656 (0.956)	5.212*** (0.936)	5.475*** (0.851)	4.938*** (1.512)
Priority Initiative	13.895*** (2.069)	8.064*** (2.149)	6.981*** (1.943)	4.910 (5.517)
Historically Underserved	18.918*** (0.870)	15.715*** (0. 790)	17.030*** (0. 687)	15.507*** (4.020)
Inverse Mills Ratio	---	---	---	1.477 (3.832)
County FE	No	Yes	Yes	Yes
Time FE	No	No	Yes	Yes
R-squared	0.125	0.123	0.250	---

Note: Standard errors in parentheses, p-values * p < 0.10, ** p < 0.05, *** p < 0.01. This table reports coefficients from models following Eq. (7) estimating the relationship between per-acre NRCS payments and contract types. Winter-kill is an indicator equal to one when a contract is for a winter-kill cover crop species. Multi-Species is equal to one for a multi-species cover crop, Priority Initiative is equal to one when the farm is located in a priority initiative area such as water quality priority initiatives, and Historically Underserved is equal to one for a farmer who is part of a historically underserved group. The Inverse Mills ratio represents the expected value of the error in the enrolled cover crop acreage conditional on contracts included in the NRCS data.

For reference, Table A3.3 of the Appendix shows that the average per-acre adoption costs for basic, winter-kill, and multispecies contracts for 2024 across the 12 states are $82.30, $56.04, and $102.92, respectively. Additionally, Table 3.4 indicates that the average state-level cost-share for basic, winter-kill, and multispecies contracts without historically underserved or initiative statuses are 65.22%, 68.91%, and 61.79%, respectively. We can then apply these average cost-share levels to the average published state-level costs for basic, winter-kill, and multispecies contracts for 2024 to find the average per-acre payments for basic, winter-kill, and multispecies contracts of $53.68, $38.62, and $63.59, respectively. Therefore, the results for Model 1 of Table 3.7 suggest that farmers who receive contracts are reporting lower costs and are willing to accept lower payments.

The average per-acre price premiums for priority initiatives and historically underserved statuses found in Model 1 are $13.90 and $18.92, respectively. These indicate that compared to a basic contract without these statuses, priority initiatives and historically underserved basic contracts receive average per-acre payments that are 36% and 48% higher than the baseline of $38.68. While we would expect price premiums given the higher cost-share levels associated with these statuses, the price premiums from the regression results of Model 1 have different magnitudes than expected. The average cost-share level for basic contracts without historically underserved and priority initiative statuses is 65.22%, while the average is 73.78% and 81.78% for priority initiatives and historically underserved statuses, respectively. With the average per-acre adoption cost for basic contracts of $82.30, we would expect the price premiums to be around $7.04 ($60.72-$53.68) and $13.62 ($67.30-$53.68) for priority initiatives and historically underserved statuses, respectively. These calculations are further explained in Table A3.3 of the Appendix.

Once fixed effects are included, the average price discount in per-acre payments for associated with winter-kill contracts decreases, and we see a significant price premium associated with multispecies contracts. When controlling for county and time fixed effects, Model 3 results reveal that there is a per-acre price discount of approximately $5.00 for winter-kill contracts and a price premium of $5.48 for multispecies, on average. Looking at the calculated average per-acre payments using average costs and cost-share levels, there is an average per-acre price discount for winter-kill contracts of $15.06 ($53.68-$38.62) and a price premium for multispecies contracts of $9.91 ($63.59-$53.68). Please see Table A3.3 of the Appendix for more details. These marginal price differences are higher than the average per-acre price discount of approximately $5.00 for winter-kill contracts and a price premium of $5.48 for multispecies shown by Model 3 results. The regression results suggest that winter-kill contracts receive a lower price discount than expected while multispecies contracts receive a lower price premium than expected. This indicates that when factoring in county and time fixed effects, the differences in per-acre payments for each practice type is lower than the differences shown in the published data. Farmers receiving winter-kill multispecies contracts are reporting per-acre adoption costs closer to the adoption costs of basic contracts.

Model 3 results show that priority initiative contracts receive an average associated per-acre payment premium of $7 per acre, while a historically underserved contract recipient receives an average associated per-acre payment premium of $17 per acre. The values are closer in magnitude with the expected average per-acre payment premiums of $7.04 ($60.72-$53.68) and $13.62 ($67.30-$53.68) for priority initiatives and historically underserved statuses, respectively, based average per-acre adoption cost for basic contracts and average cost-share levels. Please see Table A3.3 of the Appendix for more details. While each state provides the same cost-share level for priority initiative and historically underserved contract statues, we find a difference in the per-acre payment premiums. This is due to the distribution of contract types across states as shown in Table A3.2.

Table 3.8 provides results for the various model specifications related to cover crop contract acreage, with the last column displaying results for the full specification of Eq. (8). Model 1 results have an insignificant constant value that cannot be distinguished zero. While we see negative values associated with multispecies, and priority initiative, and historically underserved contracts, we cannot assume a state cost-share level of zero. On average multispecies, and priority initiative, and historically underserved contracts have cost-share levels of 63.94%, 73.79%, and 81.40%. The negative marginal change in enrolled cover crop acres associated with multispecies, and priority initiative, and historically underserved contracts of 225, 1,152, and 1,492, respectively, need to be put in the context of their average cost-share levels given a that a one percentage point increase in the cost-share program increases contracted cover crops by 26 acres on average.

Table 3.8: Results for Determinants of Total Enrolled Cover Crop Acreage for Contract Types in a County (n=4,177)

Variables	(1)	(2)	(3)	(4)	Preferred (5)
Constant	266.250 (315.040)	-3,911.527** (1,890.636)	-5,522.335*** (2,013.272)	-8,174.724*** (2,387.067)	-16,842.850*** (2,932.383)
State Cost-Share (%)	26.060*** (26.060)	93.329*** (29.559)	91.548*** (31.380)	91.952*** (31.419)	103.666*** (13.912)
Per-Acre Cost ($)	-1.202 (1.153)	-1.867* (1.020)	0.921 (1.112)	1.108 (1.122)	1.109 (1.006)
Winter-kill	-84.380 (145.892)	-276.569** (134.359)	-573.018*** (131.386)	-577.229*** (130.848)	-1,549.086*** (359.793)
Multi-Species	-225.211** (92.657)	-223.618** (90.628)	-268.254*** (86.655)	-271.362*** (86.804)	-799.592*** (202.406)
Priority Initiative	-1,151.872*** (165.455)	-2,735.100*** (801.844)	-2,169.674** (835.920)	-2,186.257*** (833.065)	-4,475.078*** (865.562)
Historically Underserved	-1,492.414*** (142.612)	-3,358.568*** (680.330)	-3,518.477*** (727.684)	-3,532.203*** (727.962)	-5,257.534*** (663.033)
Growing Degree Days t-1	---	---	---	1.114 (0.747)	1.177 (0.818)
Precipitation t-1 (mm)	---	---	---	3.174*** (0.953)	3.285*** (1.137)
Precipitation Squared t-1 (mm)	---	---	---	-0.003*** (0.001)	0.003*** (0.001)
Inverse Mills Ratio	---	---	---	---	1,449.39*** (509.299)
County FE	No	Yes	Yes	Yes	Yes
Time FE	No	No	Yes	Yes	Yes
R-squared	0.068	0.082	0.145	0.148	---

Note: Standard errors in parentheses, p-values * p < 0.10, ** p < 0.05, *** p < 0.01. This table reports coefficients from models following Eq. (8). State Cost-Share is the percentage of the adoption cost covered by the program, while the Per-Acre Cost is the calculated adoption cost based on Eq. (5). Winter-kill is an indicator equal to one when a contract is for a winter-kill cover crop species. Multi-Species is equal to one for a multi-species cover crop, Priority Initiative is equal to one when the farm is located in a priority initiative area, and Historically Underserved is equal to one for a farmer who is part of a historically underserved group. The PRISM weather variables include Growing Degree Days, and total Precipitation and Precipitation Squared in millimeters for the previous growing season. The Inverse Mills ratio represents the expected value of the error in the enrolled cover crop acreage conditional on contracts included in the NRCS data.

The inverse Mills ratio of Model 5 is significant, meaning that we reject the null hypothesis of that the errors are uncorrelated. We have evidence of selection bias that is impacting our regression results for Eq. (8). Therefore, Model 5 is our preferred specification as it corrects for selection bias. Focusing on the Model 5 results of Table 3.8[10], we find that a one percentage point increase in the percentage of cost covered by the cost-share program increases contracted cover crop acreage by approximately 104 acres on average across the contract types within each county for a given year. We do not find a significant relationship between cost and adopted acres. While we expected a negative relationship between adoption cost and enrolled cover crop acres in a county, the practice type binary indicators could be absorbing this relationship, given that costs vary by practice type.

When interpreting the results for Model 5, we are considering county and time fixed effects as well as a correction for selection bias. Additionally, we cannot assume that the state cost-share level equals zero. We use the basic single species contract as our baseline for the practice types. Compared to the basic contracts, the winter-kill contracts have an average of 1,549 fewer acres across the contract types within each county for a given year. The results also highlight that the multiple species contracts have an average of almost 800 fewer acres than the basic contracts. If the contract has a priority initiative or historically underserved status, there is on average, 4,475 and 5,258 fewer contracted cover crop acres, respectively. However, these numbers do not account for the average state cost shares.

The average cost-share level for contracts without initiative and historically underserved status is 64.82%, while the average is 74.42% and 81.40% for priority initiative and historically underserved statuses, respectively, as shown in Table A3.3. This equates to a 9.60 and 16.58 percentage point difference. Given that a one percentage point increase in the cost-share percentage increases contracted cover crop acreage by about 104 acres on average, these percentage point differences result in approximately 998 and 1,724 additional acres on average for the cost-share

[10] Table A3.6 shows results for alternative specifications of Eq. (8).

percentage differences associated with priority initiative and historically underserved statuses, respectively. These marginal increases in contracted acres due to higher cost-share levels do not fully offset the decrease in contracted acres associated with priority initiative and historically underserved statuses.

We can then combine the coefficient results from the priority initiative and historically underserved status indicators with the difference in acreage due to the higher cost-share percentage. When accounting for the difference in the cost-shares as well as fixed effects and selection bias, a contract awarded a priority initiative or historically underserved statuses contains, on average, 3,477 and 4,033 fewer contracted cover crop acres, respectively. Historically underserved farmers tend to operate smaller farms with Hispanic farmers operating an average of 264 acres, non-Hispanic socially disadvantaged farmers operating an average of 324 acres, and limited resource farmers operating an average of 186 acres compared to Caucasian farmers who operate an average of 419 acres (Todd et al., 2024). Additionally, priority initiatives, such as the National Water Quality Network, are restricted geographically (Lee, 2023).

We do not find a significant relationship between growing degree days from the previous growing season and cover crop contract acres. Producers use growing degree days to predict plant and pest development for management decisions, but this measure is not correlated with cover crop contract acreage decisions. For an increase in total precipitation from the previous growing season, we find cover crop contract acreage to increase at a decreasing rate up to a point before it begins to decrease. Cover crop contract acreage positively correlates with total precipitation until total precipitation during May and September reaches approximately 547.5mm. After that point, increases in total precipitation are associated with decreases in cover crop contract acreage. Given that the average total precipitation is 544mm and the standard deviation is 148mm, cover crop adoption negatively correlates with total precipitation values that are not much higher than the average.

Lastly, we present the results for our final estimation specification represented by Eq. (10) in

Table 3.9.[11] We do not find evidence that enrolled cover crop acres from the previous year impact total cover crop acreage for the county across specifications. This means we do not find any learning or peer effects that result in farmers continuing to implement cover crops after their contract has ended. However, the results indicate a positive and significant relationship between the no-tillage practice and total cover crop acres. Specifically, our preferred specification shows a one acre increase in no-tillage is associated with an average increase of 0.04 cover crop acres. While the magnitudes of these marginal effects are relatively small, Table 3.6 reports that the average no-tillage acres is 50,098. This suggests that cover crop acres and conservation tillage practices are viewed as complements for farmers interested in ecosystem benefits and regenerative agriculture.

Table 3.9: Regression Results for Determinants of Total County Cover Crop Acreage with County and Year Fixed Effects

Variables	(1)	Preferred (2)	(3)
Constant	8,683.111*** (2,007.157)	5,502.938*** (1,769.257)	5,220.135* (2,858.927)
Enrolled Cover Crop Acres t-1	0.166 (0.287)	-0.101 (0.176)	0.039 (0.174)
Per-Acre Cost t-1 ($)	-1.802 (23.629)	6.982 (20.589)	15.045 (23.304)
Reduced-Tillage Acres	---	0.013 (0.010)	0.017 (0.013)
No-Tillage Acres	---	0.038*** (0.013)	0.042*** (.012)
Reduced-Tillage Acres t-1	---	---	-0.006 (0.010)
No-Tillage Acres t-1	---	---	-0.015 (0.012)
N	1,270	1,270	1,169
R-squared	0.065	0.094	0.112

Note: Standard errors in parentheses, p-values * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. This table reports coefficients from models following Eq. (10) estimating the determinants of total cover crop acres in a county for a given year. Enrolled Cover Crop Acres are the contracted acres from the previous year, while the Per-Acre Cost is the calculated adoption cost based on Eq. (5). Reduced-tillage Acres and No-tillage acres provide the corresponding total acreage from the OpTIS remote-sensing data.

[11] Alternative specifications for Eq. (10) are provided in Table A3.7 to test the robustness of the results.

3.7. Discussion and Conclusion

We use 16 years (2008-2023) of NRCS data to understand cover crop enrollment patterns in twelve Midwestern states. Only a few studies have utilized cross-sectional (Claassen et al., 2018; Lee & McCann, 2019; Luther et al., 2020) or panel analysis data analyses (Park et al., 2023) to understand conservation practice adoption behavior. Our county-level panel dataset allows us to capture how contract component characteristics impact per-acre payments and cover crop adoption patterns. First, we expected the payment discount for winter-kill contracts and the payment premium for multiple species contracts, given the cost structure. However, the state practice scenarios guidelines estimate, on average, that winter-kill contracts cost $25 less, and the multispecies cost $20 more than the basic contracts. In contrast, we find an average price discount of $5 and a premium of about $5.50 for winter-kill and multispecies contracts, respectively. These results suggest that farmers receiving contracts report lower adoption costs than the published state cost estimates. Alternatively, the farmers could gain utility from providing ecosystem services, which would lower the payment necessary to incentivize adoption. Given that the state cost estimates provide an upper bound of the contract cost the states are willing to accept, it is in the government's best interest to provide contracts to farmers with lower adoption costs.

Additionally, contracts with a historically underserved recipient or part of a priority watershed receive higher payments. While this directly follows their higher cost-share proportion, the interesting finding is the differences between these payment premiums. While the cost-share proportion in a given state is the same given historically underserved or initiative status, the average payment premium for a historically underserved status is $10 more per acre than that of a priority initiative status. This could indicate that those within priority initiative areas have lower adoption costs or are willing to accept lower payment levels relative to historically underserved farmers.

To understand how the cost-share programs' generosity impacts enrollment of cover crop acreage, we separate per-acre payments into the cost-share proportion and the cost. While we do not find evidence of selection bias impacting the regression results with per-acre payments as our dependent variable, we do find evidence of selection bias when analyzing enrolled cover crop acres. We use the two-step Heckman selection model to correct for selection bias with enrolled cover crop acres as our dependent variable. In doing so, we find that a one percentage point increase in the percentage of cost covered by the cost-share program translates to an increase of approximately 104 acres, on average. Considering that the average contract size of a basic contract is about 1,745 acres, this is an average 5% increase in enrolled acres. Historically underserved recipients have contracts with an average of over 2,000 fewer acres when accounting for the difference in the average cost-share percentage. Given that most historically underserved farmers fall into the beginning farmers category, it is logical that these contracts contain less cover crop acreage. Contracts that are a part of initiative programs have an average of over 1,300 fewer acres, possibly due to limited geographic scope based on watersheds or migration zones.

The overall averages in the NRCS cover crop contract data show no statistically significant difference between the contracted acres in basic versus winter-kill contracts, but both contain more acres than multi-species contracts with statistical significance. However, when controlling for other factors, our regression results in Table 3.8 indicate that winter-kill and multispecies contracts have fewer average acres than the basic contract type. While the winter-kill practice specification translates to lower costs, time, and labor spent on termination, this does not appear to increase enrollment. This could be because producers must plant winter-kill species because of concerns regarding the complete termination of the plants or preferences for traits of species that are unable to be terminated by frost conditions. Alternatively, reduced per-acre payments for winter-kill contracts offset the marginal benefits associated with lower costs, time, and labor spent on termination. Meanwhile, the cost of implementing a multispecies contract is higher, but the environmental benefits of having a mix of cover crop species could also be higher. With the cost-share proportion constant across practice types—basic, winter-kill, and multispecies—the assumption is that the ratio of private benefits to public benefits is the same. Additional ecological and agronomic studies can quantify the ecosystem services provided by the diversification of cover crop species to inform farmers of the private benefits and the NRCS of the public benefits.

We can test the relationship between enrolled cover crop acreage and growing degree days and precipitation variables by utilizing PRISM data. While cover crops can improve water quality by reducing soil erosion, nitrogen leaching, and phosphorus loss, we find a negative relationship between cover crop adoption and precipitation levels from the previous year that are 5% or more above the average level. Given that the average marginal adoption of cover crop acres is largest with low precipitation levels, producers may not believe the benefits related to reductions in soil erosion outweigh the adoption costs. Alternatively, farmers may be concerned about planting timing related to excess moisture in the fields or encounter muddy conditions that prevent the planting of cover crops in a timely manner.

Our last analysis combines the NRCS cover crop contract data with OpTIS remote sensing data from 2015-2021 to test for potential lagged effects from cover crop enrollment and complementarity with conservation tillage. We do not see positive effects from previous cover crop enrollment in NRCS programs that could represent positive spillover related to learning and peer effects. However, there is a positive relationship between cover crops and no-tillage acres that suggests farmers' interest in the benefits of soil moisture and organic matter. Focus groups at the state- or conservation district-level can provide extension educators and local policymakers with information regarding the needs and concerns of their stakeholders.

Our research marks a meaningful advancement in comprehending the varying aspects of NRCS cost-share programs on cover crop adoption, but the work still has limitations. First, the inherent nature of the cost-share programs makes it difficult to quantify the benefits to ecosystem services. The goal of this paper is to understand cover crop enrollment behavior and not to measure the associated environmental benefits. Unlike voluntary programs that pay directly for ecosystem services, such as water quality or carbon markets in which credits related to pollution reduction can be sold, EQIP and CSP do not quantify the environmental benefits related to the adopted conservation practices. Thus, estimating the environmental benefits related to the policy spending is difficult. Second, we cannot control for field or farmer characteristics given that our data provides cover crop contract information at the county-level. While we can control for unobserved heterogeneity across counties, we cannot capture, for example, differences in soil type and quality within a county. Lastly, there are data access limitations due to privacy concerns. We are missing county-level observations if the contract type contains four or fewer contracts. Moreover, we cannot disaggregate county-level cover crop payments and acres by program. While we could attain state-level EQIP and CSP spending on cover crops and the corresponding acreage, these data are unavailable at the county-level.

The results from our county, year, and contract type panel into analyses highlight the importance of decomposing per-acre payments into the cost-share and cost factors to isolate the effect of the cost-share programs' coverage level. We find that an increase in the percentage of costs covered by the NRCS translates to an increase in enrolled acres. This provides evidence of additionality with an increase in the per-acre payment, separate from cost increases, incentivizing additional acreage. Given our behavioral model, we can assume that current adopters have lower marginal costs of adopting or perceive higher benefits. The NRCS must weigh the tradeoff between the intensive margins of providing higher payments to previous adopters and the extensive margins of targeting nonadopters for new contracts to incentivize the adoption of more cover crop acres. Quantifying the marginal impact of increasing the cost-share generosity provides policymakers with a measure for the behavioral responses of cover crop adopters that they can use for budgetary considerations. With their partnership with Farmers for Soil Health, the NRCS has a goal of 30 million acres of cover crops on corn and soybean acres by 2030. Achieving this goal will require the NRCS to evaluate the historical impact of payments, budget constraints, and the cost-benefit ratios of future contracts.

REFERENCES

Abdalla, M., Hastings, A., Cheng, K., Yue, Q., Chadwick, D., Espenberg, M., Truu, J., Rees, R. M., & Smith, P. (2019). A Critical Review of the Impacts of Cover Crops on Nitrogen Leaching, Net Greenhouse Gas Balance and Crop Productivity. *Global Change Biology*, *25*(8), 2530-2543.

Battel, B. (2017). *Understanding Growing Degree Days*. Michigan State University Extension. Retrieved 5/5/2024 from https://www.canr.msu.edu/news/understanding_growing_degree_days

Blesh, J. (2018). Functional Traits in Cover Crop Mixtures: Biological Nitrogen Fixation and Multifunctionality. *Journal of Applied Ecology*, *55*(1), 38-48.

Cain, Z., & Lovejoy, S. (2004). History and Outlook for Farm Bill Conservation Programs. *Choices*, *19*(4), 37-42.

Claassen, R., Duquette, E. N., & Smith, D. J. (2018). Additionality in US Agricultural Conservation Programs. *Land Economics*, *94*(1), 19-35.

Fargione, J. E., Bassett, S., Boucher, T., Bridgham, S. D., Conant, R. T., Cook-Patton, S. C., Ellis, P. W., Falcucci, A., Fourqurean, J. W., & Gopalakrishna, T. (2018). Natural Climate Solutions for the United States. *Science Advances*, *4*(11), eaat1869.

Fleming, P. (2017). Agricultural Cost Sharing and Water Quality in the Chesapeake Bay: Estimating Indirect Effects of Environmental Payments. *American Journal of Agricultural Economics*, *99*(5), 1208-1227.

Fleming, P., Lichtenberg, E., & Newburn, D. A. (2018). Evaluating Impacts of Agricultural Cost Sharing on Water Quality: Additionality, Crowding in, and Slippage. *Journal of Environmental Economics and Management*, *92*, 1-19.

Hively, W., Duiker, S., McCarty, G., & Prabhakara, K. (2015). Remote Sensing to Monitor Cover Crop Adoption in Southeastern Pennsylvania. *Journal of Soil and Water Conservation*, *70*(6), 340-352.

Kaye, J. P., & Quemada, M. (2017). Using Cover Crops to Mitigate and Adapt to Climate Change: A Review. *Agronomy for Sustainable Development*, *37*(1), 1-17.

Lee, C. (2023). *Nutrient and Pesticide Data Collected from the USGS National Water Quality Network and Previous Networks*.

Lee, S., & McCann, L. (2019). Adoption of Cover Crops by US Soybean Producers. *Journal of Agricultural and Applied Economics*, *51*(4), 527-544.

Luther, Z. R., Swinton, S. M., & Van Deynze, B. (2020). What Drives Voluntary Adoption of Farming Practices that can Abate Nutrient Pollution? *Journal of Soil and Water Conservation*, *75*(5), 640-650.

Park, B., Rejesus, R. M., Aglasan, S., Che, Y., Hagen, S. C., & Salas, W. (2023). Payments from Agricultural Conservation Programs and Cover Crop Adoption. *Applied Economic Perspectives and Policy*, *45*(2), 984-1007.

Pathak, S., Paudel, K. P., & Adusumilli, N. C. (2021). Impact of the Federal Conservation Program Participation on Conservation Practice Adoption Intensity in Louisiana, USA. *Environmental Management*, *68*(1), 1-16.

Plastina, A., Liu, F., Miguez, F., & Carlson, S. (2020). Cover Crops Use in Midwestern US Agriculture: Perceived Benefits and Net Returns. *Renewable Agriculture and Food Systems*, *35*(1), 38-48.

Poeplau, C., & Don, A. (2015). Carbon Sequestration in Agricultural Soils via Cultivation of Cover Crops–A Meta-Analysis. *Agriculture, Ecosystems & Environment*, *200*, 33-41.

PRISM Climate Group. Oregon State University. https://prism.oregonstate.edu/normals/

Prokopy, L. S., Floress, K., Arbuckle, J. G., Church, S. P., Eanes, F. R., Gao, Y., Gramig, B. M., Ranjan, P., & Singh, A. S. (2019). Adoption of Agricultural Conservation Practices in the United States: Evidence from 35 years of Quantitative Literature. *Journal of Soil and Water Conservation*, *74*(5), 520-534.

Sustainable Agriculture Research and Education (SARE). (2023). *Report 2022-2023* (National Cover Crop Survey, Issue. https://www.sare.org/wp-content/uploads/2022-2023-National-Cover-Crop-Survey-Report.pdf

Seifert, C. A., Azzari, G., & Lobell, D. B. (2018). Satellite Detection of Cover Crops and Their Effects on Crop Yield in the Midwestern United States. *Environmental Research Letters*, *13*(6), 064033.

Snapp, S. S., Swinton, S. M., Labarta, R., Mutch, D., Black, J. R., Leep, R., Nyiraneza, J., & O'neil, K. (2005). Evaluating Cover Crops for Benefits, Costs and Performance within Cropping System Niches. *Agronomy Journal*, *97*(1), 322-332.

Thompson, N. M., Reeling, C. J., Fleckenstein, M. R., Prokopy, L. S., & Armstrong, S. D. (2021). Examining Intensity of Conservation Practice Adoption: Evidence from Cover Crop Use on US Midwest Farms. *Food Policy*, *101*, 102054.

Todd, J. E., Whitt, C., Key, N., & Mandalay, O. (2024). *An Overview of Farms Operated by Socially Disadvantaged, Women, and Limited Resource Farmers and Ranchers in the United States*. (EIB-266). USDA Economic Research Service

US Department of Agriculture (USDA)-Commodity Credit Corportation (CCC). (2020). *Conservation Stewardship Program (CSP)*. Federal Register: National Archives Retrieved from https://www.federalregister.gov/d/2020-22345

USDA-National Agricultural Statistics Service (NASS). (2024). *Michigan, Table 75. Summary by North American Industry Classification System: 2022* (2022 Census of Agriculture State Level Data, Issue. https://www.nass.usda.gov/Publications/AgCensus/2022/Full_Report/Volume_1,_Chapter_1_State_Level/Michigan/st26_1_075_075.pdf

USDA-Natural Resource Conservation Service (NRCS)-CCC. (2019). *Environmental Quality Incentives Program*. Federal Register: National Archives Retrieved from https://www.federalregister.gov/d/2019-26872

USDA-NRCS. (2019). *NRCS Cover Crop Termination Guidelines Version 4*. Retrieved 7/27/2024 from https://www.nrcs.usda.gov/sites/default/files/2023-03/cover-crops-termination-guidelines-designed-v4-2019-updated.pdf

USDA-NRCS. (2020). *Conservation Practice Standard*. Retrieved from https://www.nrcs.usda.gov/sites/default/files/2022-09/Cover_Crop_340_CPS.pdf

USDA-NRCS. (2024a). *A Brief History of NRCS*. United States Department of Agriculture Natural Resources Conservation Service. Retrieved 7/27/2024 from https://www.nrcs.usda.gov/about/history/brief-history-nrcs

USDA-NRCS. (2024b). *Historically Underserved Farmers and Ranchers*. Retrieved 7/27/2024 from https://www.nrcs.usda.gov/getting-assistance/underserved-farmers-ranchers

USDA-NRCS. (2024c). *Natural Resource Concerns*. Retrieved 7/27/2024 from https://www.nrcs.usda.gov/conservation-basics/natural-resource-concerns

USDA-NRCS. (2024d). *Payment Schedules (Rates) by State*. Retrieved 7/27/2024 from https://www.nrcs.usda.gov/getting-assistance/payment-schedules

USDA. (2022). *USDA Offers Expanded Conservation Program Opportunities to Support Climate Smart Agriculture in 2022*. Retrieved 7/27/2024 from https://www.usda.gov/media/press-releases/2022/01/10/usda-offers-expanded-conservation-program-opportunities-support

Wooldridge, J. M. (2010). *Econometric Analysis of Cross Section and Panel Data*. MIT Press.

Zhou, Q., Guan, K., Wang, S., Jiang, C., Huang, Y., Peng, B., Chen, Z., Wang, S., Hipple, J., & Schaefer, D. (2022). Recent Rapid Increase of Cover Crop Adoption Across the US Midwest Detected by Fusing Multi-Source Satellite Data. *Geophysical Research Letters*, *49*(22), e2022GL100249.

APPENDIX 3

For the NRCS cover crop data we obtained from our FIOA request, we identified three main practice types: a basic contract that contains a single species cover crop that is chemically or mechanically terminated, a winter-kill contract that contains a single species that is terminated by frost conditions, and a multiple species contract that is chemically or mechanically terminated. Additionally, the component name can specify a priority initiative program, such as a water quality initiative, or indicate a historically underserved contract recipient. With three primary practice types, priority initiative status, and historically underserved status, we have twelve possible contract types within a county for a given year. Table A3.1 provides the attribute combinations that characterize the twelve contract types and their corresponding totals.

Table A3.1: Attributes and Totals for each Contract Type for NRCS Cover Crop County-Level Contract Data (from 2008-2023, n=4,177)

Basic	Winter-kill (WK)	Multispecies (Multi)	Historically Underserved (HU)	Priority Initiative (Init)	Contract Type	Totals
1	0	0	0	0	Basic	2,040
1	0	0	**1**	0	Basic, HU	224
1	0	0	0	**1**	Basic, Init	90
1	0	0	**1**	**1**	Basic, HU, Init	9
0	**1**	0	0	0	WK	556
0	**1**	0	**1**	0	WK, HU	65
0	**1**	0	0	**1**	WK, Init	15
0	**1**	0	**1**	**1**	WK, HU, Init	1
0	0	**1**	0	0	Multi	1,015
0	0	**1**	**1**	0	Multi, HU	121
0	0	**1**	0	**1**	Multi, Init	39
0	0	**1**	**1**	**1**	Multi, HU, Init	2
2,363	637	1,177	422	156	**Totals**	4,177

As shown in Table A3.1, we have twelve possible contract types within a county for a given year. Table A3.2 provides a breakdown of the totals for each contract type in each of the states included in our analysis.

Table A3.2: Total Contracts of each Contract Type by State for NRCS Cover Crop County-Level Contract Data (from 2008-2023, n=4,177)

Contract Type	IL	IN	IA	KS	MI	MN	MO	NE	ND	OH	SD	WI
Basic	151	243	535	4	92	98	285	126	1	215	54	236
Basic, HU	1	1	88		11	4	32	24		40	1	22
Basic, Init		6	57		2	24		1				
Basic, HU, Init			9									
WK	39	368	120			11	5			9		4
WK, HU		51	14									
WK, Init			15									
WK, HU, Init			1									
Multi	47	68	249	84	8	103	24	143	50	41	143	55
Multi, HU			56	14	1	17		13	2	3	12	3
Multi, Init			37								2	
Multi, HU, Init			2									
Totals	238	737	1,183	102	114	257	346	307	53	308	212	320

As shown by Table A3.2, we utilize the component names of our county-level data to categorize the observations into 12 contract types. While this allows us to determine how these contract characteristics impact payments and enrolled acreage, we do lose observations if the county-year-component combination has four or fewer contracts due to privacy concerns. We also obtained state-level data for cover crop contract via a FOIA request. To understand the share of total enrolled cover crop acreage represented in our county-level data, we compare the totals for a given state and year from our county-level data to the corresponding totals from our state-level data.

In our county-level data, we aggregate the enrolled cover crop acres for each state for each year. This represents the total enrolled cover crop acres for a given state and year combination included in the county-level data. We then divide those totals by the totals for a given state and year combination from our complete state-level data to calculate the share of total enrolled cover crop acreage represented in our county-level data. We assign these shares to the county-level contract type, county, and year combinations that correspond to a given state and year combination. We find that the share of total cover crop acreage represented in our county-level data for each state and year combinations has an average of 0.667, meaning that an average of 66.7% of total acreage is represented. Out of our 4,177 contract type, county, and year observations, 3,725 correspond to a share of total cover crop acreage represented in the county-level data for the corresponding state and year of over 50%. Figure A3.1 provides a distribution of the calculated shares of total cover crop acreage represented in the county-level data.

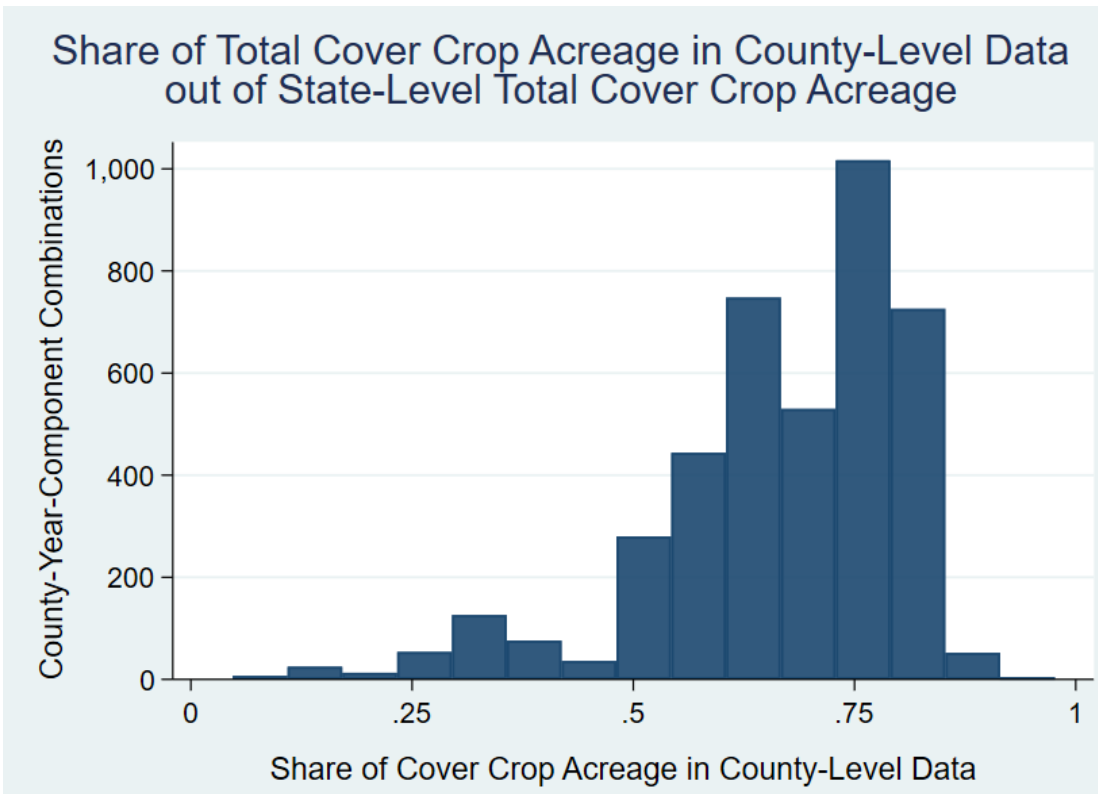


Figure A3.1: The graph above shows the distribution of the frequency of shares of total cover crop acreage in the county-level data for each state and year combinations out of the total cover crop acreage in the state-level data for the corresponding state and year combination.

Table A3.3 provides the average adoption cost based on published 2024 state cost estimates for the various practice types (USDA-NRCS, 2024d) as well as the average cost-share values from our county-level data. By multiplying these values, we calculate the average expected payments.

Table A3.3: Average Adoption Cost Estimates for 2024 from NRCS Payment Schedules and Average Cost-Shares from NRCS County-Level Data

Contract Characteristics	Average Cost Estimates	Average Cost-Share	Average Calculated Payment
Basic=1, Init=0, HU=0	$82.30	65.22%	$53.68
Basic=1, Init=1	$82.30	73.78%	$60.72
Basic=1, HU=1	$82.30	81.78%	$67.30
Winter Kill=1, Init=0, HU=0	$56.04	68.91%	$38.62
Winter Kill=1, Init=1	$56.04	75.00%	$42.03
Winter Kill=1, HU=1	$56.04	86.59%	$48.52
Multispecies=1, Init=0, HU=0	$102.92	61.79%	$63.59
Multispecies=1, Init=1	$102.92	75.73%	$78.00
Multispecies=1, HU=1	$102.92	77.89%	$80.16
Init=0, HU=0	---	64.82%	---
Init=1	---	74.42%	---
HU=1	---	81.40%	---

Alternative Specification for Eq. (8)

Our dependent variable, α_{jit}, is the cover crop acreage enrolled in contract type *j*, in county *i* at time *t*. In contrast to Eq. (8) in the main text, we directly include, δ_{jit}, the per acre cover crop contract payments for contract type *j*, in county *i* at time *t*. We have a vector of binary variables, $\boldsymbol{Z}$, that defines the twelve contract types with three primary practice types, the priority initiative, and historically underserved specifications as defined in Table 3.1 of the main text. We also control for county, c_i, and time, γ_t, fixed effects.

$$\alpha_{jit} = \beta_1 \delta_{jit} + \beta \boldsymbol{Z} + c_i + \gamma_t + \varepsilon_{jit} \qquad (8')$$

By including payment per acre instead of the cost-share proportion and the per-acre cost, we observe insignificant relationships between the payment amount and adoption.

Table A3.4: Regression Results for Determinants of Total Enrolled Cover Crop Acreage for Contract Types in a County Compared to Table 3.8 (n=4,177)

Variables	(1)	(2)	(3)
Constant	1,973.393***	2054.413***	285.389
	(99.856)	(77.098)	(239.979)
Per-Acre Payment	-2.126	-2.768	2.077
($)	(2.379)	(2.112)	(2.181)
Winter-kill	17.426	-302.188**	-604.112***
	(153.602)	(129.256)	(127.332)
Multi-Species	-316.365***	-213.830**	-261.007***
	(95.526)	(91.435)	(86.676)
Priority Initiative	-915.302***	-657.875***	-204.331
	(154.383)	(172.936)	(175.000)
Historically	-1,038.469***	-1,486.506***	-1,754.843***
Underserved	(99.153)	(170.33)	(186.264)
County FE	No	Yes	Yes
Time FE	No	No	Yes
R-squared	0.040	0.072	0.137

Note: Standard errors in parentheses, p-values * p < 0.10, ** p < 0.05, *** p < 0.01. This table reports coefficients from models following Eq. (8') estimating the relationship between cover crop contract acreage and contract characteristics and weather variables. Per-Acre Payment is the payment for cover crop acres enrolled in contracts. Winter-kill is an indicator for a winter-kill cover crop species. Multi-Species is equal to one for a multi-species cover crop, Priority Initiative is equal to one when the farm is located in a priority initiative area, and Historically Underserved is equal to one for a farmer who is part of a historically underserved group.

Alternative Specifications of Eqs. (7)-(9) for Robustness Checks

We model alternative specifications for Eqs. (7) and (8) by restricting the data included in the analysis. These specifications are to test the robustness of our results, given that we are missing observations for counties with four or fewer contracts for a given county-year-component combination due to privacy concerns. Tables A3.5 and A3.6 provide the results for Eqs. (7) and (8), respectively. The preferred specifications refer to the results reported in Tables 3.7 and 3.8 of the main text. Model 2 omits contracts that have historically underserved farmer or priority initiative statuses. Historically underserved farmers own less than 7% of farms in the United States (Todd et al., 2024) and priority initiatives, such as the Water Quality initiative, are restricted in geographic scope. Therefore, these contracts are less common, so our redacted data may contain more of these contracts. Model 3 omits contracts from 2008-2016. Contracts from 2017-2023 are more uniform in contract component names, so this timeframe may contain fewer omitted observations.

Additionally, Model 4 omits counties within a given state and year combination in which the share of total acres from the county-level data for a given state and year combination is less than 50% of the total acres from the state-level data for the corresponding state and year combination. While the county-level data provides disaggregated data with county and component name information, this disaggregation leads to missing observations for counties with four or fewer contracts for a given component-year combination. The state-level data does not have this omitted data issue. We aggregate the enrolled cover crop acres across our county-level observations for each state and year combination. We then divide those totals for a given state and year combination from our county-level data by the corresponding totals in our complete state-level data. This provides us with the share of total enrolled cover crop acreage represented in our county-level data. We assign these shares to the county-level observations that correspond to a given state and year combination. Figure A3.1 provides the distribution of the shares of total cover crop acreage in the county-level data out of the total cover crop acreage in the state-level data for the corresponding state and year combination.

The coefficient estimates for Eq. (7) are consistent in signs across the alternative specifications, as shown in Table A3.5. The magnitudes of the coefficient estimates are also consistent, except for Model 3. For Model 3, we restrict the timeframe to 2017-2023. By dropping 2008-2016, we would expect the magnitudes to increase proportionately, given the price increases. However, we see a larger decrease in the price discount for winter-kill contracts. This indicates that farmers have been more willing to accept lower payments to adopt winter-kill contracts in more recent years. Additionally, the price premium for priority initiatives contracts has increased, indicating that NRCS is willing to pay more for these contracts.

Table A3.5: Robustness Check for Regression Results of Table 3.7 for Determinants of NRCS Per-Acre Payments for Enrolled Cover Crop Acres for Contract Types with County and Time Fixed Effects

Variables ($/acre)	**Preferred (1)**	**(2)**	**(3)**	**(4)**
Constant	20.651*** (1.830)	20.533*** (1.830)	41.791*** (0.642)	20.899*** (1.874)
Winter-kill	-4.996*** (1.300)	-3.251** (1.347)	-12.874*** (1.057)	-4.816*** (1.339)
Multi-Species	5.475*** (0.851)	5.195*** (0.946)	8.150*** (0.851)	5.067*** (0.827)
Priority Initiative	6.981*** (1.943)	---	16.434*** (1.964)	5.867*** (1.985)
Historically Underserved	17.030*** (0. 687)	---	17.252*** (0.802)	16.782*** (0.711)
Inverse Mills Ratio	---	---	---	---
R-squared	0.250	0.167	0.508	0.260
N	4,177	3,611	2,989	3,764

Note: Standard errors in parentheses, p-values * p < 0.10, ** p < 0.05, *** p < 0.01. This table reports coefficients from models following Eq. (7) estimating the relationship between per-acre NRCS payments and contract types. Winter-kill is an indicator equal to one when a contract is for a winter-kill cover crop species. Multi-Species is equal to one for a multi-species cover crop, Priority Initiative is equal to one when the farm is located in a priority initiative area such as water quality priority initiatives, and Historically Underserved is equal to one for a farmer who is part of a historically underserved group.

Table A3.6 reports coefficient estimates from alternative models following Eq. (8). Without contracts with historically underserved farmer or priority initiative statuses in Model 2 of Table A3.6, there is not enough variation in the state cost-share variable. Therefore, the state cost-share variable is excluded from Model 2. We see smaller magnitudes for the coefficient estimates in Model 2 and 4 compared to our preferred model. The magnitudes of the coefficient estimates for Model 3 are closer to those of our preferred model, though Model 3 does not show significance for winter-kill and low significance for multispecies. The differences in the alternative models from our preferred model suggest that without correcting for selection bias, we are underestimating the effects of the coefficients in Eq. (8).

Table A3.6: Robustness Check for Results of Table 3.8 for Determinants of Total Enrolled Cover Crop Acreage for Contract Types with County and Time Fixed Effects

Variables	Preferred	(2)	(3)	(4)
Constant	-16,842.850*** (2,932.383)	-2,574.774*** (1,624.594)	-12,461.07*** (2,749.396)	-9,365.019*** (2,490.353)
State Cost-Share (%)	103.666*** (13.912)	omitted	180.842*** (40.395)	90.007*** (31.341)
Per-Acre Cost ($)	1.109 (1.006)	1.790 (1.283)	1.609 (2.737)	0.483 (1.269)
Winter-kill	-1,549.086*** (359.793)	-548.201*** (159.934)	-197.634 (203.935)	-572.009*** (138.951)
Multi-Species	-799.592*** (202.406)	-327.833*** (105.852)	-197.593* (119.343)	-298.252*** (92.542)
Priority Initiative	-4,475.078*** (865.562)	---	-4,675.520*** (1,083.816)	-2,069.716** (821.486)
Historically Underserved	-5,257.534*** (663.033)	---	-5,656.539*** (945.194)	-3,546.994*** (725.266)
Growing Degree Days t-1	1.177 (0.818)	1.238 (0.863)	1.086 (0.858)	1.810** (0.806)
Precipitation t-1 (mm)	3.285*** (1.137)	3.437*** (1.105)	2.668** (1.081)	3.462*** (1.018)
Precipitation Squared t-1 (mm)	0.003*** (0.001)	-0.003*** (0.001)	-0.002*** (0.001)	0.003*** (0.001)
Inverse Mills Ratio	1,449.39*** (509.299)	---	---	---
R-squared	---	0.096	0.175	0.148
N	4,177	3,611	2,989	3,764

Note: Standard errors in parentheses, p-values * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. This table reports coefficient estimates from alternative models following Eq. (8). State Cost-Share is the percentage of the adoption cost covered by the program, while the Per-Acre Cost is the calculated adoption cost based on Eq. (5). Winter Kill is an indicator equal to one when a contract is for a winter kill cover crop species and is zero otherwise. Multi-Species is equal to one for a multi-species cover crop, Priority Initiative is equal to one when the farm is located in a priority initiative area, and Historically Underserved is equal to one for a farmer who is part of a historically underserved group. The PRISM weather variables include Growing Degree Days, calculated using the temperature averaging method, and total Precipitation and Precipitation Squared in millimeters for the previous growing season. The Inverse Mills ratio represents the expected value of the error in the enrolled cover crop acreage conditional on contracts included in the NRCS data.

We test the robustness of our results by modeling alternative specifications for Eq. (10) by restricting the data included in the analysis. Table A3.7 reports the results. The preferred specification refers to the results reported in Table 3.9 of the main text. Since Eq. (10) does not include the contract characteristics, we do not omit contracts with historically underserved farmer or priority initiative statuses. Model 2 omits contracts from 2008-2016. Contracts from 2017-2023 are more uniform in contract component names, so this timeframe may contain fewer omitted observations. Lastly, Model 3 omits counties within a given state and year combination if less than 50% of the total acres for a given state and year from state-level data were represented in the count-level data. Therefore, Models 2 and 3 of Table A3.7 match Models 3 and 4 of Tables A3.5 and A3.6. The positive significance of no-tillage acres is consistent across specifications.

Table A3.7: Regression Results for Determinants of Total County Cover Crop Acreage by County with County and Time Fixed Effects

Variables	Preferred	(2)	(3)
Constant	5,502.938*** (1,769.257)	2,751.386 (2,958.548)	5,840.162*** (1672.829)
Enrolled Cover Crop Acres t-1	-0.101 (0.176)	-0.082 (0.166)	0.275 (0.342)
Per-Acre Cost t-1 ($)	6.982 (20.589)	17.431 (25.806)	0.098 (23.924)
Reduced-Tillage Acres	0.013 (0.010)	0.029* (0.016)	0.009 (0.013)
No-Tillage Acres	0.038*** (0.013)	0.055*** (0.022)	0.045** (0.019)
R-squared	0.094	0.111	0.085
N	1,270	1,045	1,114

Note: Standard errors in parentheses, p-values * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. This table reports coefficients from models following Eq. (10) estimating the determinants of total cover crop acres in a county for a given year. Enrolled Cover Crop Acres are the contracted acres from the previous year, while the Per-Acre Cost is the calculated adoption cost. Reduced-tillage Acres and No-tillage acres provide the corresponding acreage from the OpTIS remote-sensing data.

Alternative Specifications of Eqs. (7) and (8) to Proxy Utility from Ecosystem Services

Within our conceptual model, we define $E(\cdot)$ as non-market ecosystem services from cover cropping. If agricultural producers derive utility from the non-market ecosystem services from cover cropping, they may also gain utility from adopting conservation tillage practices. The larger the magnitude of utility derived from enrolled cover crop acres, the lower the necessary subsidy rate or cost-share proportion to induce adoption. Therefore, we would expect that more conservation tillage acres would negatively impact contract payments.

While we would expect a positive relationship between overall cover crop acres and conservation tillage acres, the relationship between conservation tillage acres and enrolled cover crop acres is more difficult to sign. There could be a positive relationship up to a point. Then, once the utility from ecosystem services is higher than the net cost of adoption, agricultural producers will not need to enroll acres in NRCS. Although the producers would continue to practice cover cropping, they would not feel the need to enroll in NRCS programs because the benefits are already high enough that they do not need to receive government funding to offset the remaining costs.

We tested a model for the determinants of NRCS per-acre payments for enrolled cover crop acres and total enrolled cover crop acreage for contract types in a county that includes reduced-tillage and no-tillage acreage lags from the OpTIS data as proxies for $E(\cdot)$. The results are shown in Tables A3.8 and A3.9, respectively. Because the OpTIS data span from 2015-2021, including these lags restricts the NRCS data to observations from 2017-2022. With this restriction, our number of observations decreases from 4,177 to 2,801.

Table A3.8 provides results for the preferred model specification from Table 3.7 of the main text as Model 1. Model 2 of Table A3.8 provides results for the model specification that includes the conservation tillage lags. We do not find significant relationships between the conservation tillage lags and NRCS per-acre payments. While the R-squared value has increased, this change is due to the restriction of years, as shown by the similarities between the results of Model 2 of Table A3.8 below and the results of Model 3 of Table A3.5.

Table A3.8: Regression Results for Determinants of NRCS Per-Acre Payments for Enrolled Cover Crop Acres for Contract Types with County and Time Fixed Effects

Binary Variables ($/acre)	**Preferred**	**(2)**
Constant	20.651*** (1.830)	40.106*** (0.959)
Winter-kill	-4.996*** (1.300)	-10.572*** (1.084)
Multi-Species	5.475*** (0.851)	7.089*** (0.902)
Priority Initiative	6.981*** (1.943)	15.373*** (1.373)
Historically Underserved	17.030*** (0. 687)	17.172*** (0.749)
Reduced-Tillage Acres t-1	---	-7.03e-6 (7.16e-6)
No-Tillage Acres t-1	---	-2.65e-6 (6.57e-6)
R-squared	0.250	0.486
N	4,177	2,801

Note: Standard errors in parentheses, p-values * p < 0.10, ** p < 0.05, *** p < 0.01. This table reports coefficients from models following Eq. (7) estimating the relationship between per-acre NRCS payments and contract types. Winter-kill is an indicator equal to one when a contract is for a winter-kill cover crop species and is zero otherwise. Multi-Species is equal to one for a multi-species cover crop, Priority Initiative is equal to one when the farm is located in a priority initiative area such as water quality priority initiatives, and Historically Underserved is equal to one for a farmer who is part of a historically underserved group. Reduced-tillage Acres and No-tillage acres provide the corresponding acreage from the OpTIS remote-sensing data.

Table A3.9 provides results for the preferred model specification from Table 3.8 of the main text as Model 1. Model 2 of Table A3.9 provides results for the model specification that includes the conservation tillage lags. The results of Model 2 indicate a negative relationship between conservation tillage acres and enrolled cover crop acres. We also included squared terms for the conservation tillage lags in Model 3 but found that a linear specification best fits the relationship between the conservation tillage acres and enrolled cover crop acres.

Table A3.9: Results for Determinants of Total Enrolled Cover Crop Acreage for Contract Types with County and Fixed Effects

Variables	Preferred	(2)	(3)
Constant	-8,174.724*** (2,387.067)	-11,061.04*** (2,602.685)	-11,209.78*** (2,585.496)
State Cost-Share (%)	91.952*** (31.419)	136.024*** (38.401)	136.565*** (38.521)
Per-Acre Cost ($)	1.108 (1.122)	2.537 (2.850)	2.619 (2.852)
Winter-kill	-577.229*** (130.848)	-369.256*** (185.937)	-368.910** (186.307)
Multi-Species	-271.362*** (86.804)	-305.051*** (111.593)	-311.763*** (111.238)
Priority Initiative	-2,186.257*** (833.065)	-3,392.751*** (1,040.935)	-3,410.943*** (1,046.877)
Historically Underserved	-3,532.203*** (727.962)	-4,633.366*** (904.823)	-4,647.056*** (907.290)
Growing Degree Days t-1	1.114 (0.747)	1.9204** (0.864)	1.995** (0.859)
Precipitation t-1 (mm)	3.174*** (0.953)	4.287*** (1.150)	4.369*** (1.154)
Precipitation Squared t-1(mm)	-0.003*** (0.001)	-0.003*** (0.001)	-0.003*** (0.001)
Reduced-Tillage Acres t-1	---	-0.007** (0.003)	-0.011** (0.004)
Reduced-Tillage Acres Squared t-1	---	---	1.28e-8 (1.01e-8)
No-Tillage Acres t-1	---	-0.003** (0.002)	0.001 (0.003)
No-Tillage Acres Squared t-1	---	---	-2.25e-8 (1.68e-8)
R-squared	0.148	0.183	0.184
N	4,177	2,801	2,801

Note: Standard errors in parentheses, p-values * p < 0.10, ** p < 0.05, *** p < 0.01. This table reports coefficients from models following Eq. (8) estimating the relationship between cover crop contract acreage and contract characteristics and weather variables. State Cost-Share is the percentage of the adoption cost covered by the program, while the Per-Acre Cost is the calculated adoption cost based on Eq. (5). Winter-kill is an indicator equal to one when a contract is for a winter-kill cover crop species and is zero otherwise. Multi-Species is equal to one for a multi-species cover crop, Priority Initiative is equal to one when the farm is located in a priority initiative area, and Historically Underserved is equal to one for a farmer who is part of a historically underserved group. The PRISM weather variables include Growing Degree Days and total Precipitation and Precipitation Squared in millimeters for the previous growing season. Reduced-tillage Acres and No-tillage acres provide the corresponding acreage from the OpTIS remote-sensing data.

Given that we define $E(\cdot)$ as non-market ecosystem services from cover cropping, no-tillage and reduced-tillage acreage lags are imperfect proxies for $E(\cdot)$. We believe that Eq. 9 best measures overall sentiments towards conservation agricultural practices and how this impacts the relationship between conservation tillage and overall cover crop acres. We have proof of complementarity between reduced-tillage acres and overall cover crop acres from the regression results for determinants of total county cover crop acreage, as shown in Table 3.8.