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MEASURING IMPACTS OF UNCERTAINTY, IRREVERSIBILITY, AND LOSS AVERSION ON THE ADOPTION OF CROP CANOPY SENSORS AMONG NEBRASKA CORN PRODUCERS

by

Brooks Ronspies

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MEASURING IMPACTS OF UNCERTAINTY, IRREVERSIBILITY, AND LOSS AVERSION ON THE ADOPTION OF CROP CANOPY SENSORS AMONG NEBRASKA CORN PRODUCERS

Brooks Ronspies, M.S.

University of Nebraska, 2019

Advisors: Simanti Banerjee and Taro Mieno

Understanding barriers to adoption of Precision Agricultural Technologies (PATs) is important to the growth of agricultural productivity, efficiency, and sustainability. This thesis proposes and evaluates a model for estimating the impact of uncertainty, irreversibility, and loss aversion on producers' adoption of crop canopy sensors in order to explain adoption behavior that contradicts previous expectations about the conditions necessary for technology adoption. The model is evaluated using estimated statistical distributions of price and field characteristics designed to match observations of actual corn and nitrogen prices, and of conventional and crop canopy sensor based nitrogen application. Results from this model using expected utility theory indicate that producers maximize their profit if they adopt crop canopy sensors immediately when their expected value becomes greater than the expected value of their previous nitrogen application method. According to prospect theory, producers maximize their subjective utility when they defer adoption of crop canopy sensors until they become 1.03 times more profitable than uniform rate application, greatly reducing the speed at which we expect producers to adopt crop canopy sensors. This difference implies that risk preferences and the manner

in which producer utility/value under risk and uncertainty is modeled play a significant role in the adoption of PATs such as crop canopy sensors.

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1 Introduction

Precision agricultural technologies (PATs) have generated great interest among researchers since their formal introduction in the 1990's. Stafford (2000) touted PATs as the solution to growing economic and environmental problems associated with agriculture and even went so far as to say that by the end of the decade "most arable enterprises will have taken on the concept on a whole-farm basis." We find that this prediction turned out to be overly optimistic by reviewing a report by Schimmelpfennig (2016) that looks at the adoption of PATs. In this report, Schimmelpfennig examines computer mapping, guidance systems, and variable rate technologies. Using data from the Agricultural Resource Management Survey (ARMS), he finds that each has a positive impact on operating profit however adoption of these technologies has been slow and limited to larger farms.

Certainly some non-adoption can be explained by market failures such as information asymmetry and transaction costs, however we find it important to consider the irreversible nature of the investment in crop canopy sensors because it forces producer into a long term commitment. For many PATs, once they have been purchased, they offer little or no value outside of use in production leaving producers with few options but to be used until they complete their productive lifespan or until a new technology appears that can recoup the cost of the PATs, making the investment irreversible. When an investment decision is irreversible, it forces decision-makers to evaluate risk in not only the current time period, but also the following time periods. When the risk in following time periods unknown, the decision maker faces uncertainty.

Previous authors have examined agricultural technology adoption through the lens of irreversibility and uncertainty (Purvis et al. 1995, Tozer 2009). These studies have focused on the methods presented by Dixit (1992) for examining the effects of irreversibility and uncertainty in investment decision-making. While these studies explain a small degree of non-adoption, studies like Tozer (2009) have still inaccurately predicted high levels of PAT adoption while accounting for irreversibility and uncertainty. We believe that this is caused by a failure to consider the dynamic nature of investment decision making and the failure to model producer value functions as non-linear. Given this context, in this thesis, we evaluate the magnitude of non-adoption attributable to the irreversibility of investment and uncertainty in a dynamic context where risk preferences are represented by Expected Utility Theory and Prospect Theory.

In order to address this research objective, my thesis is organized as follows. First we introduce a PAT of interest, crop canopy sensors, which will be used as an example to estimate the effects of incorporating a prospect value function into our analysis. Then we will present a review of technology adoption studies that use price and production characteristics to perform an ex ante analysis of technology adoption rates. Next we discuss the successes and shortcomings of previous ex ante technology adoption studies and present evidence that warrants the inclusion of loss aversion in our study through the consideration of a prospect theory value function. We then present two models for evaluating technology adoption among producers. The first assumes that producer behavior is in accordance with expected utility theory and the second explicitly incorporates prospect theory and loss aversion within the decision making framework. Finally, using historical corn and nitrogen price data and data from field trials using crop canopy sensors, we assign parameters to the two models to find the optimal investment behavior, conditional on individuals' risk preferences. For this purpose, we use Monte Carlo simulations. We find that when producers wait until crop canopy sensors are estimated to be 1.00 times more profitable than uniform rate application, they have the best chance to maximize their profit. We also find that producers have the best chance to maximize subjective utility, based on a prospect value function when they wait crop canopy sensors are estimated to be 1.03 times more profitable than uniform rate application. These results suggest that use of an investment trigger can improve decision making. They also illustrate the magnitude of impact that loss aversion can have on adoption.

2 Crop Canopy Sensors

Slow adoption of PATs is a topic of interest among researchers not only because they improve farm profits, but also because they offer a method for reducing the externalities caused by agricultural production, including nitrogen runoff caused by the application of nitrogen fertilizers on corn growing operations. In Midwestern corn growing states such as Nebraska, Iowa, Illinois, Kansas, and Missouri, University researchers have done excellent work to define the impacts that nitrogen runoff has on water, soil, and ecosystem health (Wortman et al. 2006). Excess nitrogen runoff is also detrimental to human health (Townsend & Howarth 2010). Mosheim and Ribaudo (2017) find that rural communities with small water systems face the highest costs of nitrogen abatement and often lack the technical knowledge and financing to properly manage groundwater. Beyond local impacts, there is also a great deal of concern about the implications of fertilizer runoff downstream away from the application site in the Gulf of Mexico (McLellan et al. 2018, Muenich et al. 2017). This includes harmful algal blooms that threaten human health, aquatic ecosystems, and marine economies (Paerl & Scott 2010).

To combat such issues, extensive work has been done to develop new technology and management practices that assist in the reduction of nitrogen application and hence runoff. Crop canopy sensors are one of the promising PATs that reduce nitrogen application on corn growing operations by sensing and delivering only the exact amount of nitrogen needed by a plant. Researchers at the University of Nebraska-Lincoln have conducted an extensive on-farm trial of the sensors titled Project SENSE. From the years 2015-2017 these researchers conducted 52 trials at different locations across southeastern Nebraska. Results from these trials are presented in Table 1 and indicate that crop canopy sensors reduce the amount of nitrogen applied, while maintaining yield, therefore improving the per acre profitability of the operation.

Table 1: Project SENSE Results

Three Year Average (2015-2017)	SENSE Method	Grower Method[1]
Total Nitrogen rate* (lb-N/ac)	161.1	189.8
Yield* (bu/ac)	218.5	219.9
Partial Profitability*[2] ($/ac) [@3.65/bu and $0.65/lb-N]	$692.82	$679.59
Partial Profitability* ($/ac) [@3.05/bu and $0.41/lb-N]	$600.39	$593.15

[1]The term Grower Method, is a term used by Project SENSE researchers to describe a variety of approaches growers take to determine a constant or uniform Nitrogen-application rate.
[2]Partial Profitability is profit resulting only from the cost of nitrogen and revenue from corn sales

Despite these promising results, adoption of SENSE technology has been limited prompting us to focus on the reasons behind producers not changing their behavior despite the presence of a more profitable technology.

3 Literature Review

3.1 Investment by Producers under Irreversibility, Risk, and Uncertainty

Capital investments undertaken by agricultural producers typically involve varying degrees of irreversibility and risk. Risks in future time periods are unknown, therefore producers are also subject to uncertainty. Producers have the ability to postpone these investments until information about the costs and returns of the investment indicate a stronger chance of the investment being more profitable than other certain investment opportunities. The degree of irreversibility and uncertainty associated with that irreversibility have a significant impact on a producer's decision to invest, however they commonly go unaccounted for in capital budgeting and ex-ante technology adoption analysis (Pindyck 1991). As a result, efforts to encourage technology adoption may be unsuccessful or inefficient due to inaccurate estimations of producer behavior.

Focusing on irreversibility, Pindyck (1991) gives two reasons to explain why investment in physical capital is at least partially irreversible. One is that physical capital is sector specific, and once procured given depreciation, the value of used machinery falls, and the other being that information about the quality of used capital is asymmetric. Regardless of the cause, irreversibility is important to consider because it increases firms sensitivity to uncertainty. For example, consider a firm that has an opportunity to make an investment with a 75% chance of recovering the investment cost. The decision to invest is straightforward. Now, consider the case where the investment is spread out over five years. In the first year, the firm has a 75% chance of recovering 1/5th of the investment cost but the probabilities of recuperating the investment cost during the next four time periods are unknown. This uncertainty makes the problem of deciding when to invest much more difficult to solve, and is not that different from the circumstances faced by agricultural producers. Take for example a producer investing in irrigation equipment given impacts of climate change. A producer may not need to irrigate now, however in ten years the situation could be very different.

One way firms may account for uncertain investment outcomes is by deferring the investment decision until projected gains are sufficiently greater than the investment cost (Dixit 1992, Ekboir 1997, McDonald 2000, Tozer 2009, Liu 2013). The degree to which returns must be greater than the investment cost is referred to as the hurdle rate by Dixit (1992). The term hurdle rate is sometimes used to describe an arbitrarily high discount rate (McDonald 2000), however in our paper we will use the definition put forth by Dixit (1992). The goal of a producer is then to set their hurdle rate at the point that captures the value of waiting, defined by risk and expected revenue of the investment (Dixit 1992).

There are a few methods of determining what the optimal hurdle rate might be for a particular investment. McDonald (2000) finds that many firms arbitrarily determine the hurdle rate based on previous investment experiences. Other approaches include models of Real Options Analysis (ROA), which have been used to determine a population wide optimal hurdle rate (Purvis et al. 1995, Carey & Zilberman 2002, Odening et al. 2005, Tozer 2009) for investment in agricultural technologies. A population wide optimal hurdle rate is the optimal hurdle rate for a set of producers who were sampled from to determine typical costs and returns of the investment. For example, if you wanted to determine the population wide optimal hurdle rate for adoption of center pivot irrigation in western Kansas, you would test the effectiveness of center pivots on randomly sampled farms in western Kansas to determine typical costs and returns of center pivot irrigation in the area. Several of these ROA models are based primarily on the work done by Dixit and Pindyck titled *Investment and Uncertainty (1994)*. In their book, Dixit and Pindyck lay out a framework for determining the hurdle rate based on four values: the expected returns of the investment, the sunk cost of initiating the project, a risk adjusted discount rate of the opportunity cost of capital, and the variance of the expected returns of the investment. This hurdle rate is then compared with the Marshallian investment trigger, which is the annual value needed to recoup the sunk cost of the investment. The difference between these two values is equal to the value of postponing the investment.

Determination of a population wide hurdle rate can be useful in a number of contexts. For example, Purvis et al. (1995) use ROA to estimate an uncertainty adjusted hurdle rate for the adoption of free stall dairy housing in Texas. They use price and production datasets from early adopters to parameterize their model and estimate the cost of the free-stall technology to be $996,200. Based on this data, the authors find that the Marshallian investment trigger is $83,448 and the Net Present Value (NPV) of the investment is $145,695. This result suggests that producers should adopt the new dairy stalls because the NPV is greater than the Marshallian investment trigger. The hurdle rate however is estimated to be $190,063, which is greater than the NPV indicating that producers are better off not adopting and waiting for conditions to improve. The authors note that the free stall dairy housing technology, enhances social welfare. Thus, given this contrary finding in order to encourage adoption, the authors suggest that state agencies should offer cost share for the capital investment equal to the difference between the NPV of the investment and the hurdle rate, $44,368. In summary, this paper provides a thorough economic explanation for why adoption of this seemingly profitable technology was being postponed and how policy makers could encourage adoption.

Tozer (2009) builds upon this work in the context of precision agricultural technologies (PATs), by applying this ROA framework to the adoption of variable rate fertilizer application in Australia. Tozer (2009) finds that the NPV of variable rate application exceeds the hurdle rate value, suggesting that adoption is likely to take place. In contradiction to these results adoption of variable rate nitrogen fertilizer application has not been widespread in Australia (Say et al. 2018). Several authors have presented explanations for why PATs as a whole are not being adopted, most of which have focused on access to PATs and user friendliness of PATs that might be creating barriers to adoption. For example, Schimmelpfennig and Ebel (2016) postulate that producers are still in the process of determining which combination of PATs are best for operations with varying characteristics. Others have examined links between producer characteristics and adoption, finding higher adoption among larger farms, irrigated farms, and farms with more technologically literate producers (Bramley 2009, Castle and Lubben 2016).

Tozer (2009) suggests that that the ROA model of variable rate technology may be inaccurate because it assumes that all machinery investment occurs during the first analysis period. He suggests a need for investment timing to be considered in a stochastic dynamic model[1]. Doing so will model decision-making in a way that accurately represents the conditions faced by producers in the real world. For example, we expect that most producers currently use a conventional uniform rate application approach and the decision to use variable rate technology is a decision to stop using the conventional system. Assuming that sunk cost for the new and conventional technologies are similar and spread out across several time periods, like they are in the scenario presented by Tozer, we infer that the decision to invest in PATs is instead based upon the relative value of returns between the conventional technologies and PATs. A stochastic dynamic model allows us to make these comparisons.

Stochastic dynamic models have been used in the past to solve similar questions about investment decision-making. Ekboir (1996) uses a stochastic dynamic model to describe capital investment behavior. In this model, the producer possesses an initial level of capital. The producer also has a desired level of capital that changes over time with changes in economic conditions to reflect the profit maximizing quantity of capital. The producer however does not change levels of capital to the profit maximizing level of

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[1] Stochastic dynamic models set of processes designed to mimic how things like prices and productivity change over time (Ross 2014)

[2] Grower-chosen methods refers to uniform rate application methods chosen by

capital when desired capital changes due to the irreversible and risky nature of the investment. Instead the producer waits until desired capital reaches some upper or lower bound such that frequent switching is avoided. Ekboir describes these upper and lower bounds as functions of the investments' technical and economic characteristics. These bounds are similar to the optimal investment trigger in the sense that they represent the degree to which a producer should wait to ensure that their investment would be profit enhancing. In that sense, Ekboir (1996) provides a framework to understand how to induce capital expansion in a manner to maximize profit and utility while ensuring that producers' uncertainty is managed.

While the context is slightly different, Ekboir's methods for estimating the optimal upper and lower bounds translate well to a technology adoption problem. Therefore, we employ a stochastic dynamic model instead of model that resembles the work inspired by Dixit (1992), to estimate optimal adoption behavior. This optimal investment trigger will represent the degree to which returns from an investment must be different from those associated with the current technology in order to maximize a producer's utility. This difference in returns will be dependent on the variability of each production method driven by the nature of the nitrogen application method as well as variability of external economic factors such as corn and nitrogen price.

3.2 Prospect Theory and Technology Adoption

Given the risk and uncertainty associated with prices and production outcomes when deciding to adopt a new technology, it is important to evaluate how producers risk preferences influence the adoption decision. The importance of considering individual risk preferences when analyzing technology adoption has been highlighted by studies such as those by Feder et al. (1985), Liu (2013), and Anand et al. (2019). In the Feder et al. (1985) paper, the authors summarize previous work done on technology adoption and argue that farmers' technology adoption decisions are based upon subjective probabilities. Furthermore, they argue that an estimate of a producer's level of risk aversion can sometimes be used to explain technology adoption. Liu (2013) uses survey information and field experiments to elicit risk preferences from Chinese farmers in the context of adoption of Bt Cotton. She finds that these risk preferences have a significant impact on adoption and that risk preferences represented by Prospect Theory is more suited to explaining producer adoption decisions than expected utility theory. Anand et al (2019) applies prospect theory to their work on the adoption of bioenergy crops. They find a significant difference in the adoption of different bioenergy crops when incorporating a prospect value function into the decision process.

There are multiple reasons as to why Prospect Theory is appropriate for the study of technology adoption given producer risk and uncertainty. First, there is strong evidence that decision-making agents in both agricultural and non-agricultural contexts behave with respect to a reference point which is in keeping with how Prospect Theory is defined. Experimental research to confirm the existence of this effect was pioneered by Kahneman and Tversky (1979) and since has been replicated in several other contexts (Tversky and Kahneman 1992, Gneezy and Potters 1997, Thaler et al. 1997, Schmidt and Traub 2002, Liu 2013). Empirical analyses outside of laboratory settings also provide a strong case for the existence of non-linear probability weighting and loss aversion among decision-making agents, two key aspects of prospect theory (Thaler & Benartzi 1995, Bowman et al. 1999, Genesove & Mayer 2001, Liu 2013). Thaler & Benartzi (1995) shows that decisions between stocks and bonds can be modeled according to prospect theory such that the predicted outcomes match observed values of behavior. Bowman et al. (1999) find evidence of behavioral asymmetries in response to income losses and gains. Specifically, the authors found in datasets from several countries that when wages change, consumption changes more sharply in response to losses opposed to gains. Genesove & Mayer (2001) find evidence in the housing market by looking at differences in pricing when sellers have either made a loss or a gain on their original purchase price.

While the existence of these behavioral tendencies may not be debated, it remains difficult to apply these ideas to some economic settings due to confusion over precise definitions of gains, losses, and reference points (Barberis 2013). Barberis (2013) gives the example of a stockholders portfolio. Should stocks be viewed individually or as an aggregate? Should gains be viewed in reference to their purchase price or in reference to their expected values? There is certainly much room for interpretation and this is no different when thinking about technology adoption. For example, when a producer considers purchasing a new seed variety do they compare gains and losses from just the sale of the crop or do they consider gains and losses at the operation level? Do they use the previous year's profitability as a reference point or do they look back at several years? Do they evaluate the potential outcomes from the new seed variety in isolation and ignore other relevant risks? In our case specifically we will need to decide what portion of a producers portfolio we focus on and what the reference point is for this portion of the producers portfolio.

To decide which portion of the producer's portfolio we should focus on we look to the work of Barberis, Huang, & Thaler (2003) on narrow framing. In this paper the authors study decision making under risk and find that the concept of narrow framing, in which individuals analyze risks in isolation from other risks they already face, was the best explanation of individual decision making in the experiments they conducted. Barberis, Huang, & Thaler (2003) use this result to argue that individuals analyze risks individually rather than as a whole. In the context of crop canopy sensor adoption this implies that producers would only be concerned with gains and losses attributable to crop canopy sensors, therefore we use information about the gains and losses from nitrogen expenses and corn yield to define our decision making process.

The work of Koszegi and Rabin (2006, 2007, 2009) provides some guidance for thinking about where the values needed to evaluate a decision according to prospect theory come from. Kosezegi and Rabin argue that reference points are rational expectations based on individual recent outcomes. Work done on reference points used by agricultural producers corroborates the idea that reference points are based on individual recent outcomes (Mattos & Zinn 2016, Tonsor 2018). Tonsor (2018) concludes that in cattle markets, producers use their best-experienced outcome as a reference point in their decision-making. This literature leads us to believe that the profit reference point that corn producers use when making decisions is a value somewhere between the maximum profit they've previously received and their average profit.

4 Methods and Data

4.1 Farmer's Optimization Problem

4.11 Expected Utility Theory

The farmer solves the following optimal switching problem:

$$\max_{k} E\left[\sum_{t=1}^{k} \sigma^{t-1}\, U\big(\phi(t)\big)\right] + E\left[\sum_{t=K+1}^{T} \sigma^{t-1} U\big(\phi(t)\big)\right] \tag{1}$$

where k is the decision variable (the time period at which the farmer adopts the SENSE technology), $U(\cdot)$ is the utility function, $\varphi(t)$ is the profit in year t. Let $Y(t)$ and $N(t)$ denote yield and nitrogen application rate in year t. Further, let $P_C(t)$ and $P_N(t)$ denote the price of corn and nitrogen in year t, respectively. Then, profit in year $\varphi(t)$ can be written as follows.

$$\phi(t) = P_C(t)\times Y(t) - \ P_N(t)\times N(t) \tag{2}$$

The distribution of both prices stay the same over the years as the adoption of SENSE technology should not affect the market prices. Their joint distribution is denoted as $h(P_{c,}P_N)$. The joint distribution of yields and nitrogen rate differ before and after the adoption of the SENSE technology. Let $f(Y,N)$ and $g(Y,N)$ represent the joint distribution of yield and nitrogen before and after the adoption of the SENSE technology, respectively. Then, the fully explicit version of the optimal switching problem represented by equation (1) can be written as follows:

$$\max_k \int\int\int\int \left[\sum_{t=1}^{k} \sigma^{t-1}\, U\big(P_C(t)\times Y(t) - P_N(t)\times N(t)\big)\right] h(P_C,P_N) f(Y,N)\cdot dP_C\cdot dP_N\cdot dY\cdot dN$$
$$+ \int\int\int\int \left[\sum_{t=1}^{k} \sigma^{t-1}\, U\big(P_C(t)\times Y(t) - P_N(t)\times N(t)\big)\right] h(P_C,P_N) g(Y,N)\cdot dP_C\cdot dP_N\cdot dY\cdot dN \tag{3}$$

4.12 Prospect Theory

When we assume that the producer behaves according to prospect theory, the following optimization problem is solved

$$\max_k E\left[\sum_{t=1}^{k} \sigma^{t-1}\, U\big(\phi(t)\big)\right] + P\left[\sum_{t=K+1}^{T} \sigma^{t-1} U\big(\phi^{+}(t) + \phi^{-}(t)\big)\right] \tag{4}$$

where $\varphi^{+}(t)$ is the utility from gains in year t and $\varphi^{-}(t)$ is the utility from losses in year t. If the producer reaps a gain $\varphi^{+}(t)$, the losses are replaced by zero and similarly upon incurring a loss of $\varphi^{-}(t)$, gains are replaced by zero in the objective function. Gains and losses are determined in relation to the reference point *f*, which represents a producer's rational expectation of profit. The degree to which producers are averse to losses is denoted λ and α represents the degree to which gains and losses become weighted more or less according to their distance from the reference points. Then, the two components that determine utility in year t $\varphi^{+}(t)$ and $\varphi^{-}(t)$ can be written as follows.

$$\phi^{+}(t) = f + \left[\big(P_C(t)\times Y(t) - P_N(t)\times N(t)\big)^{+} - f\right]^{\alpha} \tag{5}$$

$$\phi^{-}(t) = f - \lambda\left[f - \big(P_C(t)\times Y(t) - P_N(t)\times N(t)\big)^{-}\right]^{\alpha} \tag{6}$$

Then, the fully explicit version of the optimal switching problem subject to a prospect value function represented by equation (4) can be written as follows:

$$\max_{k} \int\int\int\int \left[\sum_{t=1}^{k} \sigma^{t-1}\, U\big(P_C(t)\times Y(t) - P_N(t)\times N(t)\big)\right] h(P_C, P_N) f(Y, N)\cdot dP_C \cdot dP_N \cdot dY \cdot dN$$
$$+ \int\int\int\int \Bigg[\sum_{t=K+1}^{T} \sigma^{t-1} U\Big(\Big(f + \big[\big(P_C(t)\times Y(t) - P_N(t)\times N(t)\big)^{+} - f\big]^{\alpha}\Big) \qquad (7)$$
$$+ \Big(f - \lambda\big[f - \big(P_C(t)\times Y(t) - P_N(t)\times N(t)\big)^{-}\big]^{\alpha}\Big)\Big)\Bigg] h(P_C, P_N) g(Y, N)\cdot dP_C \cdot dP_N \cdot dY \cdot dN$$

4.2 Data and Model Parameterization

In order to model commodity prices and to select the most appropriate one for our model we consider two criteria. First, the model should produce a schedule of prices consistent with general fluctuations in corn price. We are not interested in the effects of specific events, but in typical price movements because it is unlikely that events such as the ethanol boom are incorporated into a producer's expectations about prices. In other technology adoption studies we find a similar approach to modeling future prices (Anand et al. 2019).

4.21 Corn and Nitrogen Price

Corn and Nitrogen prices are key parameters that determine the profitability of the two nitrogen application options. We will model the joint distribution of corn and nitrogen prices change ($h(P_C, P_N)$) over time in two steps. (Schnitkey 2016). We first model corn price using the Ornstien-Uhlenbeck (OU) process, and then, we use the relationship between corn and nitrogen prices developed in Schnitkey (2016) to find nitrogen price.

The OU process has been used to model commodity prices in previous studies of financial decision (Schwartz 1997, Schwartz and Smith 2000, Duffie 2010). The OU process is considered suitable for modeling commodity prices as it can model mean-reversion. Mean reversion refers to a stochastic process in which values tend to revert back to a long-term mean, and some commodity prices are considered to follow such a process (Schwartz 1997). The OU process is written mathematically as follow:

$$dS_t = \Phi(\mu - S_{t-1})dt + \sigma dW_t \tag{8}$$

where Φ is the mean reversion rate, μ is the long term mean, σ is a measure of variability, and S_t is the value of the stochastic process in time period t, in our case this is the value of corn price during time period t. To calibrate these parameters, we use historical corn price data from the USDA's ARMS database on commodity prices. We use a sample of monthly prices at the national level from 2014 to 2018. This time period is chosen because it overlaps with the Project SENSE test period and leads up to the present. This allows the results of our simulation to be compared with the results gathered by project SENSE and tested against observed rates of adoption going forward. Table 2 shows the results of the Augmented Dickey Fuller (ADF) test of unit root. We use this test to confirm that the ARMS data on corn prices exhibits mean reverting behavior in order to justify use of an OU process in simulating the corn prices in our model.

Table 2: ADF Test for Mean Reversion

Type 1: No Drift No Trend

lag	ADF	p.value
0	-0.912	0.349
1	-0.269	0.563
2	-0.336	0.544
3	-0.393	0.528

Type 2: With Drift No Trend

lag	ADF	p.value
0	-3.275	0.023
1	-2.538	0.123
2	-2.010	0.325
3	-2.017	0.322

While we cannot reject the null hypothesis of no drift (Type 1), we do when the test allows for it with a lag of 0 (Type 2). By rejecting the null hypothesis in Type 2 of our test, the result indicates that our sample of corn price data is trend stationary and can be used to parameterize our utility maximization model.

OLS estimate of the three parameters using the USDA ARMS data are $\Phi = 0.2969$, $\mu = 3.4765$, and $\sigma = 0.1279$. Given these parameters, we are able to create simulated corn price schedules that will be used in our simulation. To generate nitrogen price schedules, we plug the corn price values into the following yield-nitrogen price equations developed by Schnitkey (2016) that estimates per ton nitrogen price (P_N) as a function of per bushel corn price (P_C) and per cubic thousand feet natural gas price (z).

$$P_n = -255.14 + 123.83P_c + 42.72z \tag{9}$$

Equation 9 is a simple linear model created by Schnitkey (2016) using datasets from the USDA's ERS and ARMS as well as the Energy Information Agency (EIA). Both corn price and natural gas price are used as explanatory variables in determining nitrogen price. Corn price is included because a higher price of corn spikes the demand for nitrogen, increasing its price. Natural gas price is included because it is an important component in the manufacture of nitrogen fertilizer production. The r-squared of the model is 0.88. Lastly, to incorporate the impact of varying natural gas prices into our equation for determining nitrogen price we use a simple normal distribution based on a natural gas historical price dataset provided by the EIA.

4.22 Yield-Nitrogen relationship

Our goal in this section is to create the joint distributions f(Y,N) and g(Y,N) of field characteristics that match observations made in the field trials carried out by Project SENSE. The field trials carried out by Project SENSE tested grower-chosen[2] and sensor-based[3] nitrogen application rates for their profitability. These trials were carried out from the years 2015 to 2017 at 52 sites in south central Nebraska. Some sites participated in each of the three years, while some sites only participated once. Results from field trials were recorded annually. For each application treatment two variables were recorded: corn dry yield[4] in bushels per acre and pounds of nitrogen per acre.

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[2] Grower-chosen methods refers to uniform rate application methods chosen by producers. While producers may have used different methods in determining the constant rate of N application, such as historical rates or soil sampling, they each applied N at a constant rate across their operation.

[3] Sensor based nitrogen application used equipment provided by the University of Nebraska-Lincoln to apply nitrogen on an as needed basis across the field then averaged to find a per acre application rate.

[4] Dry yield is the weight of corn grain when the moisture content is equal to 15%.

To model field characteristics as stochastic variables that capture the range and variation exhibited by the two application practices during field trials, we employ a two-step process. First we select mean values for the amount of nitrogen applied per acre and yield per acre from a theoretical distribution that matches the distribution observed in field trials. Second, we allow the values for each of these two variable to vary annually based on the year to year variation observed within field trial variations.

Intuitively we expect these variables to be strongly correlated to one another. Calculating the Pearson correlation coefficients (presented in Table 3), we find that the amount of nitrogen applied using each application method is significantly correlated with each other, as well as the yield using each application method. Based on this information we find it appropriate to assign values of field characteristics for each iteration using a multivariate distribution.

Table 3: Field Characteristic Correlation Test

Item		Pearson Correlation Coefficient	p-value
SENSE-N	SENSE-Y	0.050	0.736
SENSE-N	Grower-N	0.294	0.044
SENSE-Y	Grower-N	-0.047	0.749
SENSE-N	Grower-Y	-0.054	0.717
SENSE-Y	Grower-Y	0.950	0.000
Grower-N	Grower-Y	0.086	0.561

These distributions are presented in Figure 1 which indicate that the distributions of applied N are symmetric and the yield distributions are skewed. Testing the project SENSE data for skewness yields the values in Table 4. They indicate distributions for applied N are symmetric, while distributions of yield are moderately skewed.

Figure 1: Density Distribution of Observed Yield (bu/acre) & N-Rate (lbs/acre)

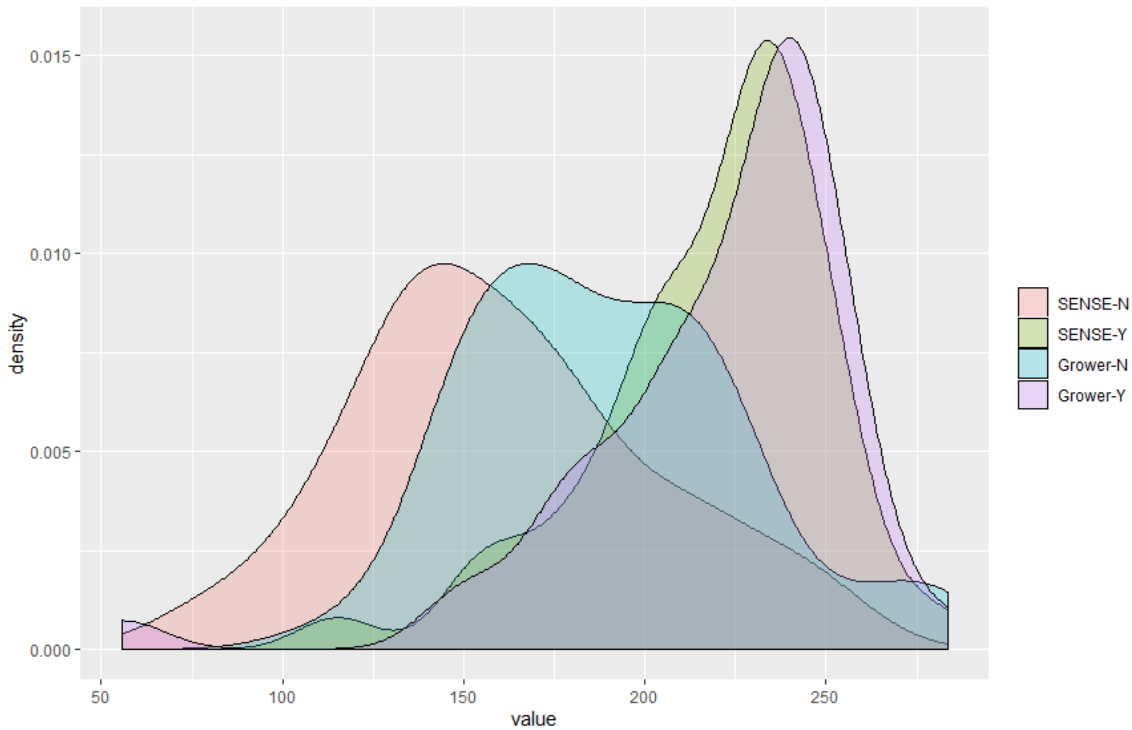


Table 4: Moment Coefficient of Skewness in Observed Field Characteristics

Item	Skewness
SENSE - N	0.307
SENSE - Y	-0.925
Grower - N	0.507
Grower - Y	-1.839

To account for the distributions asymmetry we employ a multivariate skewed normal distribution. This distribution is similar to that of a multivariate normal distribution, with the addition of a skewness term. We use the R package ‘sn’ to parameterize a distribution from the SENSE observations that we can sample from. While there may be no appropriate test to compare the observed and sampled distributions as a whole, we can compare the individual elements of using Kolmogorov-Smirnov tests. Results from these tests are presented below and indicate how well the sampled data matches the observed data.

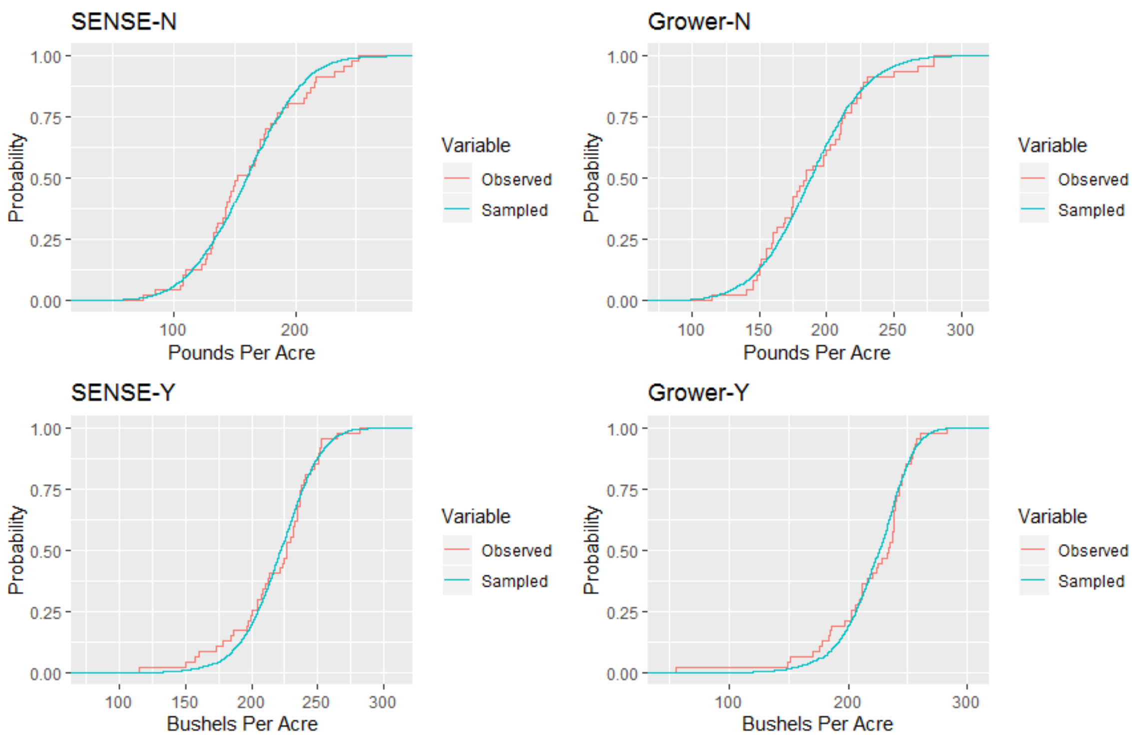
Table 5 Two-sample Kolmogorov-Smirnov test

Item	D	P-Value
SENSE - N	0.090	0.846
SENSE - Y	0.098	0.758
Grower - N	0.086	0.884
Grower - Y	0.150	0.245

The D value in Table 5 indicates the maximum distance between the cumulative distribution functions of the two samples.

The multivariate distribution of yields and N-rates matches observed data well from Project SENSE plots, but in order to produce a schedule of yields and N-rates that matches the values a single producer faces we need to consider the variation within subjects of observed field data. Unfortunately not every observation has multiple years. Out of 41 there are about 10 operations that only did the study one year and the rest did two or three. Since this data is somewhat limiting, we take a simple approach to estimating annual change using another multivariate normal distribution.

Figure 2: Cumulative Distribution Functions of Observed and Sampled Field Characteristics



To create a multivariate distribution of annual changes we restructure our dataset to now show us the annual changes in each field characteristic value. For each plot that has more than one year of observed data we find the average absolute value of annual change. Since we only have three years of data we cannot assume any type of trend and assume that these annual changes are just as likely to be positive, as they are negative giving rise to an increasing or decreasing trend. Therefore, we use the variance and covariance of the absolute values of change to create a multivariate normal distribution to describe the typical magnitudes in annual variation.

Table 6: Field Characteristic Annual Change Correlation Test

Item		cor	p
SENSE-N	SENSE-Y	-0.164	0.557
SENSE-N	Grower-N	-0.174	0.534
SENSE-Y	Grower-N	-0.000	0.999
SENSE-N	Grower-Y	-0.394	0.145
SENSE-Y	Grower-Y	0.865	0.000
Grower-N	Grower-Y	0.042	0.879

Using these two distributions we can now simulate a set of potential field characteristics, or "states of the world", that a producer might encounter. We start by first drawing from our skewed normal distribution to select a set of baseline characteristics that a producer faces. Then in each time period we randomly select a change value from our second distribution. Finally, we repeat this process for the number of time periods included in our simulation.

4.3 Monte Carlo Simulation

Faced with an uncertain choice between maintaining uniform rate nitrogen application and switching to crop canopy sensor based nitrogen application, corn producers select the time period they switch (k) based on an investment trigger that maximizes their utility given the uncertainty. While producers may do this heuristically, we estimate the optimal investment trigger by conducting a Monte Carlo simulation of the producer's decision-making process. By evaluating the optimal investment trigger in multiple simulation iterations and finding the mean of these iterations we will estimate a population wide optimal investment trigger that leads producers to maximize their chances of obtaining the highest level of profit possible. We will evaluate this optimal investment trigger under both Expected Utility Theory and Prospect Theory and test to see if there is a difference in optimal behavior between the two utility functions.

To estimate a producer's optimal investment trigger, we employ a method called stochastic approximation. The idea of stochastic approximation was first presented by Robbins and Monro in 1951 as an approach to solving optimization problems subject to noise. Kiefer and Wolfowitz augmented this process in 1952 to solve for a maximum using a gradient like process of finite steps. Their work forms the theoretical basis of our model and provides a novel approach to finding the optimal switching point. One reason for employing stochastic approximation is because it does not force us to find a theoretical solution. This allows us to easily test and modify our functional form to account for changes in stochastic processes or value functions. Solving a stochastic approximation problem requires a significant number of computations and to do this we employ a Monte Carlo simulation.

Using the distributions $h(P_c,P_N)$, $f(Y,N)$ and $g(Y,N)$ we simulate to produce a set of potential states of the world that a producer might face. We repeat this process a total of n times so that we have a diverse array of potential situations a producer might face. With these states of the world defined, we find the economic returns for each n using a given investment barrier. We begin by finding the profit a producer will receive in a given time period using the traditional uniform rate and the new variable rate SENSE application method. Producer profit in time point t using method m is given by

$$\pi_m(t) = Y_m(t) \times P_C(t) - N_m(t) \times P_N(t) \tag{10}$$

The profit calculated in equation (10) will define the value that producers receive in time period t. However, the decision about what production method to use will be made using an expected value for time period t based on field and price information from time period t-1 as is common in Markov models of decision making (Sonnenberg and Beck 1993). Equation 11 & 12 below show the parameters for determining the expected value in a given time period, where *m=0* is the grower method and *m=1* is the SENSE method.

$$E(\pi_0(t)) = \int\int [Y(t) \times P_C(t-1) - N(t) \times P_N(t-1)] f(Y,N) dY dN \tag{11}$$

$$E(\pi_1(t)) = \int\int [Y(t) \times P_C(t-1) - N(t) \times P_N(t-1)] g(Y,N) dY dN \tag{12}$$

By creating a schedule of expected values for both Uniform and SENSE application, we can observe the time period that a producer chooses to adopt SENSE application, given their investment criteria which is explained later in equation 15. Using this approach, their income in each time period is given by the following.

$$\pi(t) = \begin{cases} \pi_0(t), & E(\pi_1(t)) \leq E(\pi_0(t)) \\ \pi_1(t), & E(\pi_1(t)) > E(\pi_0(t)) \end{cases} \tag{13}$$

If producers were able to switch back and forth between technologies, Equation 13 would describe their profit in each time period. Due to the irreversible nature of the investment in consideration, if a producer adopts the SENSE technology, profit in the subsequent time periods is defined using the SENSE field characteristics. To account for this irreversibility we add additional notation in Equation 14 to define profit subject to irreversibility.

$$\pi^* (t) = \begin{cases} \pi(t), & \pi^* (t-1) \neq \pi_1(t-1) \\ \pi_1(t), & \pi^* (t-1) = \pi_1(t-1) \end{cases} \tag{14}$$

Solving equation 13 for each t will give us a schedule of producer profits by time period.

4.31 Optimal Investment Subject to Expected Utility Theory

In order to find the optimal investment trigger under expected utility theory we must evaluate profits using different investment barriers. To do this we must evaluate Equations 12 & 13 with an additional term *j*. This term *j* will represent each investment barrier we are interested in, taking on a finite sequence of values *j* = 1.00, 1.01, 1.02…*j*. Intuitively what this means is that expected profit using SENSE application must be greater than expected profit using uniform application by a factor of *j* for investment to occur. Equations 15 & 16 show modified versions of Equations 13 & 14 with the inclusion of our *j* term.

$$\pi_j(t) = \begin{cases} \pi_{j0}(t), & E(\pi_1(t)) \leq E(\pi_0(t)) \times j \\ \pi_{j1}(t), & E(\pi_1(t)) > E(\pi_0(t)) \times j \end{cases} \tag{15}$$

$$\pi_j^*(t) = \begin{cases} \pi_j(t), & \pi_j^*(t-1) \neq \pi_{j1}(t-1) \\ \pi_{j1}(t), & \pi_j^*(t-1) = \pi_{j1}(t-1) \end{cases} \tag{16}$$

Once we evaluate equations 15 & 16 for each t & j, we have a set of vectors that describe the producer's returns subject to each j. The process is then repeated such that another hypothetical producer is created using the same parameters set forth. We then find the producers returns using each investment barrier again until we have a number of profit schedules that sufficiently captures all likely outcomes a producer is to face.

From here we take the Kiefer-Wolfowitz gradient approach[5] to solve for the investment barrier that maximizes producer utility. Let *j* be a value from the finite sequence investment barriers and *n* be the number of iterations in the simulation. Equations 17 thru 18 below show the process for finding the average value of returns under each j.

$$x_{nj} = \frac{1}{t}\sum_{t=1}^{t} \pi_{jn}(t) \tag{17}$$

$$\overline{x_j} = \frac{1}{n}\sum_{n=1}^{n} x_{nj} \tag{18}$$

[5] The Kiefer-Wolfowitz gradient approach is a method to stochastically estimate the maximum of a function when the exact specification of the function is unknown.

This approach provides us with the average value of returns using each investment trigger. By finding the maximum value of $\overline{x_j}$, we solve our optimization problem and find the optimal investment trigger (j`) for our given set of producers. This process is described by equation 19.

$$j^{`} = \max_{j} \overline{x_j} \tag{19}$$

4.32 Optimal Investment Subject to Prospect Theory

In order to find a producer's optimal switching point subject to loss aversion we use a prospect theory value function put forth by Kahneman and Tversky (1992) to evaluate gains and losses using the alternative technology. Let *f* represent the reference point used by the producer which is obtained from their production history, λ be the coefficient of loss aversion, and α be the coefficient of risk aversion.

$$\pi'_{1}(t) = \begin{cases} f + (\pi_1(t) - f)^{\alpha}, & f \leq \pi_1(t) \\ \pi_1(t) - \lambda(f - \pi_1(t))^{\alpha}, & f > \pi_1(t) \end{cases} \tag{20}$$

Using this prospect value function, we re-evaluate the value of returns generated by equation 16. If the returns in a given time period were generated using uniform rate application technology, they remain unchanged. If the returns in a given time period were generated using SENSE application their value is evaluated according to Equation 20. This process is described by equation 21 below.

$$\grave{\pi_j}(t) = \begin{cases} \pi_0(t), & E(\pi_1(t)) \leq E(\pi_0(t)) \times j \\ \grave{\pi_1}(t), & E(\pi_1(t)) > E(\pi_0(t)) \times j \end{cases} \tag{21}$$

We again apply our Kiefer-Wolfowitz approach to find the optimal investment barrier. This is done by repeating equations 17 thru 19 using the prospect theory altered values. This allows us to determine the value of waiting when we assume that producers' risk preferences are in accordance with prospect theory rather than expected utility theory.

4.4 Numerical Solution

With the parameters for our price and field characteristics defined by the equations and distributions developed in section 3.2 we can now run our simulation. The simulation is composed of 1,000 iterations with t=45 individual time periods occurring in each iteration. The process for each iteration is as follows. Using the methods from the previous section schedules of corn price, nitrogen price, SENSE nitrogen quantity, SENSE yield, grower nitrogen quantity, and grower yield are created. The expected values of yield and nitrogen using either method is equal to the value selected as the producers baseline productivity, before these values are allowed to vary annually. Using the price and grower values from the time periods t(1:15) we calculate the returns per acre during this time period. We use these values to establish a grower's expectations about uniform rate application. These values are what we use to determine the reference point used in each iteration. Based on the literature we reviewed that tries to empirically estimate reference points used by agricultural producers (Mattos and Zinn 2016, Tonsor

2018) we select a reference point equal to the third quartile of the values calculated in this section.

Once the reference point has been selected we next determine the producers switching behavior using 51 different investment barrier levels (*j*). We chose to use 51 barrier levels because testing any more or less only increases the computational strain without any significant change in the value of the result. The barriers we evaluate range from 0.75 to 1.25 with an interval of 0.01. Values below 0.75 and above 1.25 aren't tested because adoption is either complete or nonexistent respectively at these investment barriers. For each level of *j* we record the time periods during t(16:30) where the use of SENSE application is more profitable than Grower application, given the investment barrier. Since investment is irreversible, we are interested in the first time period in which expected profits using SENSE application are greater than expected profits using Grower application, given the investment barrier.

With this information we can now create a vector of the producer's annual per acre profit for each *j*. If during the time periods t(16:30) the producer does not switch, the vector will contain producer revenue for time periods t(16:30) using only the grower method. If the producer does switch, the revenue before the time period of the switch t^* will be determined using the Grower variables. After the switch the revenue from the next 15 time periods will be determined using the SENSE variables for N application rate per acre and yield per acre. The reason we use this amount of time periods is because the technology experts estimate that the lifespan of the investment is 15 years. The result will be a vector containing the revenue in each time period pre-switch and the revenue in 15 time periods post-switch.

Next we create an alternate set of vectors where the returns from investment are subjective values of utility characterized by Prospect Theory. We use the initial estimates made by Kahneman and Tversky (1992) for the loss aversion parameter ($\lambda = 2.25$) and the risk aversion parameter ($\alpha = 0.88$). Work done by Liu (2013) has shown that these parameters may be affected by producer characteristics, however previous authors such as Anand et al. (2019) have used the values of λ and α estimated by Kahneman and Tversky for simplicity. Using the previously described Value function in Equation 1.10, we evaluate the value of returns in each time period such that returns using the grower method are unchanged, but the value of returns using the SENSE technology are now reference dependent. To determine a producers reference point we establish a distribution of their returns across growing seasons, then select the value of the upper quartile as the reference point.

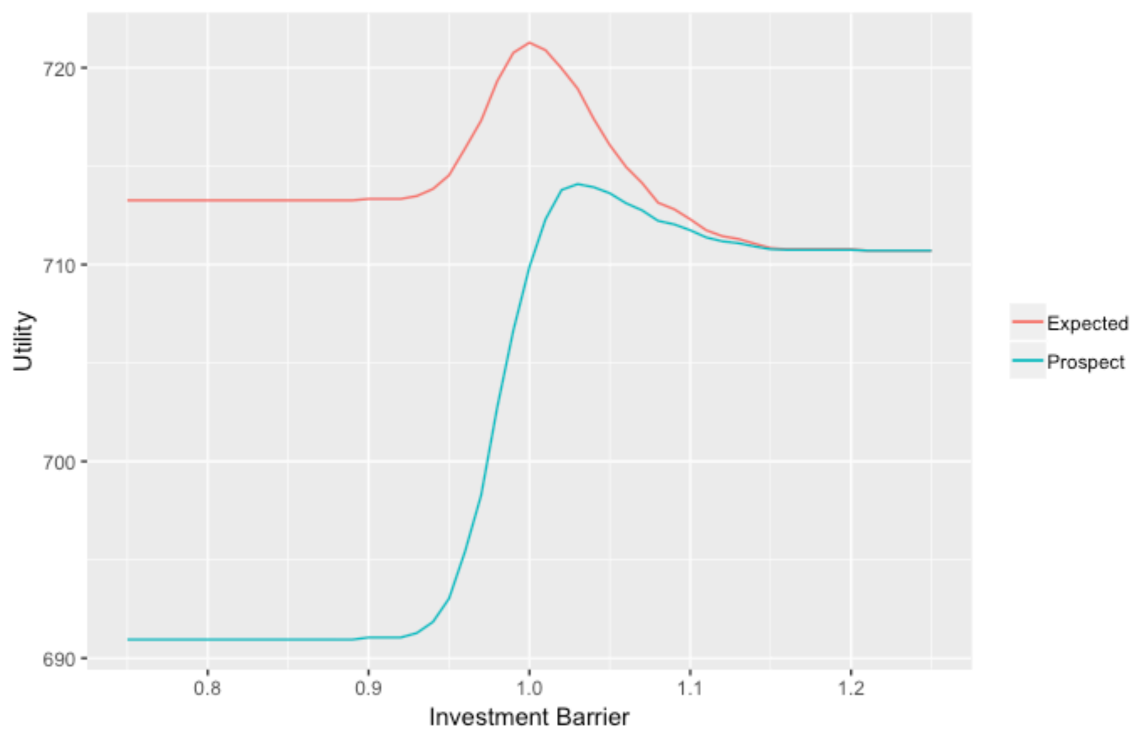
Now that we have a vector for each j for both EUT and PT formulations, we find the mean value of returns for each j. If we were looking at only this iterations optimal investment barrier, we would select the barrier with the greatest average return. Since we are looking for a general optimal investment barrier we store the average returns for each barrier in each iteration and repeat this process for a total of 1,000 iterations. With this data stored we find the average optimal investment barrier subject to each value function. This value represents the optimal investment barrier given a producers risk preferences.

5 Results and Implications

5.1 Optimal investment barrier under expected utility and prospect theory

We first conduct simulation for the case where investment is irreversible and the investment lifespan is 15 years. Figure 2 below shows the distribution of optimal switching points. If producers are not loss averse and risk preferences are characterized by expected utility theory, we find the mean optimal investment barrier to be 1.00. If producers are loss averse and Prospect Theory characterizes their decision making under risk, we obtain the mean optimal investment barrier to be 1.03.

Figure 3: Optimal Investment Timing Using Expected Utility Theory and Prospect Theory



Thus, a producer's investment barrier is higher under Prospect Theory, a finding that has been obtained in the non-adoption of new seed varieties (Liu 2013) and in the financial context of the equity premium puzzle (Benartzi & Thaler 1995). A two-sample Wilcoxon test with Continuity Correction indicates that the two investment barriers obtained under the two theoretical specifications are statistically significantly different from each other at the 1% level of significance. Thus, the manner in which decision making under risk is theoretically modeled and empirically represented has significant bearing on the rate at which a new technology is expected to be adopted by a group of stakeholders, here corn producers.

5.2 Varying Costs

Up to this point we have assumed that the equipment necessary to operate crop canopy sensors have a per acre cost equal to that of uniform rate application. This may be the case for producers who use high clearance applicators for their regular uniform rate application or producers who's costs are distributed widely across their operation. Whatever the case, it is likely that for some producers the cost of equipment needed to operate crop canopy sensors is greater than that of the equipment needed to operate using a uniform rate approach. Therefore, we estimate the optimal adoption triggers under both Expected Utility Theory and Prospect Theory when the equipment needed to use crop canopy sensors is $10 more expensive per acre.

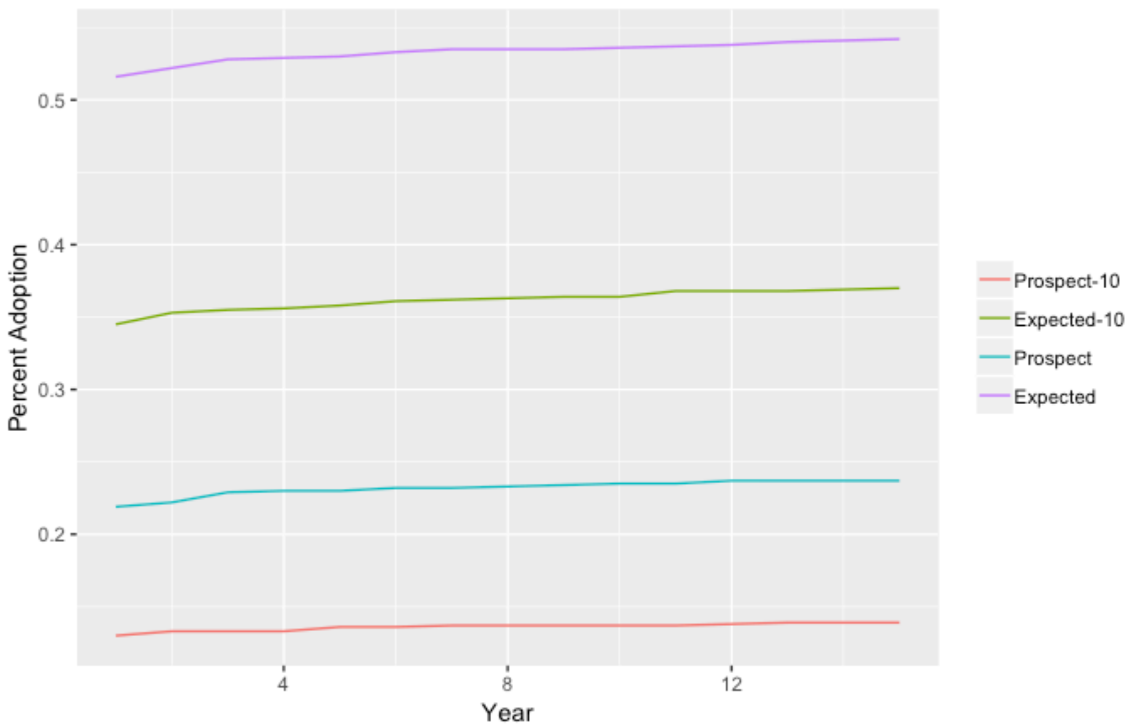
When the price of the equipment needed to operate crop canopy sensors is greater by $10 we observe that if producers are not loss averse and risk preferences are characterized by expected utility theory, the mean optimal investment barrier is 1.00. If producers are loss averse and Prospect Theory characterizes their decision making under risk, we obtain the mean optimal investment barrier to be 1.03. These values are the same as the condition where uniform and sensor application are the same price. They are also found to be different from one another using a two-sample Wilcoxon test with Continuity Correction. While the optimal investment behavior may not be different, we find that increasing the price has implications for diffusion that are discussed in the following section.

5.3 Rate of Diffusion of Crop Canopy Sensors

Using the same parameters of determining corn prices, nitrogen prices, and field characteristics that were used to determine the optimal investment trigger we estimate the rate of diffusion of crop canopy sensors, when producers use the computed optimal investment triggers. When producers behave according to their optimal investment barrier under expected utility, we would expect to see approximately 54% of corn producers to be using crop canopy sensors 15 years from the current period. We choose to look at 15 years because this is the estimated lifespan of crop canopy sensors. Using the barrier estimated under Prospect Theory we would expect 24% of the population to use SENSE application in 15 years.

Under the assumption that crop canopy sensors are $10 more expensive per acre than uniform custom application we obtain a different outcome. When we use the optimal investment barrier according to expected utility theory we expect that around 37% of producers will use crop canopy sensors by the end of the 15 year time period. Using the optimal investment trigger according to prospect theory, we find that this value drops such that we only expect roughly 14% of producers to use crop canopy sensors by the end of the 15 year time period.

Figure 4: Predicted Diffusion of SENSE Technology



In Figure 4 we observe the predicted diffusion using both the investment barriers estimated according to Expected Utility Theory and Prospect Theory under conditions of equal cost and an additional $10 cost. We see that both the additional cost of equipment and inclusion of loss aversion decrease the amount of adoption that is projected to occur.

5.4 Yield, Nitrogen Use, and Profit

Potential adoption of crop canopy sensing technologies is likely to cause some reduction in N use among producers and alter the overall productivity of corn operations. Using the same 15 year period of characteristics that we use to study diffusion, we can investigate different special cases to find the impacts on average per acre yield, nitrogen rate, and profit. Table 7 shows the results for 7 different cases. First we look at outcomes when producers only use crop canopy sensors regardless of investment barrier. Next we look at outcomes when producers only use uniform application regardless of which option is more profitable for producers. Then we look at three more cases when adoption is irreversible and producers employ investment barriers at 1.00, 1.06, and 1.11. Finally we look at two cases of custom application using investment barriers of 0.94 and 1.06 as obtained previously.

Table 7: Average Yield, N-Rate, and Profit during 15 Year Diffusion Period

Special Case	Yield (bu/acre)	N-Rate (lbs/acre)	Profit ($/acre)
Crop Canopy Sensor application Only	221.11	159.66	717.79
Uniform Rate Application Only	222.98	188.33	715.19
1.00 Investment Barrier	223.69	175.54	721.23
1.03 Investment Barrier	223.72	184.62	716.42
1.00 Investment barrier with added cost	223.98	181.12	717.01
1.03 Investment barrier with added cost	223.25	186.07	715.16

From the table we first see that yield remains similar in each case. However with high year to year variability of required nitrogen rate and yield, and the choice of nitrogen application method predicated on the results of the previous year's growing season this profit premium begins to make some sense. A conclusion that we can draw from this finding is that producers are better off when they look at conditions over an aggregate of several years when making their decisions, rather than changing their application method when they see one bad year.

In this table we also observe that risk preferences have a negative impact on the amount of profit received by producers. In the case of equal costs we see that profit is $5less per acre on average when producers maximize utility according prospect theory compared to when they maximize utility according to expected utility. This result closely mirrors the equity premium puzzle presented by Mehra and Prescot (1988). The equity premium puzzle describes the situation that despite stocks greatly outperforming bonds, many individuals still choose to invest in bonds. Benartzi and Thaler (1993) explain this phenomena using prospect theory by showing that when the potential losses from investing in stocks are weighted more heavily, investors should prefer bonds. In the context of crop canopy sensors, overweighting losses not only results in decreased profit, it also greatly increases average nitrogen use.

Next, we observe that loss aversion has a positive impact on the amount of nitrogen applied by producers. In the case of equal costs we see that on average 9 more pounds of nitrogen are applied per acre when producers maximize utility according prospect theory compared to when they maximize utility according to expected utility. This difference has extensive implications for environmental quality.

Finally, we observe that additional equipment costs decrease the magnitude of differences between the Expected Utility case and the Prospect Utility case. This is a result of less total producers switching to crop canopy sensors.

6 Conclusion

The results of our simulation indicate that the diffusion of crop canopy sensor technology will differ significantly based on the degree of irreversibility associated with the investment and the manner in which producers' risk preferences are modeled – either on the basis of Expected Utility Theory or Prospect Theory. As evidence grows to support the use of prospect theory to represent risk preferences in agricultural decision making contexts, it is more and more likely that ex ante technology adoption research will overestimate the speed and breadth of adoption among agricultural producers. Underestimation may lead to inefficient policy responses and overproduction among agricultural technology providers. Whatever the difference may be for optimal investment timing between estimates using expected utility and prospect utility, the results of our simulation indicate that waiting for optimal investment conditions can increase both producer profit and utility. This provides an economically centered explanation as to why agricultural producers to forgo adoption of a technology that improves long run farm profitability.

Taking irreversibility and risk preference into account may allow policymakers and private firms to increase adoption and decrease nitrogen runoff. This may come in the form of changes in insurance policies that provide additional support to farmers who adopt crop canopy sensors. Extension agents may encourage producers to evaluate long term gains rather than making decisions based on annual fluctuations. Cost share programs may be a tool to increase adoption to desired levels. Whatever the case may be it is made clear by our results that risk preferences and irreversibility present two factors which need to be considered when focusing on rate of technology adoption.

It is important to note that the three main factors studied in this paper, uncertainty, irreversibility, and loss aversion, are unlikely to be the only forces driving non adoption or slow adoption rates. Heterogeneity of cost structures, timing and credit constraints, and explanations using non-economic factors such as information availability, social networks, environmental motivations, and education should all be considered when studying technology adoption. In the future, extensive ex post analysis of crop canopy sensor adoption should consider the items mentioned in this paragraph as well as uncertainty, irreversibility, and loss aversion. In doing so we can test the predictive accuracy of these models and continually improve upon them.

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