The Roles of Risk and Ambiguity in Technology Adoption

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Abstract

We study the impacts of risk and ambiguity aversion on the adoption of new technologies, specifically genetically modified (GM) corn and soy seeds. We conduct experiments measuring risk and ambiguity aversion with Midwestern grain farmers. Risk aversion has only a small impact on the timing of adoption of GM soy, while ambiguity-aversion has a large impact speeding up farmer adoption of GM corn. We hypothesize that this unusual finding is due to the fact that GM corn often contains an insect-resistance trait which reduces the ambiguity of pest damages for adopters. GM soy never contains this insect-resistance trait. This highlights the importance of distinguishing between risk and ambiguity when studying the effects of aversion to uncertainty on adoption of new technologies.

1. Introduction

Empirical evidence that most individuals are risk averse (e.g., Binswanger, 1980; Gollier, 2001; Lin et al., 1974) has stimulated much research on the effects of risk and risk-aversion on technology adoption (Feder, 1980; Foster and Rosenzweig, 2010; Knight et al., 2003; Liu, 2011; Sunding and Zilberman, 2001). More recently, researchers have begun to distinguish the impact of risk from that of ambiguity (Bryan, 2010; Engle-Warnick et al., 2011; Rigotti et al., 2008; Ross et al., 2010). Consistent with that literature and the recent call to action by Herberich et al. (2009), this article combines experimental data on risk and ambiguity aversion with survey data on adoption decisions to identify the extent to which risk and ambiguity aversion impact adoption decisions. We look at Minnesota and Wisconsin farmers' adoption of genetically modified (GM) corn and soybean seeds and provide new and surprising insights on the respective roles of risk and ambiguity.

We define uncertainty to be made up of two components, risk and ambiguity. We distinguish between risk and ambiguity aversion as proposed in Klibanoff et al. (2005). Risk aversion is the aversion to a set of outcomes with a known probability distribution. Ambiguity aversion is the additional aversion to being unsure about the probabilities of outcomes. In

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addition to risk aversion (Pratt, 1964), ambiguity aversion (Halevy, 2007) also appears to be a common characteristic of economic behavior. For example, Chen and Epstein (2002) show that the addition of an ambiguity premium to the more commonly explored risk premium can explain the equity premium puzzle of the higher return of stocks compared to bonds.

Under the expected utility model commonly used in technology adoption studies, farmers choose the technology that provides the highest expected utility conditional on their aversion to risk (Feder et al., 1985; Foster and Rosenzweig, 2010; Isik and Khanna, 2003; Marra et al., 2003; Sunding and Zilberman, 2001). But, new technologies often involve ambiguity such that the probabilities of different outcomes are not known. Thus, there is room for ambiguity aversion to play an important role in adoption decisions as well (Bryan, 2010).

Most analyses assume that new farming technologies involve more uncertainty (including both risk and ambiguity) than do traditional technologies (Engle-Warnick et al., 2011; Feder et al., 1985; Liu, 2011; Lybbert and Bell, 2010). This assumption is commonly made in the literature on technology adoption (see Rigotti et al. (2008)). Under this framing of the adoption choice, risk-averse and ambiguity-averse farmers would be less likely to adopt new technologies. But, whether this framing applies to all technologies is an empirical question. For example, Bryan (2010) studies the adoption of a new insurance product which may decrease risk while increasing ambiguity.

Our analysis focuses on farmers' adoption of GM corn and soybean seeds in Wisconsin and Minnesota. Over the last two decades, the adoption of GM corn and soy in the US has been rapid (Board on Agriculture and Natural Resources (BANR), 2010; Fernandez-Cornejo, 2010). GM seeds with two main traits have become available: herbicide-tolerance (HT) traits which facilitate weed control, and insect-resistance (IR) traits which reduce damages from pests.

While the spread of weeds is relatively easy to predict, pest dynamics appear to be harder to predict (Rebaudo and Dangles, 2011). An important contrast between corn and soybeans is that corn has benefited from both HT and IR traits(with some corn including only the HT trait, some including only the IR trait, and some including both), while soy has been limited to the HT technology. We discuss the two technologies more in the Section 3. Because HT traits may not have a strong impact on ambiguity, while IR traits reduce ambiguity, we hypothesize that ambiguity aversion will play a larger role in the adoption of GM corn than it does in GM soy.

A contribution of our research is that we find a new result regarding technology adoption. Unlike most of the recent papers distinguishing between risk and ambiguity which find that ambiguity aversion deters technology adoption (Bryan, 2010; Rigotti et al., 2008; Ross et al., 2010), we document a case in which ambiguity aversion actually increases the pace of adoption. We find a significant difference between the determinants of farmers' adoption of GM corn and GM soy, with ambiguity aversion significantly speeding up the adoption of GM corn, but not soybeans. This suggests that the IR technology reduces the ambiguity related to pest damages and that ambiguity-averse farmers value this trait. Risk aversion, on the other hand, has little power in explaining the adoption of GM corn.[2]

One reason our results differ from those in the previous literature may be because of the setting. Most empirical papers which find that ambiguity aversion deters adoption of new technologies do so in a developing country context. We conduct our research with US farmers who are significantly more educated and have greater access to information regarding new technologies from extension agents, field trials, and seed dealers. In such a setting, there may be relatively little ambiguity regarding the performance of the new technology, so that the role of ambiguity aversion will be primarily vis-à-vis the new technology's direct impact on the uncertainty of outcomes. In a developing country context, ambiguity regarding the new technology's performance may have a stronger impact in deterring adoption.

The paper is organized as follows. Section 2 lays out a model of adoption under uncertainty and shows that the effects of risk and ambiguity on adoption can be either positive or negative. Section 3 provides information regarding the two GM technologies under consideration. Section 4 describes the data collection and Section 5 provides the summary statistics. Section 6 presents the econometric specification and results. Finally, Section 7 concludes.

2. The Roles of Risk and Ambiguity Aversion in Technology Adoption

In this section, we present a model which divides uncertainty into two pieces: risk and ambiguity. As discussed in the introduction, we use the term uncertainty to include both risk and ambiguity: risk occurs when the probability distribution of the random payoff is known; and ambiguity arises in situations where the probability distribution is not known with certainty by the decision maker. The model gives useful insights on how risk and ambiguity can affect technology adoption. Consider an agent making a decision $x \in X$ under uncertainty. Uncertainty is represented by a random vector e. The distribution of e may be ambiguous and depend on some parameter v that is not known.

First, consider the case where ambiguity is absent. In this case, the true probability distribution of payoffs provides all relevant information for risk assessment. For a known v, denote the distribution of e by $F(e|v)$. Under the expected utility model, the decision maker would choose x so as to maximize $\left\{\mathrm{E}_{e|v}U(\pi(x,e)) : x \in X\right\}$, where $\mathrm{E}_{e|v}$ is the expectation operator based on the distribution function $F(e|v)$, $\pi(x,e)$ is the payoff obtained under decision x and state e, and $U(\pi)$ is a von-Neumann Morgenstern utility function representing the risk preferences of the decision maker. We assume that $U(\pi)$ is a strictly increasing function. Then, following Pratt (1964), risk neutrality corresponds to $U(\pi)$ being linear, while risk aversion is obtained when $U(\pi)$ is concave.

Second, consider the case where ambiguity is present, i.e. where the true probability distribution of payoffs, v, is not known with certainty. From the Ellsberg paradox (Ellsberg, 1961), we know that ambiguity about v can affect preferences and decisions. Assuming that the true probability distribution of payoffs depends on uncertain parameters, Klibanoff et al. (2005) propose a model that separates risk aversion from ambiguity aversion. Consider that

[2] Ross et al. (2010) run an experiment similar to ours in Laos and find that ambiguity aversion is related to technology adoption among farmers while risk aversion is not.

the decision maker associates the v's with a distribution function $G(v)$. Following Klibanoff et al. (2005), assume that the choice of x is made to maximize

$$W(x) \equiv \left\{ \mathrm{E}_v h[\mathrm{E}_{e|v} U(\pi(x,e))] : x \in X \right\}, \tag{1}$$

where $h[\cdot]$ is a strictly increasing function. As shown by Klibanoff et al. (2005) and Neilson (2010), the function $h[\cdot]$ in (1) reflects ambiguity preferences; the decision maker is neutral toward ambiguity when h is linear, but he is ambiguity averse (in the sense of being made worse off in the presence of ambiguity) when h is concave. As proved by Klibanoff et al. (2005), model (1) reduces to Gilboa and Schmeidler's (1989) maxmin expected utility model when h is very concave.

We can measure an uncertainty premium which measures the combined level of risk and ambiguity involved with each choice of x. For a given $x \in X$, let $M(x) \equiv \mathrm{E}_v \mathrm{E}_{e|v}(\pi(x,e))$ be the ex-ante mean payoff. For each x, define the uncertainty premium as the sure amount of money $R(x)$ satisfying

$$W(x) \equiv h[U(M(x) - R(x))]. \tag{2}$$

Equation (2) shows that, for a given x, $R(x)$ is the agent's willingness-to-pay to eliminate all uncertainty and replace it by the ex-ante mean payoff $M(x)$. As such, $R(x)$ measures the implicit cost of uncertainty. Importantly, $R(x)$ is a measure of the overall cost of uncertainty, including both risk (captured by e) and ambiguity (captured by v).

To identify the part of $R(x)$ due to ambiguity we use the notation $Ev = E_v(v)$, and define the sure amount $R_a(x)$ that satisfies, for each x,

$$W(x) \equiv h[\mathrm{E}_{e|\mathrm{Ev}} U(\pi(x,e) - R_a(x))]. \tag{3}$$

Equation (3) shows that $R_a(x)$ is the willingness-to-pay to eliminate ambiguity by replacing v with its mean Ev. As such, $R_a(x)$ measures the implicit cost of ambiguity (as captured by v). Since $R(x)$ in (2) is a measure of the overall cost of uncertainty, we can define $R_r(x) \equiv R(x) - R_a(x)$ as the cost of risk aversion (i.e., the cost of risk associated with the random variables e). Indeed, in the absence of ambiguity (where v is known for sure), $R_a(x) = 0$ in (3) and $R(x) = R_r(x)$ reduces to the standard Arrow-Pratt risk premium measuring the cost of risk associated with the random variables e.

Comparing (1) and (2), it is clear that the optimal choice of x is the one that maximizes the certainty equivalent $[M(x) - R(x)]$. Given $R(x) = R_r(x) + R_a(x)$, it follows that the optimal choice of x is obtained by maximizing $[M(x) - R_r(x) - R_a(x)]$. This shows that three terms are relevant in choosing x: expected payoff $M(x)$, minus the cost of risk aversion $R_r(x)$, minus the cost of ambiguity aversion $R_a(x)$. The cost of risk aversion $R_r(x)$ depends on both risk exposure (given by the distribution function $F(e|v)$) and risk aversion (given by the curvature of $U(\pi)$). And the cost of ambiguity aversion $R_a(x)$ depends on both ambiguity exposure (given by the distribution function $G(v)$) and ambiguity aversion (given by the curvature of $h[\cdot]$).

This treatment of uncertainty shows how both risk aversion and ambiguity aversion can affect economic decisions. Which one is more important is an empirical matter and there is no general answer. We explore this issue in the context of technology adoption. Consider the case where the decision x is a discrete choice: choose between old technology $x = 0$ or adopt a new technology $x = 1$. As just discussed, the optimal choice is the one maximizing the certainty equivalent $[M(x) - R_r(x) - R_a(x)]$. This generates the following decision rule:

$$\text{choose } x^* = \begin{Bmatrix} 0 \\ 1 \end{Bmatrix} \text{ when } M(1) - R_r(1) - R_a(1) \begin{Bmatrix} < \\ \geq \end{Bmatrix} M(0) - R_r(0) - R_a(0). \tag{4}$$

This shows that the new technology $x = 1$ tends to be preferred when its expected payoff $M(1)$ is higher, when its cost of risk aversion $R_r(1)$ is lower, and when its cost of ambiguity aversion $R_a(1)$ is lower. This is consistent with previous literature that has stressed that higher profitability contributes to adoption incentives, while the novelty of new technology may increase risk and lower adoption rates (Feder et al., 1985; Foster and Rosenzweig, 2010). Equation (4) extends this argument to ambiguity; if there is imprecise knowledge of the new technology, then ambiguity can also affect adoption decisions.

Applying these arguments to agriculture is of special interest. Indeed, production uncertainty is pervasive in agriculture due to unpredictable weather shocks and unanticipated damages from pests, diseases, and weed infestation. While previous research has usually treated agricultural production uncertainty as risk, part of this uncertainty could actually be ambiguity. Current and new technologies likely expose farmers to differing levels of both risk and ambiguity. In this context, equation (4) provides useful insights. It shows that risk decreases adoption incentives whenever $R_r(1) > R_r(0)$. Thus, highly risk-averse individuals may become early adopters if the new technology reduces their exposure to production risk. A similar argument applies to ambiguity. Equation (4) indicates that ambiguity decreases adoption incentives whenever $R_a(1) > R_a(0)$. Alternatively, it shows that ambiguity-averse individuals may possibly become early adopters if the new technology reduces their exposure to ambiguous aspects of the production process. In agriculture we anticipate finding risk when probability assessments are relatively easy, and finding ambiguity when probability assessments prove more difficult.

Thus, uncertainty (whether in the form of risk or ambiguity) is a fundamental characteristic of agricultural production. In situations where the new technology exhibits larger exposure to risk and/or ambiguity, uncertainty aversion would provide a disincentive to adopt the new technology. But, the new technology may contribute to a reduction in exposure to risk and/or ambiguity, for example if the new technology helps reduce pest damages. By reducing pest damages, the new technology would reduce risk (opposite to the conventional wisdom that risk aversion has adverse effects on adoption rates). If pest damages are difficult to predict, the new technology could reduce ambiguity exposure by making the outcomes more predictable. In this case, ambiguity aversion would contribute to hastening the adoption of a new technology. This stresses the importance of distinguishing between risk aversion and ambiguity aversion and the need for empirical analyses of the roles of risk and ambiguity aversion in technology adoption.

3. Herbicide Tolerant (HT) and Insect Resistant (IR) Seeds

Genetically modified seeds introduce transgenes into standard seeds to give them new characteristics such as resistance to herbicide or resistance to pests. These new seeds impact the moments of yields such as their average and their variance. Although GM seeds cost more than conventional seeds, there is evidence that GM seeds exhibit "yield lag" and "yield drag" Board on Agriculture and Natural Resources (BANR) (2010); Shi et al. (2013). Yield lag means that when new GM seeds are first introduced, their yields may be lower than those of conventional seeds. There is also evidence that GM seeds exhibit "yield drag" whereby yields decrease due to the insertion of the new genes. Yield lag and yield drag have negative effects on yield, although these effects can decrease and even disappear over time with improved genetic selection. Given that GM seeds cost more than conventional seeds, early adopters must find some characteristic of the new cultivar to be beneficial.

HT technology involves the introduction of a transgene into standard seeds that makes the plant resistant to a broad spectrum herbicide. This resistance in turn allows the farmer to spray herbicide to kill all weeds without killing the crop. Thus, HT technology simplifies weed management, reducing the need for cultivation and usually eliminating the need for more selective herbicides (Shaner, 2000). For the most part, weed infestation is a reasonably predictable component of crop cultivation (Alexander et al., 2002; Cousens and Mortimer, 1995). Observing weed infestation in a field is relatively easy for farm managers, as is observing the effectiveness of any weed control method. This indicates that the HT technology may not have a large impact on ambiguity, both because of the predictability of weed infestation and its treatment.

IR traits, on the other hand, involve the insertion of transgenes using genetic material from a bacterium (*Bacillus thuringiensis*, or Bt) that can limit the impacts of two major pest insects: the European corn borer and root worms. The plant produces a toxin that eventually kills the targeted pest. Identifying insect infestation in the field is typically not easy; it requires special scouting efforts by the farm manager. And the complex dynamics of insect populations mean that predicting infestations over time and space can be difficult (Dent, 2000; Pilcher and Rice, 2001; Showers, 1993). Although many farmers have been planting corn for decades, pest dynamics vary significantly over time and so implementing pest control strategies may be subject to both risk and ambiguity.

Shi et al. (2013) find that the IR traits in GM corn lead to a decrease in the variance of corn yields as well as increasing skewness (decreasing downside risk) and decreasing kurtosis (thinner tails). These effects are much smaller or non-existent for the HT trait when it is not paired with IR traits. Although we know that GM corn decreases the variance of yields, it is not clear how much of this variance is risk and how much is ambiguity. The key to the distinction is whether or not farmers can assess these probabilities. Unfortunately, current data and previous research do not help with this. We do have some a priori information about how difficult it is to assess the uncertainty of pest versus weed infestations. Weeds are easy to observe, while pests such as the European corn borer (ECB) and rootworm (RW) are less easy to observe.

Thus IR technologies, which substitute for traditional pesticide application and associated scouting efforts, provide farmers with an opportunity to not only save time and use less pesticide, but also to reduce the ambiguity associated with pest damages on their farms. This ambiguity-reduction aspect of the IR technology raises an interesting possibility. In previous literature, the novelty of a new technology is often interpreted to mean that it increases the decision maker's exposure to uncertainty (both risk and ambiguity), which in turn slows adoption. But, it seems possible that adoption of a new IR technology can help reduce exposure to the ambiguity associated with pest damages, potentially reversing the standard prediction that risk and ambiguity-averse farmers will be later adopters.[3]

While this reasoning suggests HT would have no impact on ambiguity, while IR would decrease ambiguity, the new technologies' impacts on risk remain unclear. If the old technology is riskless and the new technology is risky, then higher risk aversion will necessarily slow down adoption rates. (This is the point commonly made in previous literature.) However, if the old technology is also risky, then the effect of risk aversion is ambiguous. The reason is that the adoption decision becomes a choice between two risky options, i.e. it is a portfolio selection problem. It is well known from the portfolio selection literature that, depending on the correlation coefficient between the risky outcomes, risk aversion can provide an incentive to diversify. This may induce risk-averse farmers to speed up the adoption of the new technology.

Other authors have also noted the distinction between HT and IR in terms of ambiguity reduction. On page 138, Alexander et al. (2002) discuss results from focus groups with farmers: "overall, farmers are better able to cope with weed pressure than European Corn Borer (ECB) pressure. Farmers know which fields will have severe weed pressure but they cannot predict ECB pressure ... In addition, farmers said that alternative herbicides were effective at controlling weed pressure but it is difficult to effectively control ECB with pesticides." The farmers also report that they do not know in which years ECB will be a large problem. "They believe it [IR seed] is good insurance against the possibility of high ECB pressure. 'Of course, the Bt takes care of the corn borers and there haven't been any for 2 years. However, one of these days ... '" [page 138].

Marra et al. (2003) sum up the distinction between HT and IR technologies as follows: "For transgenic crops with herbicide tolerance, ... there seemed to be initial uncertainties about relative profitability compared to conventional weed control systems ... For insect resistant varieties, the uncertainty comes primarily from variable pest infestations."

4. Data Source and Experimental Procedures

Experimental and survey data were collected from corn and soybean farmers in Minnesota and Wisconsin in two rounds. The first round of 75 observations was collected between Jan-

[3]We often think of options as either being ambiguous or non-ambiguous. Our model in Section 2 shows how to conceptualize what it means for a technology to be more or less ambiguous. The more certain a farmer is of the "true" probability distribution of a given technology, the less ambiguous that technology is. An ambiguity averse farmer is more averse to the subjective uncertainty about priors related to the technology than he is to the known risks involved in the technology.

uary and March of 2010, while the second round of 116 observations was collected in July and August of 2010. Farmers were recruited through the mail and phone calls. In both instances, researchers explained the opportunities for farmers to keep their winnings from the experimental games, to receive reimbursement for travel, and to hear an extension presentation on the economics of corn seeds over a meal following the session. The experimental sessions occurred at county extension offices, local colleges, and other meeting sites throughout the region.

The sample of farmers was selected in three main ways. For the winter round of surveys, 456 grain farmers were invited to participate in experiments at six different sites across the region. These farmers had responded in 2006 to a survey on GM seed use sent to a random sample of farmers across the state. Recruitment involved the classic Dillman methods of an invitation letter and two repeat letters with follow-up phone calls.[4] For the summer sessions, we used a 2010 list of 1254 farmers who had completed the 'Pesticide Application Training' (PAT) certification that is required if a farmer wishes to apply restricted-use pesticides commonly used on corn-soy operations. This certification must be renewed every five years.[5] We also contacted 1400 farmers from the Wisconsin Agricultural Statistics Service (WASS) lists who lived in counties near the six experimental sites. Finally, we recruited a handful of farmers at a corn conference and through extension agents.

Overall, approximately 15% of contacted farmers chose to participate in the winter sessions and 5% chose to participate in the summer sessions. Overall, 37% of our sample comes from the PAT lists, 30% were recruited from the sample of previous GM survey respondents, 20% were from the WASS list, 6% were recruited at a corn conference, and 6% were recruited directly by extension agents. It proved difficult to recruit a random sample of farmers to participate in live experimental sessions.[6] We compare the characteristics of farmers in our sample with those of the average Wisconsin farmer in Section 5.

Each session consisted of two parts. First was the experiment itself, which focused on a series of games that was used to gather information on risk aversion, ambiguity aversion, and learning. The second part had two components: a survey on demographic and farm characteristics and a history of technology choices with respect to GM seed use; and a set of tests to measure cognitive ability. The whole session was conducted on computers, and the games and tests were programmed with the software z-Tree (Fischbacher, 2007). On

[4] For those farmers we invited who did not attend, the reasons for not attending (from an open-ended question) were: cannot attend/too busy/full-time job (39%), not interested (22%), no longer farming (24%), too old/health issues/deceased (9%), and live too far away (6%).

[5] While IR crops are resistant to some pests (European corn borer or rootworm or both) they are not resistant to all pests. As such, IR corn adopters will still have reason to use pesticides on corn and other crops as well. That said, we also re-run all our regressions excluding the farmers who were recruited through the PAT lists and our results do not differ qualitatively.

[6] There is evidence from adult populations (Anderson et al., 2010) and student populations (Falk et al., 2010) that the social preferences of participants and non-participants do not differ. Harrison et al. (2009) show that the size of fixed participation fees and ranges of potential winnings affect the risk aversion of the sample which self-selects into participating, but this sample selection does not impact inferences regarding the correlation between risk aversion and other demographics.

average, the experimental session generally took less than two hours to complete, and was followed by a meal and extension presentation that lasted another hour.

4.1. Experimental Design

Upon arrival to the experiment site, the 19% of farmers who were not familiar with computers or wanted a refresher received a brief computer training which consisted of instruction regarding how to point and click and how to type in responses to questions. During the sessions, instructions were read aloud and also appeared on the farmers' computer screens. Participants also had at their disposal a written copy of the instructions that they could refer to during the games; however, they were instructed not to read ahead.

The session leader explained at the outset that payoffs for the experiments were part of a research grant, and that the individuals running the experiment received no personal gains from the experiments or the payoffs made to participants. The explanation was meant to minimize the extent to which participants might assume that the experimenters would benefit if the subjects earned less money. The average payoff for the games was $73 plus another $30 for travel. One day's wages in this sample is approximately $135. Our experiments were scheduled after typical morning farm chores and before afternoon chores.

The experimental session consisted of two uncertainty games (where probabilities were not known) and two risk games (one 50/50 and one rare event), as well as two learning games. Payoffs were determined after the completion of all of the games and the survey, and farmers were paid for all six games. For the purposes of this paper, we focus on the 50/50 uncertainty and risk games. The design of these games is a multiple price list (MPL). In the original MPL (Holt and Laury, 2002), participants were offered a series of choices between a safe bet and a risky bet. We slightly alter this design, as did Moore and Eckel (2006) and Ross et al. (2010), and offered the farmers a series of choices between a certain payout and a bet.

The experiment began with a practice game which did not count for payoffs, the purpose of which was to help subjects understand the basic logic of the games. It was similar to the rest of the games in several ways. First, farmers made a series of 11 decisions, which were presented en suite rather than sequentially. Each decision was a choice between a sure payoff and an uncertain payoff that, in this practice game, depended on the weather two weeks later. If it rained or snowed two weeks from the session date, the hypothetical payoff was higher than if it did not snow or rain. After all subjects made the 11 decisions, they received an explanation about the payoffs that they would have received if the game had counted for payoffs.

Likewise, in the uncertainty and risk games, every farmer had to make 11 decisions between a sure payoff and an uncertain payoff. These decisions were again made all at once rather than sequentially. The sure thing involved a certain payoff of $10 while the payoff for the risky option depended on the color of the chip drawn out of a bag. The payoffs for each decision were the same for both the risk and uncertainty games and are shown in Table 1. Even though all subjects made 11 decisions in each game, only one decision per game affected their earnings. That decision was determined at the end of the experimental session by the roll of a die for each of the games.

Table 1: Uncertainty and Risk Experiments

Decision	Sure Thing	Gamble		CRRA
		Red	Black	
1	\$10.00	\$20.00	\$10.00	∞
2	\$10.00	\$20.00	\$8.00	3.76
3	\$10.00	\$20.00	\$6.50	1.86
4	\$10.00	\$20.00	\$5.00	1.00
5	\$10.00	\$20.00	\$4.00	0.65
6	\$10.00	\$20.00	\$3.50	0.52
7	\$10.00	\$20.00	\$3.00	0.40
8	\$10.00	\$20.00	\$2.50	0.31
9	\$10.00	\$20.00	\$2.00	0.22
10	\$10.00	\$20.00	\$1.00	0.09
11	\$10.00	\$20.00	\$0.00	0.00

Each game had its own bag containing 100 chips, some of which were black and some of which were red. In the uncertainty game, farmers had to make their decisions without any prior information about the number of red and black chips in the bag. In the 50-50 risk game, farmers were told that there were 50 red and 50 black chips in the bag. The uncertainty games were played prior to the risk games to avoid providing focal points for farmers in the uncertainty games.

4.2. Survey and Cognitive Ability Data

After the experiment all farmers completed a survey which, in addition to asking about demographic and farm characteristics, included retrospective questions about the farmers' use of GM seed in corn and soy production. In particular, farmers were asked in what year they first adopted GM corn and in what year they first adopted GM soy. The first year these technologies were available for purchase was 1996.

Participants also performed a digit span exercise testing short-term memory. In this exercise, they saw a number for the same number of seconds as the quantity of digits of that number. Then, they were asked to re-enter the number they had just seen. This exercise started with three-digit numbers and continued up to a maximum of 11 digits. If a farmer made a mistake at a certain level, he was given a second chance with a different number. After the second mistake at the same level, the exercise ended.

Digit span is a measure of short-term or working memory. It is a sign of sequential processing ability that measures how able a person is to take in and process information in an orderly fashion (Dempster, 1981). Economists have found that entrepreneurs in Russia have higher digit-span scores than non-entrepreneurs (Djankov et al., 2005), and that Sri Lankan entrepreneurs with higher digit-span scores earn higher profits (de Mel et al., 2008).

One criticism with some of the previous work measuring the impacts of uncertainty aversion on technology adoption is the fact that most authors do not have measures of cognitive ability. If cognitive ability is correlated with both uncertainty aversion and technology adoption, then results excluding those variables may be biased. Cognitive ability is found to be negatively correlated with risk aversion (Benjamin et al., 2012; Dohmen et al., 2010; Frederick, 2005). Although we do not know of any empirical evidence regarding the correlation between cognitive ability and ambiguity aversion, Sherman (1974) predicts that this relationship would also be negative.[7] Foster and Rosenzweig (2010) suggest that the positive relationship often found between education and technology adoption is due to the fact that more educated people are better able to learn.

5. Summary Statistics

We first discuss the uncertainty, risk, and ambiguity aversion variables created from the experimental data. Then we consider the survey data, including the adoption variables.

5.1. Uncertainty, Risk, and Ambiguity Aversion Measures

We use the results from the game in which farmers are not told the share of red and black chips to measure aversion to uncertainty, and we use the results from the 50/50 game to measure risk aversion. Uncertainty includes both risk and ambiguity. By subtracting our measure of risk aversion from our measure of uncertainty aversion, we construct a measure of ambiguity aversion.

Our experiments are similar to Cohen et al.'s (1985), with one choice between a sure thing and a risky lottery, and a second choice between a sure thing and an uncertain lottery. We subtract risk aversion from uncertainty aversion to measure ambiguity aversion. This is similar to the two-color Ellsberg problem with one choice between a sure thing and a risky lottery, and a second choice between a risky lottery and an uncertain lottery (Ross et al., 2010).

Using the row in the risk game at which the farmer chose the 'sure' option for the first time, we assign him a coefficient of relative risk aversion. Specifically, under risk, we assume preferences exhibiting constant relative risk aversion (CRRA), with a utility function over payoff $\pi > 0$ given by $U(\pi) = \frac{1}{(1-\gamma)}\pi^{1-\gamma}$, where γ is the CRRA coefficient (Pratt, 1964). We assign the coefficients presented in Table 1 which measure the farmer's minimum coefficient given that he accepted that gamble and turned down the subsequent one. For example, farmers who chose the gamble three times and then chose the sure thing in the fourth decision row were assigned a coefficient of relative risk aversion equal to one.

We prefer to use coefficients of relative risk aversion, rather than the row at which the farmer switched from the gamble to the sure thing. This is because the CRRA coefficient is a cardinal number with meaningful orders of magnitude. The value of the CRRA depends on the dollar amounts in the actual decision the farmer is making. On the other hand, the

[7] In our case, cognitive ability is negatively but insignificantly correlated with both ambiguity aversion and risk aversion.

row at which he switches is a purely ordinal variable which depends on the design of the experiment, but not on the actual dollar amounts under consideration.[8]

In the uncertainty game, under an uninformative prior, we assume a subjective expectation of a 50/50 distribution of red and black chips. In this context, we calculate a coefficient similar to the CRRA coefficient with values given in Table 1. By analogy to the case of risk aversion, this provides a measure of uncertainty aversion.

Note that if the decision maker were ambiguity neutral, she would make the same choice in the risk game and the uncertainty game. In that case the uncertainty aversion measure would equal our CRRA coefficient. Alternatively, if a person is ambiguity averse, then the difference between the measure of uncertainty aversion and the CRRA coefficient would be positive and reflect the strength of her ambiguity aversion (as noted in Section 2. Thus any difference between the uncertainty aversion measure and the CRRA coefficient can be attributed to ambiguity aversion. We discuss the theoretical reasoning behind our ambiguity aversion measure in In Appendix Appendix B.

Two people may play differently in the uncertainty game because they have different levels of uncertainty aversion, or because they have different subjective probabilities regarding how many black and red chips were in the bag. A person who trusts more in general or who is more trusting of us and extension agents in specific, may think we stacked the bag with red chips and such a person will appear less ambiguity averse. We discuss this possibility in more detail with the econometric results.

While there is no definitive way to estimate the minimum coefficient of relative risk aversion for those who always chose the gamble (since the minimum could be negative infinity), this behavior remains rational. It simply implies risk neutrality or risk lovingness. Thus, we assign these farmers a CRRA of -0.09.[9][10]

Under expected utility, farmers should switch at most once from the risky choice to the sure thing. They should also always choose the risky gamble in the first row since in that row the sure thing is strictly dominated by the gamble. However, of the 191 observations, only 131 and 151 observations in the uncertainty and risk games, respectively, behave in such a way, leaving us 123 observations for ambiguity aversion. This implies a rate of multiple switching behavior of 19-27% in our sample of U.S. farmers. Holt and Laury (2002) report a rate of 13% among U.S. university students and faculty while Jacobson and Petrie (2009) report rates of 55% among Rwandan adults and 44-52% among Peruvian adults.

Here we exclude those farmers who were multiple switchers. The excluded farmers tend

[8] If we instead use the row at which the farmer switched in our analysis, the ambiguity coefficient keeps the same sign but sometimes loses significance.

[9] We applied this scheme to the uncertainty game as well. The value -0.09 is in line with the other values in Table 1. That said, our results are robust to assigning other reasonable values such as 0 or -1, as well as to dropping those observations.

[10] Rather than using the minimum CRRA, we could choose the midpoint of the range. To do so, we would have to choose an adhoc maximum CRRA for those who rejected all ten non-dominated gambles and we prefer not to do so. But, when we rerun the analysis setting the midpoint for those individuals to be 6.5, a number in line with the other values, we find very similar results.

to be less educated and more likely to have needed the computer refresher course. This suggests these farmers may have been uncomfortable with the computer and may not have made the effort to fix mistaken clicks of the mouse.[11] We have also constructed a second set of uncertainty measures which include those farmers whose decisions, with minor modifications, can be made to appear consistent. Results (not shown here) do not differ much with different ways of reclassifying the multiple switchers.

Table 2 presents the summary statistics for our measures of uncertainty, risk, and ambiguity aversion. The average coefficient of relative risk aversion in our sample is 0.8. This indicates that risk aversion is prevalent in our sample, and the magnitude is in line with the results from many other experiments (see the survey in Cardenas and Carpenter (2008)). We also find that ambiguity aversion is positive on average, as the average uncertainty aversion measure is higher than the average coefficient of relative risk aversion. But, this difference is not significant ($p = 0.23$).[12]

In our sample, 34% of people are ambiguity averse, 38% ambiguity neutral, and 28% ambiguity loving. Camerer and Weber (1992) reviewed the literature 20 years ago, and presented evidence that many papers find 50% of the population to be ambiguity averse. Akay et al. (2012) review five more recent studies in which the share of ambiguity averse individuals varies between 42 and 61%. These numbers are slightly higher than the numbers we find.

Part of the reason for our finding of a lower population tendency towards ambiguity aversion may be due to the experimental design. Fox and Tversky (1995) propose the comparative ignorance hypothesis. They find some evidence of ambiguity aversion using a within subjects design, but not when the individual evaluates one prospect in isolation using a between subjects design. Fox and Weber (2002) take this one step further and look at order effects. They hypothesize that if a participant makes two decisions, the first decision will be analyzed non-comparatively whereas the second will be analyzed comparatively. They present evidence showing that measures of ambiguity aversion are lower in experiments (such as ours) in which the ambiguous bet comes before the risky bet. This suggests that we may underestimate ambiguity aversion. As long as these order effects do not vary with timing of GM adoption, this should not affect our results.

5.2. Survey Variables

The other key variables in our analysis are the numbers of years since the farmer first planted GM corn or soy.[13] These variables exclude those farmers who have never planted corn or soy at all, but they do include farmers who have only planted conventional corn or soy. (For these farmers, the number of years planting GM varieties is 0.)

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[11] Many farmers were not very experienced or comfortable with using a mouse.

[12] The correlation between uncertainty aversion and risk aversion is 0.65 and is significantly different from 0 at the 1% significance level.

[13] In the winter sessions we ask the farmers their planting plans for 2010. In the summer sessions we ask them their actual planting decisions for 2010.

Table 2: Summary Statistics

Variables	Obs	Mean	Std Dev	Min	Max
Uncertainty, Risk, and Ambiguity Aversion					
Uncertainty aversion	131	0.79	0.75	-0.09	3.76
Risk aversion	151	0.77	0.64	-0.09	3.76
Ambiguity aversion = uncertainty minus risk	123	0.06	0.56	-1.34	3.11
Individual Characteristics					
Age	191	53.2	12.6	20	80
Female	191	6.3%			
Education					
High school or less	191	31.9%			
No degree or 2-year college degree	191	35.6%			
4-year college degree	191	20.4%			
Some graduate school	191	12.0%			
Family size	191	2.7	1.3	1	7
Household Income before taxes 2009 (Thousands)					
Under $20	191	9.9%			
$20 - $59	191	33.5%			
$60 - $99	191	27.7%			
$100 or more	191	28.8%			
Farming Characteristics					
Farming is not the principal occupation	191	16.2%			
Acres of cropland operated in 2009	191	600.2	958.6	10	8000
Years farmer has made decisions on farm	191	28.3	13.7	2	72
Corn					
Never planted corn	191	2.1%			
Planted conventional but not GM corn	191	10.5%			
Planted GM corn	191	87.4%			
Years since first planting GM corn[1]	187	7.1	4.3	0	15
Soy					
Never planted soybeans	191	18.8%			
Planted conventional but not GM soy	191	6.3%			
Planted GM soybeans	191	74.9%			
Years since first planting GM soybeans[2]	155	8.4	4.5	0	15
Digit-span: digit memory	189	7.3	1.5	3	11
Received computer refresher	191	18.8%			

[1] Excludes farmers who have never planted corn. Equals zero for farmers who have only ever planted conventional corn.

[2] Excludes farmers who have never planted soy. Equals zero for farmers who have only ever planted conventional soy.

Table 2 shows that approximately 89% of the farmers who have ever planted corn have planted GM corn, and, on average, they have been planting GM corn for eight years. Similarly, 92% of the farmers who have ever planted soybeans have planted GM soybeans, and, on average, they have been planting GM soy for nine years. The farmers who plant GM crops dedicate almost all of their acreage to GM.[14] These adoption rates (at the farmer level) are comparable to state averages (at the acreage level), which in 2010 were 80% for corn and 88% for soy (Fernandez-Cornejo, 2010).

Once farmers try GM seed, they tend to continue planting it thereafter. We asked the farmers in what years they first adopted GM corn and GM soy, and then we asked them what they planted in 2009 and 2010. Of the 157 farmers who adopted GM corn in 2008 or earlier, 99% of them planted some corn in 2009 and/or 2010. Of those previous GM corn adopters who planted corn in 2009 and/or 2010, 97% of them planted at least some GM corn. Of the 129 farmers who adopted GM soy in 2008 or earlier, 91% of them planted some soy in 2009 and/or 2010. Of those, 99% planted at least some GM soy. Thus, we see that disadoption is quite rare and so we ignore it in the rest of our analysis.

A shortcoming of our data is that when we asked farmers in which year they first planted GM corn, we did not ask farmers to distinguish between the use of IR and HT corn seeds. The share of GM corn planted in Wisconsin including the IR trait has remained relatively constant over time, at 78% in 2000 and 64% in 2010 (Fernandez-Cornejo, 2010). This is contrasted to GM soy for which there is no IR trait, so that 100% is HT. Since the IR trait is commonly present in GM corn hybrids but is never present in GM soy, finding significant differences in the impact of ambiguity aversion on the timing of adoption of GM corn versus GM soy may potentially be attributed to the differences between what the IR and HT traits offer. Moreover, it also suggests that our measure of the impact of ambiguity aversion on corn seed choice is conservative, since some farmers reporting GM corn adoption have been using corn with only the HT trait (Fernandez-Cornejo, 2010).

Table 2 also shows that the farmers are of diverse ages, education levels, and wealth levels. The majority of participants were male, and almost half of the sample (44%) had obtained at least a 2-year college degree. Around 16% of the respondents do not consider farming to be their principal occupation. Farmers in the sample are relatively experienced in farming: on average, they have been making decisions on a farm for 28 years.[15]

In Appendix Appendix A, we compare the average characteristics of our sample with those of the average Wisconsin farmer from the most recent agricultural census. Our sample consists of significantly more full-time farmers, farmers who manage significantly larger farms, and more male farmers than in the census. This is probably due to the fact that our experimental sessions were held during week-days when part-time farmers might be at their other job. Although our sample is not representative of Wisconsin farmers, the fact that our sample consists of more larger farmers means that results from our sample may be

[14] This is one of the reasons why we do not conduct a tobit analysis of acreage in the new technology as do Ross et al. (2010).

[15] Note that some farmers began making decisions on a farm at a very young age.

more representative of behavior on the average acre. This is evidenced by the fact that if we compare our numbers to those in the Wisconsin Agricultural Survey, the ratio of GM corn to total corn and the ratio of GM soy to total soy in our sample appears similar to that in Wisconsin more generally.[16]

Finally, Table 2 also presents the results of the digit span test described above and shows that the farmers' average digit span is seven. This result is on-par with Miller's (1956) findings that an average adult has a digit-span of seven (plus or minus two).

6. Econometric Specification and Results

This section deploys a survival model to estimate the effects of risk and ambiguity aversion on the likelihood of adopting GM corn and GM soybeans. We are particularly interested to see whether the ambiguity associated with pest damages, which IR technologies help to reduce, will lead to a larger role for ambiguity aversion in the adoption of GM corn.

An early article reviewing survival and duration models by Kiefer (1988) notes that economics most commonly uses duration models to analyze spells of unemployment. He lists other potential areas of application, one of which is technology adoption. Since then, many papers have used survival models to analyze the diffusion of new technologies; see Fuglie and Kascak (2001) for one example. Kiefer (1988) suggests that survival models are useful for "economic data that can be modeled as generated by series of sequential decisions." This is the case for farmer technology adoption, as farmers make a decision in each year regarding whether they should try a new technology for the first time conditional on their previous decisions not to adopt.

Let $S(z,t)$ denote the probability that a farmer exhibiting attributes z would not adopt a new technology before time t. In a standard survival model, the associated hazard function is $\lambda(z,t) = \frac{-d \ln S(z,t)}{dt}$, which measures the adoption rate at time t conditional on not having adopted before time t. Let $\lambda(z,t) = g(\exp(-z\beta))$ where β is a vector of parameters capturing the effects of z on $\lambda(\cdot)$. Different specifications of the hazard rate have been proposed in the literature. We use the Weibull distribution with $\lambda(z,t) = e^{-z\beta}k[e^{-z\beta}t]^{k-1}$ because this allows the probability of adopting to increase or decrease over time. It includes the exponential distribution as a special case when $k = 1$, which restricts the probability of adopting to be constant over time. Our data faces right censoring since some of our farmers have not adopted by 2010, and we do not know what they go on to do after that. Thus, the likelihood function we maximize looks as follows:

$$\ln L = \sum_{\text{uncensored observations}} \lambda(z,t|\theta) + \sum_{\text{all observations}} \ln S(z,t|\theta).$$

In our analysis, t does not represent calendar years, but years in which a farmer could have adopted GM technologies. In our sample, the first farmers to use GM technologies

[16]Unfortunately we cannot test if they are the significantly different because we could not get access to the data on the number of observations and the standard deviation of the Agricultural Survey data.

adopted in 1996. And yet, there are quite a few farmers in our sample who were not yet farming in 1996. We consider that, for those farmers who were already farming by 1996, the earliest possible year of GM adoption was 1996. For those farmers who began farming after 1996, their first year making decisions on a farm was treated as the earliest possible adoption year.[17][18]

Because the adoption of GM technologies started slowly in the first few years and then increased rapidly in later years, we also include dummies for each calendar year in which a farmer could adopt. Including year fixed effects means we are estimating whether, within a given year, a more ambiguity-averse farmer is more or less likely to adopt than a less ambiguity-averse farmer. To account for the fact that GM technologies may be more beneficial in certain areas, we control for Crop Reporting District (CRD) fixed effects. CRDs are defined by the US Department of Agriculture to reflect local-agro-climatic conditions. Minnesota and Wisconsin consist of 18 CRDs, from which we have observations in 15 CRDs. In a survival model, when we look at the impact of ambiguity aversion while controlling for such fixed effects we are asking whether, in any given year and any given CRD, a more ambiguity averse person is more or less likely to adopt than a less ambiguity averse person.[19]

In our application of the survival model, the dependent variable is years since first adoption of GM corn or soy, with a higher value reflecting earlier adoption. The regression results reported in Table 3 compare the results for corn and soy across our measures of risk and ambiguity aversion. Remember that our sample contains 187 farmers who have ever planted corn and 155 who have ever planted soy. The sample sizes are lower in this table since it excludes those farmers whose behavior in the experiments was inconsistent.[20]

It is possible that our results pick up reverse causation since the experiments occurred after the adoption decision had been made. We think it is unlikely that the experience of planting GM crops would significantly impact risk or ambiguity aversion. Harrison et al. (2005) present evidence that risk preferences among students are stable over a six month period while Love and Robison (1984) present similar evidence for Midwestern farmers over a 2 year period.

For any given regressor, a hazard ratio greater than one hastens adoption, while a hazard ratio of less than one is associated with slower adoption. For the regression as a whole, an

[17]In our regressions, we include the seven farmers who claim that GM was planted on their farm before they started making decisions. Our findings are robust to excluding these observations.

[18]We have also tried including an indicator variable for those farmers who began farming after 1996 and its interaction with our experimental measures of risk and ambiguity aversion. This would capture the fact that farmers who enter farming later may enter the farming business with less uncertainty about the GM technology since it would have been available longer by then. This interaction is not significant and the experimental results do not change qualitatively.

[19]In results not shown here we conduct the same analysis without year fixed effects and the results are quite similar. The main difference is that the Weibull distribution parameter becomes larger and more significant. This may be because, without the year fixed effects, the Weibull parameter is the only way to take account of the fact that adoption rates differ across years.

[20]When we try different methods of reclassifying the behavior of farmers who behave inconsistently, our results (not shown here) are qualitatively similar.

estimate of k greater than 1 implies that the probability of adopting increases over time. The first column for each crop provides the results associated with risk aversion while the second column provides the results for the ambiguity aversion measure. Finally, the third column includes both risk aversion and ambiguity aversion (the sum of which would equal our measure of uncertainty aversion). We present results in Panel A which only control for the experimental measures of risk and ambiguity aversion as well as the CRD and year fixed effects, and results in Panel B which additionally control for other explanatory variables. Our preferred specification is that in Panel B since it is less likely to suffer from omitted variable bias, but the results in Panel A are included as a robustness check since one might argue that Panel B includes some endogenous explanatory variables.

For the corn regression, the hazard ratio of ambiguity aversion (columns 2 and 3) is significantly greater than one while the hazard ratio of risk aversion (columns 1 and 3) is not significantly different from one. Higher levels of ambiguity aversion are associated with early adoption of GM corn.[21] We can use the coefficient from the regression in Panel B to interpret the magnitude of the impact in column 2. Imagine two farmers who have not yet adopted GM corn. If one's ambiguity aversion is one standard deviation higher than that of the other, he will be 50% more likely to adopt in that period.

Comparing the results for corn with those for soy, we find that the hazard ratio of ambiguity aversion is usually not statistically different from one in the HT soy regressions (it is only significant one out of four times in columns 5 and 6 of Panel B). The magnitude is also smaller, such that in column 5 of Panel B a farmer who has not yet adopted GM soy with an ambiguity aversion measure one standard deviation higher than another farmer is only 13% more likely to adopt at any point in time. In the final row of the table we report the results from a χ^2 test of whether the coefficients on the experimental measures of risk and ambiguity aversion differ across the soy and corn regressions. We find that the coefficients are significantly or close to significantly different across the two regressions.

This difference between the significant role of ambiguity aversion in shaping the early adoption of GM corn but not GM soy is consistent with the hypothesis that there are basic differences in the ambiguity surrounding the two technologies of insect resistance (IR) and weed resistance (HT). While IR corn has the potential to reduce ambiguity over pest damages, HT soy helps with the management of weeds, which are less subject to ambiguity than pests.

The results in Table 3 show that risk aversion is uncorrelated with the adoption of GM corn. In column 1 of Panel B a farmer who has not yet adopted GM corn with a risk aversion measure one standard deviation higher than another farmer is 8% less likely to adopt at any point in time. There is weak evidence that more risk-averse individuals are more likely to adopt GM soy, but this result is only significant when risk aversion and ambiguity aversion

[21] Another interpretation for the correlation between ambiguity aversion and GM corn adoption is that ambiguity-averse people are more likely to search out information (in order to reduce the ambiguity they face) and so they adopt earlier because they have more information and figure out more quickly that the new technology is an improvement. The fact that ambiguity aversion is not correlated with GM soy adoption suggests that this is not the case.

Table 3: Hazard Ratios from Survival Model for Adoption of GM Corn and Soy

	Corn			Soybeans		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A						
Risk Aversion	0.889		0.945	1.248		1.486
	[0.104]		[0.135]	[0.237]		[0.252]**
Ambiguity Aversion		1.791	1.759		1.252	1.366
		[0.297] ***	[0.303]***		[0.202]	[0.211]**
k	1.23	1.27	1.27	1.05	1.14	1.17
	[0.154]	[0.171]*	[0.171]*	[0.117]	[0.140]	[0.145]
Corn RA = Soy RA (p-value)				0.08		0.04
Corn AA = Soy AA (p-value)					0.03	0.16
Panel B						
Risk Aversion	0.887		1.002	1.213		1.367
	[0.135]		[0.152]	[0.263]		[0.223]*
Ambiguity Aversion		2.049	2.050		1.250	1.339
		[0.436]***	[0.433]***		[0.267]	[0.280]
Age	0.972	0.987	0.987	0.985	0.996	0.998
	[0.016]*	[0.019]	[0.020]	[0.019]	[0.021]	[0.021]
Female	0.691	0.815	0.815	1.458	1.128	1.095
	[0.236]	[0.302]	[0.302]	[0.952]	[0.719]	[0.696]
No or 2-year degree	1.161	1.204	1.204	0.753	1.004	1.016
	[0.303]	[0.340]	[0.349]	[0.251]	[0.373]	[0.381]
4-year degree	1.694	1.346	1.347	0.833	0.851	0.957
	[0.418]**	[0.341]	[0.352]	[0.311]	[0.323]	[0.363]
Some grad school	1.491	1.165	1.167	1.278	2.004	1.812
	[0.455]	[0.431]	[0.441]	[0.478]	[0.879]	[0.855]
Acres operated (1000s)	1.249	1.365	1.365	1.275	1.343	1.391
	[0.133]**	[0.157]***	[0.157]***	[0.268]	[0.220]*	[0.229]**
Farming not principal occup	0.566	0.437	0.437	1.115	0.685	0.737
	[0.139]**	[0.141]***	[0.141]***	[0.297]	[0.223]	[0.250]
Years made farming decisions	1.010	1.002	1.002	0.972	0.966	0.966
	[0.018]	[0.020]	[0.021]	[0.016]*	[0.018]*	[0.018]*
Digit-span	1.172	1.214	1.215	0.963	0.938	0.932
	[0.093]**	[0.093]**	[0.097]**	[0.094]	[0.115]	[0.115]
Received computer refresher	0.903	0.894	0.894	0.788	1.063	0.979
	[0.238]	[0.246]	[0.244]	[0.314]	[0.466]	[0.443]
k	1.53	1.63	1.63	1.45	1.56	1.58
	[0.215]***	[0.263]***	[0.263]***	[0.186]***	[0.223]***	[0.228]***
Corn RA = Soy RA (p-value)				0.13		0.16
Corn AA = Soy AA (p-value)					0.07	0.13
No. of Subjects	148	121	121	122	101	101

All regressions assume a Weibull survival distribution and include year and CRD dummies as controls. Excluded education level is high school or less. Robust standard errors in brackets. Significantly different from 1 at * - 10%, ** - 5%, and *** - 1% levels. We show the p-value from a χ^2 test that the risk and ambiguity aversion coefficients are equal across the soy and corn regressions.

are controlled for simultaneously. In column 4 of Panel B a farmer who has not yet adopted GM soy with a risk aversion measure one standard deviation higher than another farmer is 13% more likely to adopt at any point in time.[22] This is in line with results from Ross et al. (2010) who find that risk aversion does not impact Lao farmers' adoption of non-glutinous rice while ambiguity aversion does. This implies that our measure of risk aversion is not a strong predictor of the timing of adoption of GM corn. That it does have some explanatory power in the adoption of GM soy again confirms our hypothesis that GM soy impacts risk (since it decreases negative impacts due to exposure to weeds - a known risk) while GM corn is more likely to decrease ambiguity (since that GM corn which has the IR trait decreases negative impacts due to exposure to pests - an unknown ambiguity).

The rest of the coefficient estimates in Table 3 are consistent with the results of GM adoption models estimated elsewhere (Aldana et al., 2011; Alexander, 2006; Alexander and Mellor, 2005; Fernandez-Cornejo, 2010; Useche et al., 2009). In all regressions with controls, k is significantly greater than 1, implying that the probability of adoption does increase over time. As others have found, farm size, education level, and full-time farming are all positively associated with early adoption. The most significant coefficient estimates are those for farmers operating more acreage; they are more likely to be early adopters of GM.

One other striking result in Table 3 is that the farmers with higher digit-span recall were more likely to be early adopters of GM corn. This result suggests the potential role of cognitive ability in helping to speed the adoption of new technologies. Comparing the results in Panels A and B, we find that controlling for education and digit span recall (in addition to the other controls) seems to slightly *increase* the impact of ambiguity aversion on adoption of GM corn and slightly decrease the impact of risk aversion on adoption of GM soy, but these differences are not significant.

We can also consider whether there are heterogeneous impacts of ambiguity aversion on corn adoption. Our sample size is rather small, so we do not have a lot of power. But we find some interesting suggestive evidence. Ex ante we do not have any specific hypotheses about which populations should be impacted most. We have rerun the regression in column 2 Panel B, additionally including, one at a time, the interaction between the ambiguity aversion measure and each explanatory control variable included in the regression. We find significant positive interactions with "female" and "received computer refresher" meaning that the impact of ambiguity on encouraging adoption is stronger for females and those who are unfamiliar with computers. We find significant negative interactions with "acres operated" and "digit-span" meaning that the impact of ambiguity aversion is smaller for those with fewer acres or with higher cognitive skills. This seems to be a promising avenue for future investigation with a larger data set.

Although we do control for many farm and farmer characteristics, there is still a potential for omitted variables. We might think that people who are more trusting in general or who

[22]Looking at these magnitudes as well as the magnitudes for ambiguity aversion suggest that the effect of ambiguity aversion on the adoption of GM corn is by far the largest in terms of both magnitude and significance.

trust us and extension agents more will appear less ambiguity averse since they may believe we stacked the bag with more (good) red chips. We might also expect that these would be the farmers who adopt the new technology more quickly. We do not have measures of either generalized trust or trust in extension agents in specific. But, this omitted variable bias would lead to less ambiguity averse individuals adopting more quickly, which is the opposite of what we find. And, this omitted variable should impact the timing of the adoption of GM corn and GM soy in a similar manner, so it cannot explain the difference in the impact of ambiguity adoption on adoption across crops. In addition, our results are robust to including whether a farmer relies on extension agents or publications for advice (a potential measure of their trust in us) as a covariate.

We also don't have data on social networks. We might think that people who are more well-connected in social networks may tend to be early adopters and they may also tend to be less ambiguity averse. Both missing data on social networks and missing data on trust would bias our results toward finding a negative correlation between adoption and ambiguity aversion. Thus, we think our results may actually be conservative.

7. Conclusion

Using data from experimental games, this article examines how risk and ambiguity aversion shape the adoption of GM crops with distinctive traits, namely insect resistance and herbicide tolerance, among grain farmers in Minnesota and Wisconsin. The analysis suggests that, in general, the roles of risk and ambiguity can vary with the nature of the new technology under consideration.

GM corn seeds offer farmers improved insect and weed control, while GM soy seeds offer only improved weed control. Because of the higher potential degree of ambiguity associated with pest infestation and management, we hypothesized that ambiguity aversion might play a larger role in hastening the adoption of GM corn relative to GM soy. We tested this hypothesis using a survival model including experimental measures of risk and ambiguity aversion.

We find that ambiguity aversion does play an important role, but only for GM corn. In contrast with previous empirical tests of the roles of risk and ambiguity, we find that ambiguity aversion hastens rather than delays the adoption of GM corn. This difference may be due to the fact that most of the experimental literature thus far has been conducted in developing countries. In such a setting, new technologies may be more ambiguous for less-educated farmers with less access to extension materials. In contrast, farmers in the United States have access to reasonably good information regarding new seeds from seed dealers and extension agents, and they have the requisite level of education to properly understand the information they are presented. In this setting, the impact of ambiguity aversion may have more to do with the underlying characteristics of the new technology, rather than the fact that it is a new and relatively unknown technology.

Although ambiguity aversion hastens the adoption of GM corn, it has no impact on the adoption of GM soy. The key difference between GM corn and GM soy is that only the former may contain an insect-resistant trait. Our results are consistent with the fact that GM corn reduces the ambiguity associated with pest damages. In Wisconsin only approximately 70% of GM corn has the IR trait (while the other 30% has only the HT trait), but in our data we only asked the first year of adoption of GM corn seed, not which specific traits the farmer adopted. We think that this should make our results conservative. But, our results suggest that a fruitful area of future research would be to explore the adoption of IR versus HT versus stacked GM varieties to explore which traits appeal to which farmers in more depth.

This article has several implications for the understanding and continuing study of technology adoption. First is the need to distinguish between risk and ambiguity in the analysis of technology adoption. Second, the roles of risk and ambiguity can vary with the characteristics of the technology. This implication underscores the need to continue to explore ways to distinguish between them in theoretical and empirical analysis. Third, our analysis indicates that new technologies can sometimes help reduce farmers' exposure to uncertainty. If most farmers are indeed both risk averse and ambiguity averse, this indicates that technological progress in agriculture can also contribute to reducing the costs of risk and ambiguity.

Our research also has implications for the collection of data related to the study of technology adoption. Our results suggest that there are payoffs from combining experimental methods to measure variables that are otherwise difficult to identify (such as risk and ambiguity aversion) with survey methods. Given the degree to which farmers and other entrepreneurs inherently face basic challenges of managing uncertainty in an increasingly volatile global economy, the imperative to deepen our understanding in this area seems high. In addition, the empirical result that cognitive ability hastens adoption suggests the potential value of further study of the ways in which learning shapes individuals' capacities to manage uncertainty related to the adoption of new technologies.

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Appendix A. Comparison between the Experimental Sample and Wisconsin

Table A-1: Experimental Sample vs Wisconsin data

	Experimental Sample						Wisconsin Census	
	WI		MN		Total			
Average age	52.7$^{?}$	168	57.0	23	53.2$^{?}$	191	52.9	120,934
Female (% of all farmers)	7.1%***	168	0.0%	23	6.3%***	191	30.8%	120,934
Female (% of non-principal operators)	17.7%***	62	0.0%	4	16.7%***	66	66.1%	42,471
Farming is not principal occupation	16.7%***	168	13.0%	23	16.2%***	191	55.0%	120,934
Principal operator in the farm	63.1%	168	82.6%	23	65.5%	191	64.9%	120,934
Harvested cropland in acres[2]								
Less than 50	6.6%***	168	0.0%	23	5.8%***	191	23.0%	54,105
50 to 99	8.3%***	168	8.7%	23	8.4%***	191	17.5%	54,105
100 to 179	22.0%	168	26.1%	23	22.5%	191	19.3%	54,105
180 to 259	7.1%**	168	0.0%	23	6.3%***	191	12.8%	54,105
260 to 499	19.1%	168	30.4%	23	20.4%	191	16.4%	54,105
500 to 999	20.2%***	168	21.7%	23	20.4%***	191	7.4%	54,105
1000 to 1999	10.1%***	168	8.7%	23	10.0%***	191	2.5%	54,105
2000 and above	6.6%***	168	4.4%	23	6.3%***	191	1.0%	54,105
Average soy acreage per farm[1]	210.0$^{?}$	110	240.6	18	214.3$^{?}$	128	93.9	14,513
Average corn acreage per farm[13]	274.2$^{?}$	153	494.3	22	301.9$^{?}$	175	93.0	42,843
GM soy as % of all soy acres[2]	79.6%$^{?}$	168	98.0%	23	82.5%$^{?}$	191	85.0%	
GM corn as % of all corn acres[2]	82.4%$^{?}$	168	98.1%	23	85.7%$^{?}$	191	77.0%	

Sources: Census of Agriculture 2007 and Agriculture Survey 2009 (USDA-NASS, Web).
Significantly different from Wisconsin Census data at * - 10%, ** - 5%, and *** - 1% levels. We do not know standard errors for the census data so this test is only conducted on the binary data. We do not test the Minnesota data. (? - denotes unsure.)

[1] This data only includes farms with non-zero cropland harvested for that crop.

[2] 2009 Agriculture Survey data excludes farms with no harvested cropland.

[3] This assumes that only corn for grain or corn for silage was harvested, not both.

Appendix B. Theoretical Discussion of Ambiguity Aversion Measure

The measurement of risk aversion is well developed in the literature. In the context of the utility function $U(\pi)$ in (1), Pratt (1964) showed that risk aversion can be measured by one of two measures: the absolute risk aversion coefficient $\alpha(\pi) = -U''/U'$, or the relative risk aversion coefficient $\gamma(\pi) = -\pi U''/U'$. For a given risk, Pratt also showed that an increase in risk aversion (as measured by a rise in either $\alpha(\pi)$ or $\gamma(\pi)$ for all π) is equivalent to an increase in the risk premium R_r (Pratt, 1964, p. 128 and 135). This makes it clear that risk aversion ($R_r > 0$) corresponds to a concave utility function ($U'' < 0$). With a constant relative risk aversion (CRRA) utility function, γ is a sufficient statistic for the degree of risk aversion.

Klibanoff et al. (2005) and Neilson (2010) established similar results linking ambiguity aversion to the concavity of the function $h[\cdot]$ in (1). For example, Klibanoff et al. (2005, p. 1865) showed that $\beta(u) = -h''/h'$ is a measure of ambiguity aversion, with a rise in $\beta(u)$ for all u being associated with an increase in ambiguity aversion and a rise in the ambiguity premium R_a.

Note that equation (2) can be alternatively written as

$$h^{-1}[W(x)] = U(M(x) - R_a(x) - R_r(x)) \tag{B.1}$$

where $R_a(x)$ is defined in (3) and $[R_a(x) + R_r(x)]$ is defined in (2). Equation (B.1) shows that an increase in ambiguity aversion (as measured by a rise in $R_a(x)$) is equivalent to a rise in $R_r(x)$. And as established by Pratt (1964, p. 128 and 135), a rise in $R_r(x)$ has the same additive effect as a rise in either $\alpha(\pi)$ or $\gamma(\pi)$ for all π. Under CRRA and in situations of ambiguity, it follows from (B.1) that an ambiguity-averse individual would behave *as if* he/she faced only risk but with a higher level of risk aversion γ. In other words, with a CRRA utility function, finding that an individual appears to have a larger value for γ under uncertainty than under pure risk can be used as evidence of ambiguity aversion. We make use of this convenient property when calculating ambiguity aversion as the difference between the two coefficients of relative risk aversion.