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 little impact on the timing of adoption, but more ambiguity-averse farmers are the early adopters of GM corn. We hypothesize that this unusual finding is due to the fact that GM corn typically contains an insecticide-resistance trait which reduces the ambiguity of pest damages for adopters. This highlights the importance of distinguishing between risk and ambiguity when studying the effects of aversion to uncertainty on adoption.

1 Introduction

Empirical evidence that most individuals are risk averse (e.g., Lin et al. 1974, Binswanger 1980, Gollier 2001) has stimulated much research on the effects of risk and risk-aversion on technology adoption (Feder 1980, Sunding & Zilberman 2001, Knight et al. 2003, Foster & Rosenzweig 2010, Liu 2011). More recently, researchers have begun to distinguish the impact of risk from that of ambiguity (Rigotti et al. 2008, Bryan 2010, Ross et al. 2010, Engle-Warnick et al. 2011). Consistent with that literature and the recent call to action by Herberich et al. (2009), this article combines experimental data on risk and ambiguity

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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, distinguishing between risk and ambiguity aversion as do 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 addition to risk aversion (Pratt 1964), ambiguity aversion (Ellsberg 1961, Halevy 2007) also appears to be a common characteristic of economic behavior. For example, Chen & 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, Sunding & Zilberman 2001, Isik & Khanna 2003, Marra et al. 2003, Foster & Rosenzweig 2010). 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 (both risk and ambiguity) than do traditional technologies (Feder et al. 1985, Lybbert & Bell 2010, Engle-Warnick et al. 2011, Liu 2011). This assumption also holds in much of the more general literature on technology adoption (see Rigotti et al. (2008)). Under this framing of the adoption choice, risk-averse and ambiguity-averse farmers will 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. An important contrast between corn and soybeans is that corn has benefited from both HT and IR traits, 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 (Rigotti et al. 2008, Bryan 2010, Ross et al. 2010), we demonstrate a case in which ambiguity aversion actually increases the pace of adoption. We find a significant difference between 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 seeds.[1]

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 impact 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 discusses 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.

[1] 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.

2 The Roles of Risk and Ambiguity Aversion in Technology Adoption

In this section, we divide uncertainty into two pieces, risk and ambiguity, and explore the effects of both on technology adoption. 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.

First, consider the case where ambiguity is absent. In this case, the probability distribution of payoffs provides all relevant information for risk assessment. Under the expected-utility model, risk preferences are represented by a von Neumann-Morgenstern utility function. Risk aversion then corresponds to situations where the decision maker is willing to pay a positive amount of money to eliminate risk (by replacing the random payoff with its mean). This will occur when the utility function is concave (Pratt 1964).

Second, consider the case where ambiguity is present, i.e., where the probability distribution of payoffs is not known with certainty. From the Ellsberg paradox, we know that ambiguity can affect preferences and decisions. Ambiguity aversion corresponds to situations where a decision maker is made worse off by being exposed to ambiguity. Several approaches have been proposed to model ambiguity and aversion to it. They include the maximin model of Gilboa & Schmeidler (1989) and the smooth preference model of Klibanoff et al. (2005). Assuming that the probability distribution of payoffs depends on uncertain parameters, Klibanoff et al. (2005) propose a model that separates risk aversion from ambiguity aversion.

Exposure to risk, ambiguity, or both have adverse effects on the welfare of risk averse and ambiguity averse decision makers. Under this scenario, economic agents have an incentive to reduce their exposure to both risk and ambiguity. This indicates that both risk and ambiguity can have significant effects on economic decisions. Which one is more important is largely an empirical matter and depends on the situation at hand.

In this paper, we explore this issue in the context of technology adoption. Consider the case of a choice between two technologies: an old technology and a new technology. Each technology can affect exposure to risk as well as ambiguity. In general the decision maker would tend to prefer the technology that offers greater expected payoff.

But as just discussed, under risk aversion and ambiguity aversion, she may also prefer the technology that reduces her exposure to risk and ambiguity. This indicates that the new technology would be preferred when its expected payoff is higher and its exposure to risk and ambiguity is lower. Alternatively, if the new technology is associated with higher risk and ambiguity, then uncertainty aversion would reduce the incentive to adopt the new technology. 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 & Rosenzweig 2010). Our discussion extends this argument to ambiguity: if there is imprecise knowledge of the new technology, then ambiguity can adversely 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. If the decision maker can assess the probability distributions of payoffs then we are in a situation of risk; otherwise, we are in a situation of ambiguity. This provides useful insights for distinguishing between risk and ambiguity. 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

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 (Cousens & Mortimer 1995, Alexander et al. 2002). 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 (Showers 1993, Dent 2000, Pilcher & Rice 2001). 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.

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.

While this suggests HT would have no impact on ambiguity, while IR would decrease ambiguity, the new technologies' impacts on risk remain unclear. In relation to pest management, Horowitz & Lichtenberg (1994) find that the effect of risk aversion on pest management choices may go in either direction. Pesticides decrease uncertainty arising from pest populations, but since pest populations are often high when growing conditions are good, they may increase risk by increasing output in states of nature which are already good. Pannell (1995) likewise finds that the effect of risk aversion on herbicide use may go in either direction. Hurley et al. (2004) find that IR corn may either increase or decrease risk, depending on its price and thus on its impact on corn acreage.

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 January 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.[2] For the summer sessions, we used a 2010 list of 1254 farmers who had completed the 'Pesticide Application Training' (PAT) certification that is required for the use of certain pesticides. 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.[3]

In 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 more full-time farmers and farmers who manage larger farms than in the census, 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 more representative of behavior on the average acre.

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 average, the experimental session generally took less than two hours to complete, and was followed

[2]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%).

[3]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.

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. For the purposes of this paper, we focus on the 50/50 uncertainty and risk games. The design of these games is similar to those designed by Holt & Laury (2002) in which participants were offered a series of choices between a safe bet and a risky bet. We slightly alter this design, as did Moore & Eckel (2006) and Ross et al. (2010), so that the farmers were offered 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. 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. The sure thing involved a sure payoff of $10

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

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.

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 demographic and farm characteristics, included retrospective questions about their 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).

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. As do Cohen et al. (1985), we subtract risk aversion from uncertainty aversion to measure ambiguity aversion. This is related to the two-color Ellsberg problem with one choice between a sure 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 $U(\pi) = \frac{1}{(1-\alpha)}\pi^{1-\alpha}$, where α 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 is an economically meaningful 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 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.[4]

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. Thus any difference between the uncertainty aversion measure and the CRRA coefficient can be attributed to ambiguity aversion.

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.[5]

Under expected utility, farmers should switch at most once from the risky choice to the

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

[5]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.

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 & Laury (2002) report a rate of 13% among U.S. university students and faculty while Jacobson & Petrie (2009) report rates of 55% among Rwandan adults and 44-52% among Peruvian adults.

In the main text, we exclude those farmers who behaved irrationally. In a multivariate analysis, farmers who are classified as irrational are 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.[6] In the appendices, we discuss a second set of uncertainty measures which include those farmers whose decisions, with minor modifications, can be made to appear consistent. We discuss the construction of these measures in Appendix B and show our regression results using these measures in Appendix C. Making those changes leaves us with a sample of 154 observations for uncertainty aversion, 173 for risk aversion, and 150 for ambiguity aversion (out of a total of 191).

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 & Carpenter (2008)). We also find that farmers do tend to be ambiguity averse, as the uncertainty aversion measure is higher on average than the coefficient of relative risk aversion.[7] Fox & Weber (2002) present evidence on order effects showing that ambiguity aversion will be lower in experiments (such as ours) in which the ambiguous bet comes before the risky bet. This suggests that we may underestimate ambiguity aversion; in our sample, 34% of people are ambiguity averse, 38% ambiguity neutral, and 28% ambiguity loving. As long as these order effects do not vary with timing of GM adoption, this should not affect our results.

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

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

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.

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.[8] 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.)

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.[9] 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).

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. While our survey did not ask farmers to distinguish between the use of IR and HT corn seeds, we know that IR corn is commonly present in GM corn hybrids. This means that finding significant differences between the timing of GM corn adoption and GM soy adoption may 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 most farmers reporting GM corn adoption have been using corn with both the HT and IR traits (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 taking a lead on decisions on their farm for 28 years.

Comparing these statistics with data from the Wisconsin Census of Agriculture (USDA 2007),[10] we find that our participants are more likely to be full-time farmers than the Wisconsin average. As discussed above, this may be due to the fact that the experimental

[8]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.

[9]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).

[10]Appendix A contains more detailed comparisons between our sample and the average Wisconsin farmer.

sessions were conducted on weekdays, excluding many of those who held a second job. Also, our farmers work on larger farms than the average Wisconsin farmer and are more likely to be male.

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, uncertainty, 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.

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.

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 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.[11][12] Because the adoption of GM technologies started slowly in the first few

[11] 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.

[12] We have also tried including an indicator variable for those farmers who began farming after 1996 and its interaction with our experimental measures of uncertainty, 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.

years and then increased rapidly in later years, we also include dummies for calendar year.

In our application of the survival model, the dependent variable is years since first adoption of GM corn or soy adoption, 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 uncertainty, 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 irrational or inconsistent. Appendix C shows the robustness of our results to including more of the inconsistent observations.

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, uncertainty, or ambiguity aversion. Harrison et al. (2005) present evidence that risk preferences among students are stable over a six month period while Love & 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 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 uncertainty aversion while the second column provides the results for the risk aversion measure. Finally, the third column provides the pure ambiguity aversion measure (obtained by subtracting risk aversion from uncertainty aversion).

Table 3 shows weak evidence that more risk-averse individuals are less likely to adopt (CRRA coefficient in columns 2 and 5). This implies that our measure of risk aversion is not a strong predictor of the timing of adoption of these two GM crops. 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.

For the corn regression, the hazard ratio of ambiguity aversion (column 3) is significantly greater than one. Higher levels of ambiguity aversion are associated with early adoption of IR corn.[13] We can use the coefficient from the regression in Panel B to interpret the

[13] 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) Uncertainty	(2) Risk	(3) Ambiguity	(4) Uncertainty	(5) Risk	(6) Ambiguity
Panel A						
Unc/Risk/Amb	1.021	0.797	2.050	1.259	1.095	1.240
	[0.160]	[0.110]	[0.387]***	[0.177]	[0.144]	[0.240]
k	1.32	1.25	1.31	1.19	1.11	1.21
	[0.176]**	[0.160]*	[0.171]**	[0.134]	[0.118]	[0.142]
Corn U/R/A = Soy U/R/A (χ^2, p-value)				0.29	0.08	0.01
Panel B						
Unc/Risk/Amb	1.115	0.698	2.218	1.243	1.008	1.282
	[0.176]	[0.121]**	[0.544]***	[0.196]	[0.157]	[0.300]
Age	0.990	0.975	0.996	0.979	0.979	0.984
	[0.019]	[0.016]	[0.018]	[0.023]	[0.017]	[0.024]
Female	0.826	0.576	0.593	1.685	1.911	1.438
	[0.314]	[0.181]*	[0.232]	[1.185]	[1.152]	[1.025]
No or 2-year degree	1.481	1.289	1.373	0.703	0.485	0.669
	[0.394]	[0.309]	[0.350]	[0.261]	[0.171]**	[0.265]
4-year degree	1.793	1.549	1.355	0.677	0.523	0.594
	[0.462]**	[0.397]*	[0.360]**	[0.242]	[0.185]*	[0.221]
Some grad school	1.280	1.539	1.200	1.439	0.797	1.339
	[0.410]	[0.453]	[0.407]	[0.657]	[0.349]	[0.592]
Acres operated (1000s)	1.400	1.214	1.447	1.374	1.231	1.379
	[0.142]***	[0.095]**	[0.159]***	[0.170]***	[0.096]***	[0.180]**
Farming not principal occup	0.573	0.489	0.461	0.673	1.034	0.621
	[0.144]**	[0.122]***	[0.135]***	[0.216]	[0.252]	[0.198]
Years made farming decisions	0.998	1.003	0.994	0.985	0.980	0.983
	[0.018]	[0.017]	[0.020]	[0.022]	[0.016]	[0.022]
Digit-span	1.212	1.136	1.182	0.949	0.952	0.948
	[0.100]**	[0.085]*	[0.102]*	[0.117]	[0.092]	[0.124]
Received computer refresher	1.091	1.061	1.072	0.854	0.607	0.791
	[0.391]	[0.284]	[0.370]	[0.382]	[0.244]	[0.368]
No. of Subjects	129	148	121	107	122	101
k	1.69	1.64	1.71	1.58	1.49	1.58
	[0.267]***	[0.238]***	[0.274]***	[0.222]***	[0.165]***	[0.242]***
Corn U/R/A = Soy U/R/A (χ^2, p-value)				0.60	0.08	0.04

All regressions assume a Weibull survival distribution and include year and game session 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.

magnitude of the impact in column 3. 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 57% more likely to adopt in that period.

The hazard ratio of uncertainty aversion is not significantly different from one. While more risk-averse farmers are slightly more likely to adopt GM corn *later*, more ambiguity-averse farmers are more likely to adopt GM corn *earlier*. When looking at uncertainty aversion, which combines ambiguity and risk, we find no significant impact overall.

Comparing the results for corn with those for soy, we find that the hazard ratios of uncertainty and ambiguity aversion are not statistically different from one in the HT soy regressions (Unc/Risk/Amb in columns 4 and 6). The magnitude is also smaller, such that in column 6 a farmer who has not yet adopted GM soy with an ambiguity aversion measure one standard deviation higher than another farmer is only 15% 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, uncertainty, and ambiguity differ across the soy and corn regressions. We find that the coefficients for ambiguity are significantly different across the two regressions.[14]

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 rest of the coefficient estimates in Table 3 are consistent with the results of GM adoption models estimated elsewhere (Alexander & Mellor 2005, Alexander 2006, Useche et al. 2009, Fernandez-Cornejo 2010, Aldana et al. 2011). 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. One criticism with some

[14] In a regression including both ambiguity aversion and risk aversion as explanatory variables, one finds that only ambiguity aversion is significant for corn, while neither is significant for soy.

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. Cognitive ability tends to be negatively correlated with uncertainty aversion and positively correlated with technology adoption. (In our case, cognitive ability and ambiguity aversion are negatively but insignificantly correlated.) Comparing the results in Panels A and B, we find that controlling for education and digit span recall has no significant impact on the coefficients of the experimental uncertainty, risk, and ambiguity aversion measures.

Although we do control for many farm and farmer characteristics, there is still a potential for omitted variables. For example, 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.

We might also think that people who are more trusting in general or who 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. 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.

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, uncertainty, 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 on this topic 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 focuses on insect control. Our results are consistent with the fact that GM corn reduces the ambiguity associated with pest damages.

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.

References

Aldana, U., Foltz, J. D., Barham, B. L. & Useche, P. (2011), 'Sequential adoption of package technologies: The dynamics of stacked corn adoption', *American Journal of Agricultural Economics* **93**(1), 130–143.

Alexander, C. (2006), 'Farmer decisions to adopt genetically modified crops', *CAB Reviews: Perspectives in Agriculture, Veterinary Science, Nutrition and Natural Resources* **1**, 1–9.

Alexander, C., Fernandez-Cornejo, J. & Goodhue, R. E. (2002), Determinants of GMO use: A survey of Iowa maize-soybean farmers' acreage allocation, *in* V. Santaniello, R. E. Evenson & D. Zilberman, eds, 'Market Development for Genetically Modified Foods', New York, NY: CABI Publishing, chapter 11, pp. 122–139.

Alexander, C. & Mellor, T. V. (2005), 'Determinants of corn rootworm resistant corn adoption in Indiana', *AgBioForum* **8**, 197–204.

Anderson, J. C., Burks, S. V., Carpenter, J. P., Goette, L., Maurer, K., Nosenzo, D., Potter, R. & Rustichini, A. (2010), Self-selection does not increase other-regarding preferences among adult laboratory subjects, but student subjects may be more self-regarding than adults. Unpublished Manuscript.

Binswanger, H. P. (1980), 'Attitudes toward risk: Experimental measurement in rural India', *American Journal of Agricultural Economics* **62**(3), 395–407.

Board on Agriculture and Natural Resources (BANR) (2010), *The Impact of Genetically Engineered Crops on Farm Sustainability in the United States*, Washington DC: The National Academies Press.

Bryan, G. (2010), Ambiguity and insurance. Unpublished Manuscript.

Cardenas, J.-C. & Carpenter, J. (2008), 'Behavioural development economics: Lessons from field labs in the developing world', *Journal of Development Studies* **44**(3), 311–338.

Chen, Z. & Epstein, L. (2002), 'Ambiguity, risk, and asset returns in continuous time', *Econometrica* **70**(4), 1403–1443.

Cohen, M., Jaffray, J. Y. & Said, T. (1985), 'Individual behavior under risk and under uncertainty: An experimental study', *Theory and Decision* **18**(2), 203–228.

Cousens, R. & Mortimer, M. (1995), *Dynamics of Weed Populations*, Cambridge: Cambridge University Press.

de Mel, S., McKenzie, D. & Woodruff, C. (2008), 'Returns to capital in microenterprises: Evidence from a field experiment', *Quarterly Journal of Economics* **123**(4), 1329–1372.

Dempster, F. N. (1981), 'Memory span: Sources of individual and developmental differences', *Psychological Bulletin* **89**(1), 63–100.

Dent, D. (2000), *Insect Pest Management*, Cambridge: CABI Publishing.

Djankov, S., Miguel, E., Qian, Y., Roland, G. & Zhuravskaya, E. (2005), 'Who are Russia's entrepreneurs?', *Journal of the European Economic Association* **3**(2-3), 587–597.

Ellsberg, D. (1961), 'Risk, ambiguity and the Savage axioms', *Quarterly Journal of Economics* **75**, 643–669.

Engle-Warnick, J., Escobal, J. & Laszlo, S. (2011), 'Ambiguity aversion and portfolio choice in small-scale Peruvian farming', *B.E. Journal of Economic Analysis and Policy* . Forthcoming.

Falk, A., Meier, S. & Zehnder, C. (2010), Did we overestimate the role of social preferences? The case of self-selected student samples. Unpublished Manuscript.

Feder, G. (1980), 'Farm size, risk aversion and the adoption of new technology under uncertainty', *Oxford Economic Papers* **32**, 263–283.

Feder, G., Just, R. E. & Zilberman, D. (1985), 'Adoption of agricultural innovations in developing countries: A survey', *Economic Development and Cultural Change* **33**(2), 255–98.

Fernandez-Cornejo, J. (2010), Adoption of genetically engineered crops in the U.S., ERS, USDA, `http://www.ers.usda.gov/Data/BiotechCrops/`.

Fischbacher, U. (2007), 'Z-tree: Zurich toolbox for ready-made economic experiments', *Experimental Economics* **10**(2), 171–178.

Foster, A. D. & Rosenzweig, M. R. (2010), 'Microeconomics of technology adoption', *Annual Review of Economics* **2**, 395–424.

Fox, C. R. & Weber, M. (2002), 'Ambiguity aversion, comparative ignorance, and decision context', *Organizational Behavior and Human Decision Processes* **88**(1), 476–498.

Gilboa, L. & Schmeidler, D. (1989), 'Maxmin expected utility with a non-unique prior', *Journal of Mathematical Economics* **18**, 141–153.

Gollier, C. (2001), *The Economics of Risk and Time*, Cambridge: MIT Press.

Halevy, Y. (2007), 'Ellsberg revisited: An experimental study', *Econometrica* **75**, 503–536.

Harrison, G. W., Johnson, E., McInnes, M. M. & Rutström, E. E. (2005), 'Temporal stability of estimates of risk aversion', *Applied Financial Economics Letters* **1**(1), 31–35.

Harrison, G. W., Lau, M. I. & Rutström, E. E. (2009), 'Risk attitudes, randomization to treatment, and self-selection into experiments', *Journal of Economic Behavior and Organization* **70**(3), 498–507.

Herberich, D. H., Levitt, S. D. & List, J. (2009), 'Can field experiments return agricultural economics to the glory days', *American Journal of Agricultural Economics* **5**, 1259–1265.

Holt, C. A. & Laury, S. K. (2002), 'Risk aversion and incentive effects', *American Economic Review* **92**(5), 1644–1655.

Horowitz, J. K. & Lichtenberg, E. (1994), 'Risk-reducing and risk-increasing effects of pesticides', *Journal of Agricultural Economics* **45**(1), 82–89.

Hurley, T. M., Mitchell, P. D. & Rice, M. E. (2004), 'Risk and the value of Bt corn', *American Journal of Agricultural Economics* **86**(2), 345–358.

Isik, M. & Khanna, M. (2003), 'Stochastic technology, risk preferences, and adoption of site-specific technologies', *American Journal of Agricultural Economics* **85**(2), 305–317.

Jacobson, S. & Petrie, R. (2009), 'Learning from mistakes: What do inconsistent choices over risk tell us?', *Journal of Risk and Uncertainty* **38**(2), 143–158.

Klibanoff, P., Marinacci, M. & Mukerji, S. (2005), 'A smooth model of decision making under ambiguity', *Econometrica* **73**, 1849–1892.

Knight, J., Weir, S. & Woldehanna, T. (2003), 'The role of education in facilitating risk-taking and innovation in agriculture', *Journal of Development Studies* **39**, 1–22.

Lin, W., Dean, G. W. & Moore, C. V. (1974), 'An empirical test of utility vs. profit maximization in agricultural production', *American Journal of Agricultural Economics* **56**(3), 497–508.

Liu, E. (2011), Time to change what to sow: Risk preferences and technology adoption decisions of cotton farmers in China. Unpublished Manuscript.

Love, R. O. & Robison, L. J. (1984), 'An empirical analysis of the intertemporal stability of risk preference', *Southern Journal of Agricultural Economics* **16**(1), 159–165.

Lybbert, T. J. & Bell, A. (2010), 'Stochastic benefit streams, learning and technology diffusion: Why drought tolerance is not the new Bt', *AgBioForum* **13**(1), 13–24.

Marra, M., Pannell, D. J. & Ghadim, A. A. (2003), 'The economics of risk, uncertainty and learning in the adoption of new agricultural technologies: Where are we on the learning curve?', *Agricultural Systems* **75**(2-3), 215–234.

Miller, G. A. (1956), 'The magical number seven, plus or minus two: Some limits on our capacity for processing information', *Psychological Review* **63**, 81–97.

Moore, E. & Eckel, C. (2006), Measuring ambiguity aversion. Unpublished Manuscript.

Pannell, D. J. (1995), 'Optimal herbicide strategies for weed control under risk aversion', *Review of Agricultural Economics* **17**(3), 337–350.

Pilcher, C. D. & Rice, M. E. (2001), 'Effect of planting dates and *Bacillus thuringiensis* corn on the population dynamics of European corn borer', *Journal of Economic Entomology* **94**(3), 730–742.

Pratt, J. W. (1964), 'Risk aversion in the small and in the large', *Econometrica* **32**, 122–136.

Rigotti, L., Ryan, M. & Vaithianathan, R. (2008), Tolerance of ambiguity and entrepreneurial innovation. Unpublished Manuscript.

Ross, N., Santos, P. & Capon, T. (2010), Risk, ambiguity and the adoption of new technologies: Experimental evidence from a developing economy. Unpublished Manuscript.

Shaner, D. L. (2000), 'The impact of glyphosate tolerant crops on the use of other herbicides and on resistance management', *Pest Management Science* **56**(4), 320–326.

Showers, W. B. (1993), Diversity and variation of European corn borer populations, *in* K. C. Kim & B. A. McPheron, eds, 'Evolution of Insect Pests', New York, NY: John Wiley and Sons, chapter 14, pp. 287–309.

Sunding, D. & Zilberman, D. (2001), The agricultural innovation process: Research and technology adoption in a changing agricultural sector, *in* R. Evenson & P. Pingali, eds, 'Handbook of Agricultural Economics', Vol. 1, chapter 4, pp. 207–261.

USDA (2007), State level data (Wisconsin), *in* 'Census of Agriculture, Full Report', `http://www.agcensus.usda.gov/Publications/2007/index.asp`.

Useche, P., Barham, B. L. & Foltz, J. D. (2009), 'Integrating technology traits and producer heterogeneity: A mixed-multinomial model of genetically modified corn adoption', *American Journal of Agricultural Economics* **91**(2), 444–461.

A Comparison between the Experimental Sample and Wisconsin

Table A-1: Experimental Sample vs Wisconsin data

	Experimental Data	Wisconsin Data
Average age	53.2	52.9
Female (% of all farmers)	6.3%	30.8%
Female (% of farmers that are not principal operators)	16.7%	66.1%
Farming is not principal occupation	16.2%	55.0%
Principal operator in the farm	65.5%	64.9%
Distribution of farmers according to their cropland[2]		
Less than 50	5.8%	23.0%
50 to 99	8.4%	17.5%
100 to 179	22.5%	19.3%
180 to 259	6.3%	12.8%
260 to 499	20.4%	16.4%
500 to 999	20.4%	7.4%
1000 to 1999	10.0%	2.5%
2000 and above	6.3%	1.0%
Average soy acreage per farm[1]	144.7	93.9
Average corn acreage per farm[13]	296.7	93.0
GM soy acres as percent of all soy acres[2]	82.2%	85.0%
GM corn acres as percent of all corn acres[2]	82.4%	77.0%

[1] This data refers to farms with cropland harvested (80% of the farms with cropland).
[2] This information comes from the Agriculture Survey.
[3] This assumes that only corn for grain or corn for silage was harvested, not both.
Sources: Census of Agriculture 2007 and Agriculture Survey 2009 (USDA-NASS, Web).

B Second Set of Experimental Measures

Table B-1 describes the changes made to the decisions of farmers who made inconsistent choices in the construction of our second set of experimental measures. Because a number of farmers were not very experienced using a mouse, and from conversations with farmers after the experiments, we believe that some of the "multiple switching behavior" may have been due to uncorrected mistakes with a mouse rather than purposeful switching. For each of the experiments, the farmers' decisions were grouped in four categories. Table B-1 presents an example of each and the share of farmers whose responses were classified in each sub-category.

The first group consists of those farmers who did not change their decision. This includes those farmers who only chose the sure thing, which is represented by "A", and those who only chose the gamble, represented by "B". The former is coded as irrational, as it involves choosing a strictly dominated option. The latter is rational under risk-neutrality or risk-lovingness. The second group consists of farmers who switched their choices once from the gamble (B) to the sure thing (A), but not from the sure thing (A) to the gamble (B). This behavior is also rational and so rows 2 and 3 are included in the first set of experimental measures used in the regressions in the main text. These responses were not modified in order to be included in the second measure. In the ambiguity experiment, 69% of the farmers were categorized in one of these two groups while in the risk experiment, this percentage is higher at 79%.

The third group includes farmers who only switched from the sure thing (A) to the gamble (B), but not from B to A. This group of farmers is divided in three sub-groups (rows 4, 5 and 6). The first two sub-groups included those farmers' decisions that with just one change would have chosen all A or all B. The third sub-group includes other cases, where switching all the A's to B's results in consistent decisions.

The last group includes those farmers that both switched their choice from the sure thing (A) to the gamble (B), and then back from B to A. For those cases in rows 7, 8, and 9 we can just change one decision to result in a consistent series. We make this change, under the assumption that the person clicked incorrectly for one decision. For those cases in row 10 we need to change one decision and then switch all A's to B's.

The next four sub-categories (rows 11 to 14) include those individuals who switched back and forth more than once but the first two choices were the same and the last two choices were the same. In these cases, we just considered the first time they chose A (in row 12, after switching all A's and B's). For example, row 12 presents those farmers' responses that began with two A's and ended with two B's. To consider these responses, we switched A's and B's, so that the responses can be considered similar to the cases in row 11. Then, as shown in the example, we just find the number of the choice in which the farmer selected A for the first time. The last four sub-categories could not be rendered rational by slight changes so they were dropped from the analysis. Summary statistics for this second set of uncertainty measures can be found in Table B-2.

Table B-1: Creation of the Second Set of Experimental Measures

Cases	Changes We Made	Examples: Original	Examples: Result	Examples: First A	Uncertainty Game: No.	Uncertainty Game: Share	Risk Game: No.	Risk Game: Share
Farmers who did not change their choice					19	9.9%	12	6.3%
1. All choices are A	Coded as irrational	AAAAAAAAAAA			8	4.2%	4	2.1%
2. All choices are B	None	BBBBBBBBBBB	BBBBBBBBBBB	12	11	5.8%	8	4.2%
Farmers who switched their choice once from B to A, but not from A to B					120	62.8%	143	74.9%
3. All cases	None	BBBBBAAAAAA	BBBBBAAAAAA	6	120	62.8%	143	74.9%
Farmers who switched their choice once from A to B, but not from B to A					4	2.1%	4	2.1%
4. Changing one choice, then "All choices are A"	Coded as irrational	AAAAAAAAAAB			0	0.0%	0	0.0%
5. Changing one choice, then "All choices are B"	Change the A for a B	ABBBBBBBBBB	BBBBBBBBBBB	12	1	0.5%	1	0.5%
6. Others	Switch A's and B's	AAAAAABBBBB	BBBBBBAAAAA	7	3	1.6%	3	1.6%
Farmers who switched their choice from A to B and from B to A					48	25.1%	32	16.8%
7. Changing one choice, then "All choices are A"	Coded as irrational	AAAABAAAAAA			0	0.0%	0	0.0%
8. Changing one choice, then "All choices are B"	Change the A for a B	BBBBBBBBABB	BBBBBBBBBBB	12	0	0.0%	1	0.5%
9. Changing one choice, then can be counted as "Switched once from B to A, but not from A to B"	Fix change	BBBABBBAAAA	BBBBBBBAAAA	8	10	5.2%	5	2.6%
10. Changing one choice, then can be counted as "Switched once from A to B, but not from B to A"	Fix change and then switch A's and B's	AAABABBBBBB	BBBAAAAAAAA	4	2	1.0%	2	1.0%
11. BBxxxxxxAA	Counted as "Switched their choice once from B to A"	BBABABABAAA	BBABABABAAA	3	4	2.1%	6	3.1%
12. AAxxxxxxBB	Switch A's and B's and then counted as "Switched their once from B to A"	AABAAABABBB	BBABBBABAAA	3	0	0.0%	0	0.0%
13. AAxxxxxxAA	Coded as irrational	AABAAABABAA			4	2.1%	1	0.5%
14. BBxxxxxxBB	Counted as "All choices are B"	BBBABBABABB	BBBBBBBBBBB	12	3	1.6%	4	2.1%
15. AxxxxxxxxB	Coded as irrational	ABBABBABAAB			5	2.6%	0	0.0%
16. BxxxxxxxxA	Coded as irrational	BABABBABABA			7	3.7%	5	2.6%
17. AxxxxxxxxA	Coded as irrational	ABBABBABABA			5	2.6%	4	2.1%
18. BxxxxxxxxB	Coded as irrational	BABABBABAAB			8	4.2%	4	2.1%
Total					191	100.0%	191	100.0%

Table B-2: Summary Statistics for Second Set of Experimental Measures

Variables	Obs	Mean	Std. Dev.	Min	Max
Uncertainty, Risk, and Ambiguity Aversion					
Uncertainty aversion	154	0.79	0.73	-0.09	3.76
Risk aversion	173	0.74	0.64	-0.09	3.76
Ambiguity aversion = uncertainty minus risk	150	0.06	0.58	-1.55	3.11

C Robustness Check

In Table C-1 we show the results using the second, more inclusive, experimental measure which alters the choices of some individuals who switched between the risky and safe choices. We find that the qualitative results are the same: farmers with higher levels of ambiguity aversion are more likely to be early adopters of GM corn.

Table C-1: Hazard Ratios for Adoption of GM Corn and Soy using Second CRxA Measures

	Corn			Soybeans		
	(1) Uncertainty	(2) Risk	(3) Ambiguity	(4) Uncertainty	(5) Risk	(6) Ambiguity
Panel A						
Unc/Risk/Amb	1.130	0.831	1.801	1.283	1.082	1.316
	[0.163]	[0.102]	[0.328]***	[0.179]*	[0.138]	[0.223]
k	1.25	1.33	1.35	1.16	1.11	1.18
	[0.153]*	[0.190]**	[0.186]**	[0.117]	[0.125]	[0.129]
Corn U/R/A = Soy U/R/A (χ^2, p-value)				0.47	0.09	0.05
Panel B						
Unc/Risk/Amb	1.208	0.729	2.064	1.357	0.974	1.442
	[0.173]	[0.108]**	[0.449]***	[0.196]**	[0.140]	[0.272]*
Age	0.978	0.971	0.972	0.973	0.973	0.969
	[0.017]	[0.015]**	[0.017]	[0.019]	[0.015]*	[0.020]
Female	0.856	0.784	0.850	2.446	2.406	2.759
	[0.285]	[0.238]	[0.297]	[1.478]	[1.401]	[1.721]
No or 2-year degree	1.261	1.098	1.173	0.559	0.470	0.537
	[0.303]	[0.243]	[0.271]	[0.178]*	[0.144]**	[0.169]**
4-year degree	1.975	1.745	1.748	0.642	0.568	0.578
	[0.454]***	[0.389]**	[0.392]**	[0.207]	[0.175]*	[0.185]*
Some grad school	1.330	1.229	1.320	0.776	0.853	0.722
	[0.403]	[0.330]	[0.424]	[0.375]	[0.308]	[0.355]
Acres operated (1000s)	1.499	1.282	1.559	1.498	1.283	1.484
	[0.140]***	[0.092]***	[0.161]***	[0.187]***	[0.094]***	[0.192]***
Farming not principal occup	0.734	0.634	0.625	1.101	1.039	0.950
	[0.189]	[0.142]**	[0.178]*	[0.329]	[0.240]	[0.301]
Years made farming decisions	1.015	1.009	1.017	0.993	0.990	0.994
	[0.018]	[0.015]	[0.019]	[0.020]	[0.015]	[0.021]
Digit-span	1.199	1.136	1.157	0.953	0.937	0.969
	[0.082]***	[0.079]*	[0.081]**	[0.084]	[0.078]	[0.087]
Received computer refresher	0.754	0.834	0.771	0.629	0.524	0.694
	[0.206]	[0.210]	[0.202]	[0.243]	[0.183]*	[0.270]
No. of Subjects	151	170	147	127	142	124
k	1.62	1.77	1.82	1.57	1.51	1.63
	[0.242]***	[0.288]***	[0.314]***	[0.188]***	[0.174]***	[0.212]***
Corn U/R/A = Soy U/R/A (χ^2, p-value)				0.53	0.10	0.10

All regressions assume a Weibull survival distribution and include year and game session 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.