Risk, Learning, and Technology Adoption

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Abstract: This paper explores how decision makers learn and use information, with an application to the adoption of biotechnology in agriculture. The empirical analysis relies on experimental and survey data measuring risk preferences, learning processes, and the adoption of genetically modified (GM) seeds among US grain farmers. While controlling for risk aversion, we link individual learning rules with the cognitive abilities of each decision maker and their actual GM adoption decisions. We find evidence that very few individuals are Bayesian learners, and that the population of farmers is quite heterogeneous in terms of learning rules. This suggests that Bayesian learning (as commonly assumed in the analysis of agricultural technology adoption) is not an appropriate characterization. In addition, we do not find a strong relationship between observed learning styles and the timing of GM seed adoption. To the extent that learning is a key part of the process of technology adoption, this suggests the presence of much unobserved heterogeneity in learning among farmers.

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1. Introduction

There has been much interest in analyzing the roles of risk and learning in economic decision-making (for reviews, see Feder et al., 1985; Foster and Rosenzweig, 2010). These features are pivotal in adoption choices where new technologies are imperfectly known and managers seek to acquire important information before deciding whether or not to adopt. In particular, economic agents need to learn about how a new technology works, how it might or might not be adapted to local environmental and market conditions, what its return and risk profile might be for them, and how this profile compares with other options (Rogers, 1962; Feder et al., 1985; Conley and Udry, 2010). While the roles of risk and especially risk aversion in technology adoption have been emphasized in the previous literature, the interaction between risk and learning remains poorly understood (Marra et al., 2003). This is largely because of the empirical difficulty in jointly analyzing risk and learning styles and then creating direct links to technology adoption. Such difficulties have led previous adoption analyses to focus mostly on models of Bayesian learning (Barenklau, 2005; Foster and Rosenzweig, 1995, 2010).

We examine the common case of the expected utility model. In this context, risk exposure is evaluated using probability assessments, while risk preferences are represented by the manager's von Neumann-Morgenstern utility function. Learning is represented by the evolution of assessed subjective probabilities, as new information becomes available over time. We examine the commonly assumed Bayesian learning rule while also evaluating alternative learning rules that allow for the overweighting or underweighting of new information.

Unpacking the interactions between risk and learning requires experimental methods to test how agents behave under controlled conditions. Our experimental and survey data were collected from almost 200 Minnesota and Wisconsin farmers facing similar agro-climatic and economic conditions. Our analysis focuses on farmers' decisions regarding whether or not to adopt genetically modified (GM) seeds.

GM technology is part of the biotechnology revolution that has contributed to improving US agricultural productivity over the last 15 years (Fernandez-Cornejo, 2010). Approximately 90 percent of the farmers we surveyed have adopted GM corn and soy seeds since they first became available in 1996. A similar share of corn and soy acreage in the Midwest is currently planted in GM varieties. Understanding who adopts and when is important in order to assess the process of technological change in US agriculture.

While Bayesian learning is strongly grounded in probability theory, learning can be complex. Previous research has found empirical evidence suggesting that individuals rely on a variety of learning heuristics (e.g., Cheung and Friedman, 1997; Camerer and Ho, 1999; Camerer, 2003; Gans, Knox, and Croson, 2007). Our analysis finds similar evidence and documents the diversity of learning styles. We observe that most farmers are not Bayesian learners: many farmers either forget old information or ignore new information.

The data collection and analysis proceed in four steps. First, we observe how each farmer chooses between risky and safe prospects and use this information to estimate individual risk preferences. Then, in a series of controlled learning experiments, we study how each farmer's decisions evolve with new information. Given the individual risk preferences evaluated in step 1, the second set of decisions is used to determine individual learning rules. Besides finding evidence that most individuals are not Bayesian learners, we document the presence of significant heterogeneity in learning styles across farmers.

The third step involves a set of tests of cognitive ability. Even after controlling for cognitive ability, we find significant unobserved heterogeneity in learning styles across individuals. This outcome both highlights the need for direct measures of learning styles and the challenges of explaining heterogeneity in learning. Finally, we combine survey data on farm characteristics and biotechnology use with the experimental results to examine how risk preferences (evaluated in step 1) and learning rules (evaluated in step 2) relate to farmer decisions to adopt biotechnology on their farms.

Somewhat surprisingly, we do not find a strong relationship between observed learning styles and the timing of GM seed adoption. To the extent that learning plays a key role in technology adoption, this is consistent with the presence of much unobserved heterogeneity in learning styles among farmers.[3] We interpret our findings as indirect evidence that individual learning styles are complex, and that they may involve social learning that our experiments did not measure.

In Section 2, we review the relevant literature on both learning and technology adoption. Section 3 introduces our data and experiments while Section 4 introduces the learning models. Sections 5 and 6 present results, with the former focusing on assigning learning rules to farmers and the latter relating learning rules to technology adoption. Finally, we conclude in Section 7.

2. Literature Review on Individual Learning and Technology Adoption

Individuals can employ a variety of learning rules. Bayesian learning is strongly grounded in probability theory. Under Bayesian learning, as new information becomes available,

[3] Another possibility is that we do not have enough statistical power, both in assigning learning styles to farmers (with 10 decisions per farmer) and in then correlating that with adoption decisions (with fewer than 200 farmers).

the updating of (possibly subjective) probabilities is done in a way consistent with Bayes theorem. Departures from Bayesian learning are possible in at least two directions. On the one hand, some individuals may underutilize older information and, instead, rely more on recent observations. On the other hand, some individuals may find it difficult to process new information and, as a result, rely on older information while paying less attention to new information. Cheung and Friedman (1997) develop a model in which individuals can exhibit different types of learning. They find that "players are quite heterogeneous in crucial dimensions such as effective memory length and responsiveness to evidence." As shown below, we find similar evidence of individual heterogeneity with regards to learning rules and the relationship between cognitive measures and learning rules.

Gans, Knox, and Croson (2007) use experiments to evaluate which of six different learning rules fit the individuals in their sample. They find that the simpler learning rules perform the best while the most complicated learning rule (Bayesian learning) performs the worst. They also document significant heterogeneity in learning rules across individuals.[4]

While much research has been conducted on learning rules, few papers have examined the linkages between learning styles and decisions made in the real world. As far as we know, no previous research has examined how alternative learning rules may affect technology adoption among farmers. Thus, despite the importance of technological progress and its effects on economic growth, the fundamental role of learning styles in shaping technology adoption

[4] Additional analyses of learning rules find that different learning heuristics are simultaneously important and can reinforce or conflict with each other (Charness and Levin, 2005), that individuals who underreact to information will eventually converge on accurate beliefs but that individuals who overreact may or may not do so (Epstein, Noor, and Sandroni, 2010), and that the performance of various learning heuristics often depends on the types of experiments being analyzed (Camerer, 2003). Furthermore, the experience-weighted attraction model, which integrates various heuristics as special cases, often outperforms other models (Camerer and Ho, 1999; Camerer, 2003), but it is infeasible to estimate in this paper due to the limited number of observations per farmer.

remains underexplored. This motivates our efforts to provide a deeper analysis of learning styles and their potential role in adoption decisions.

Previous research has examined the factors affecting the rate and speed of adoption among farmers (Griliches, 1957; Rogers, 1962; Feder et al., 1985; Marra et al., 2003; Foster and Rosenzweig, 2010). This literature typically views technology adoption as a gradual process based on the presence of heterogeneity among potential adopters. This heterogeneity can stem from supply-side factors, such as when a new technology becomes available in a particular location. It also arises from demand-side factors that reflect how individuals obtain information about the new technology, how they use this information in the process of deciding whether or not to adopt it, what types of preferences they have, and what types of constraints they face. We are particularly interested in the extent to which the presence of individual heterogeneity in learning styles could help to explain differential adoption rates.

The technology adoption literature has long recognized the impact of heterogeneity on adoption (Feder et al., 1985); however, most of the attention has been on observable heterogeneity of farm and farmer characteristics or unobserved risk aversion (Nielsen et al., 2013). The impact of learning styles is difficult to observe, rarely incorporated, and hence remains poorly understood.

Recent research on the role of learning in technology adoption has focused mostly on what individuals can learn from experience with technologies (Foster and Rosenzweig, 2010; Aldana et al., 2011) or from other information sources including neighbors (Barenklau, 2005; Conley and Udry, 2010, Kabunga et al. 2012). These efforts, however, use Bayesian learning to motivate their modeling frameworks, in effect assuming away the potential for distinctive learning rules to shape adoption choices. Other studies, such as de Mel et al. (2008), find that cognitive abilities can shape entrepreneurial success, but they also do not explore explicitly the learning mechanisms or different learning styles that might generate these individual differences.

3. Data Source and Experimental Procedure

Experimental methods have recently been applied to technology adoption, using farmers as participants (Engle-Warnick et al., 2011; Liu, 2013; Barham et al., 2014). These experimental procedures allow researchers to evaluate farmer risk preferences in a controlled environment while linking those results directly to actual technology choices of farmers.

Our data were collected from 191 corn and soybean farmers in Minnesota and Wisconsin between January and August of 2010 (see Barham et al., 2014 for more details). Each farmer participated in one of 16 experimental sessions and received winnings from the games and reimbursement for travel (averaging $73 and $30, respectively) as well as the opportunity to participate in an outreach presentation. Farmers were recruited either from a list of respondents to a random 2006 GM seed use survey, the 2010 list of "Pesticide Application Training" certification, or Wisconsin Agricultural Statistics Service farmer lists. In addition, a few farmers were recruited from corn conferences and by extension agents. When comparing our sample with census data on Wisconsin farmers, we found that farmers in our sample managed larger farms and were more likely to be full-time farmers (see Barham et al., 2014).

As noted in the introduction, the field experiments proceeded in several steps. First, we conducted an uncertainty game (with unknown probabilities) and a risk game (with known probabilities). Second, we implemented two controlled experiments studying how each farmer's decisions evolved with new information. These experiments were followed by a survey which included a section measuring cognitive ability. The experiments were programmed in z-Tree

(Fischbacher, 2007) and computer training was provided to the 19% of farmers who requested it. Instructions were read aloud and appeared on the computer screens.

Risk and Uncertainty Games:

The aforementioned risk and uncertainty games both involved a series of choices between a certain payout and a gamble (similar to experiments conducted by Moore and Eckel (2006) and Ross et al. (2010) and influenced by Holt and Laury (2002)). In each game, farmers had to make 11 decisions choosing between a sure payoff and a risky payoff. The sure payoff was $10 while the risky payoff involved drawing a chip from a bag of red and black chips, with a payoff of $20 if a red chip was drawn and a lower amount – that decreased in each decision – if a black chip was drawn (see Table 1). In the uncertainty game, no information was provided about the number of red and black chips while, in the risk game, farmers were told that there were 50 chips of each color. The uncertainty game was conducted first to ensure that the risk game did not provide a focal point for farmers. At the end of the entire session, a die was rolled to select one of the 11 rounds from each game and each farmer was paid the corresponding payoff.

****Table 1****

Assuming that risk preferences exhibit constant relative risk aversion (CRRA) with utility function $U\left(\pi\right)=\frac{\pi^{(1-\alpha)}}{1-\alpha}$ (see Pratt, 1964), we used the information from the risk game to estimate a coefficient of relative risk aversion α for each farmer. These CRRA coefficients, presented in Table 1, measure the farmer's minimum coefficient given that he accepted the gamble in that row and turned down the subsequent one.[5] 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.[6] Some farmers exhibited multiple-switching behavior, moving back and forth more than once from the risky to the safe option and these farmers are excluded from the analysis.

In the uncertainty game with uninformative prior beliefs, we assume a subjective expectation of a 50/50 distribution of red and black chips. In this context, we calculate an uncertainty aversion coefficient similar to the CRRA coefficient with the same values given in Table 1. 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 were 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, the difference between the uncertainty aversion measure and the CRRA coefficient is used as a measure of ambiguity preferences. The analysis of ambiguity and its role in technology adoption is presented in Barham et al. (2014).

The average coefficient of relative risk aversion in our sample is 0.8, which indicates that risk aversion is prevalent. This magnitude aligns with results from many other experiments (see

[5] This gives a lower bound value for the coefficient of relative risk aversion. Using the upper bound or the midpoint would not change our qualitative results.
[6] The data do not provide information to estimate the risk aversion coefficient for those farmers who always chose either the safe option or the risky option. For the farmers that always chose the risky option, we set their risk preferences to be -0.09. Always choosing the safe option means the farmers chose a dominated option, and these farmers are excluded from the analysis.

the survey in Cardenas and Carpenter (2008)). Furthermore, the average measure of ambiguity preferences is approximately 0.1.

Drawing Game:

Next, we conducted two learning games to evaluate how farmers learn as new information becomes available. We call the first one the "drawing game." In the drawing game, we drew chips from a bag containing 100 black and red chips, but we did not tell the farmers the composition of the chips. (In reality, there were 72 red chips and 28 black chips in the bag.) We simultaneously drew five chips with replacement from the bag and, after observing this new information, asked each farmer whether he preferred the sure thing or the risky payoff. We then drew another five chips with replacement and asked the farmer which option he preferred and repeated this process 10 times in total. At the conclusion of the experiments, we paid the farmers randomly for one of their 10 decisions.

The risky payoffs in this experiment differed across individuals.[7] The experimental payoffs were designed so that each player should prefer the sure thing before learning any information about the bag, but once he knew that the bag actually contained 72 red chips, he ought to prefer the uncertain gamble to the sure thing.

[7] Each player was assigned risky payoffs in the drawing game equal to those from the uncertainty game in the highest row for which the person still preferred the sure thing over the uncertain gamble. If the person preferred the uncertain gamble in all rows, the payoffs for the gamble in the learning game were $17 if red and $0 if black. Thus, the payoffs for each person were those of an uncertain gamble for which the order of preference would be i) the risky gamble with known probabilities, ii) the sure thing, iii) the uncertain gamble with unknown probabilities.

Seed Game:

Following the drawing game, we conducted another game involving a significantly more complex learning process which more closely resembles the seed choice that farmers face. We call this game the "seed game." In the seed game, each farmer had a field that he could sow with one of four possible seeds. The farmer was initially provided information about six years of yields for each seed and had to choose which seed to plant for the first round. Following this decision, each farmer then observed six more years' worth of yields for each seed. With this new information, the farmer again chose which seed to plant and then again observed six more years of yields for each seed. This process was repeated until each farmer had made 11 decisions. At the end of the game, a round was randomly selected to determine each farmer's payoff, with the first yield for that round (out of the six total yields) being the payoff.

The seed game was designed such that there was one high performing seed, with a high mean yield and medium variance. There were two less-good seeds with lower means but the same variance as the higher performing seed. And, there was one safe seed (with a low mean and low variance). While risk-averse farmers may have preferred the safe seed to the good seed, the game was designed such that this would only occur with implausibly high risk aversion.

Cognitive Ability Tests and Survey Data:

Summary statistics of our data are presented in Table 2. The measures of cognitive ability provide direct information on each individual's ability to process information. First, participants answered the Cognitive Reflection Test (CRT), a series of three logic questions developed by Frederick (2005). Second, participants performed a digit span exercise testing short-term memory. Digit span 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). In our digit span 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. Previous research has shown 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). After completing the digit span, farmers were given five minutes to solve 12 Raven's Standard Progressive Matrices. Each matrix contained a series of shapes with one item missing, and farmers had to pick the correct piece to complete the series from eight options.

****Table 2****

Table 2 shows that there is a significant amount of heterogeneity across farmers' cognitive ability. They have an average digit span of seven digits, which is similar to Miller's (1956) finding that an average adult has a digit span of seven digits. Similarly, we find that the average farmer correctly answered seven Raven's matrices although there was a large standard deviation. The average score out of the three CRT questions was approximately one with a standard deviation of one.

Our survey collected data on other variables including the numbers of years since the farmer first planted GM corn or soybean. The average is 7.1 years for GM corn and 8.4 years for GM soy, excluding farmers who have never planted corn or soy at all, but including farmers who have only planted conventional corn or soy. (For these farmers, the number of years planting GM is 0). Table 2 shows that approximately 89% of the farmers who have ever planted corn have planted GM corn. Similarly, 92% of the farmers who have ever planted soybeans have planted GM soybeans. 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).

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 their farm for 28 years.

Overall, the combination of our experimental games, cognitive questions, and survey comprises a rich data set with which we can analyze learning, risk, and technology adoption. The risk experiment provides a measure of individual risk preferences while the learning games enable us to evaluate learning styles for each individual. Furthermore, we examine how cognitive ability is associated with the heterogeneity of learning styles and we analyze whether the timing of GM seed adoption depends on learning styles.

4. Learning Models

We analyze learning at the individual level to explore learning styles, recalling that previous literature has found strong evidence of heterogeneity (Cheung and Friedman, 1997; Gans, Knox, and Croson, 2007). The main challenge, in our case, is the relatively small number of observations (ten) in each game with which to estimate individual learning rules. We use a goodness-of-fit measure to match each individual with the rule which provides the best explanation for his behavior.

Estimation of Learning Rules:

Previous literature on learning has shown that Bayesian learning applies in some contexts, but that many individuals rely on alternative heuristics when formulating beliefs. In this section, we define various learning rules.[8] We focus our attention on three learning rules: Bayesian learning, first-1 learning, and last-1 learning.[9] This will enable us to test whether individuals equally balance all information, overweight initial information, or overweight recent information.[10]

We assume that each individual chooses the option that maximizes her expected utility. Under a random utility model, we add an error term to the expected utility, with the error term reflecting factors that are unobservable to the econometrician. Assuming an extreme value distribution for the unobserved terms motivates using a logit model for the drawing game and the conditional logit model for the seed game.

In the drawing game, where individuals choose between a safe and a risky option, we analyze a logit model and focus on the probability of choosing the risky option in round t (Cheung and Friedman, 1997):

[8] Cheung and Friedman (1997) evaluate learning rules including Cournot, fictitious (equal weights), and adaptive learning in which the weights decline for older observations. Gans, Knox, and Croson (2007) evaluate six learning rules: a) perfect Bayesian updating; b) myopic Bayesian updating in which the individual does not take into account that current experimentation can contribute to future learning; c) simple myopic updating in which the agent categorizes options as being only either 'good' or 'bad'; d) the subject remembers only the last *n* trials; e) the "hot hand" rule under which subjects stick with a choice until it loses in *n* consecutive trials; and f) exponential smoothing in which subjects update beliefs taking a weighted average of past beliefs and the current outcome.

[9] We also examined alternative learning heuristics, including "hot-hand." However, we found that the Bayes, first-1, and last-1 rules had the best explanatory power. On that basis, the discussion presented in the rest of the paper focuses on these three learning rules.

[10] Note that these three rules are specific cases of the weighted fictitious play model (Cheung and Friedman, 1997), where the weights are a function of parameters characterizing each learning rule. But this more flexible parameterization proved difficult to implement empirically given that we only observe ten decisions per individual.

$$\Pr\{\text{choose risky in round } t\} = \frac{\exp(x_t)}{1+\exp(x_t)}$$

where x_t is the expected utility difference obtained from choosing the risky payoff. Thus, we have:

$$x_t = \begin{pmatrix} 1 & -1 \end{pmatrix} \begin{pmatrix} u(W) & u(L) \\ u(10) & u(10) \end{pmatrix} \begin{pmatrix} P_t \\ 1-P_t \end{pmatrix} = u(W)P_t + u(L)(1-P_t) - u(10)$$

where P_t measures the assessed probability of drawing a red chip, W is the winning payoff if drawing a red chip, and L is the losing payoff if drawing a black chip. We assume CRRA preferences using the individual relative risk aversion coefficient estimated in the risk game.[11]

Using a conditional logit for the seed game, the probability that an individual chose seed j out of the 4 seed options in round t can be written as:

$$\Pr\{\text{choose seed } j \text{ in round } t\} = \frac{\exp(x_{tj})}{\sum_{i=1}^{4}\exp(x_{ti})}$$

where $x_{ti} = \sum_{s\in S} P_{tsi}U(\pi_{si})$ is the expected utility for seed i at round t. The probability of state of nature s for seed i as assessed by the farmer in round t is P_{tsi}. In state of nature s, the payoff from seed i is π_{si} .

Our learning models define various ways in which each individual calculates the probability of red chips (in the drawing game) and the anticipated yields (in the seed game) as new information becomes available. In the drawing game, we consider alternative updating rules for P_t, the assessed probability of drawing a red chip in round t. We proceed similarly in the seed game, where we consider alternative learning rules for P_{tsi}, the assessed probability associated

[11] Note that our measures of risk aversion are consistent estimates of each individual's relative risk aversion coefficient. Possible efficiency gains could be obtained by considering a joint estimation of risk preferences and learning styles. This appears to be a good topic for future research.

with receiving π_{tsi}. For both games, we test how farmers form their beliefs under three learning rules, as discussed next.

Bayesian learning: Assuming uninformative priors, Bayesian learning occurs when all observations are weighted equally to determine the probability of red chips or seed yields in any given round. In the drawing game, the subjective probability of drawing a red chip in round t under Bayesian learning is $P_t = \frac{\sum_{i=1}^{t} R_i}{t}$, where R_i denotes the share of red chips drawn in the i-th round. Similarly, in the seed game, the subjective probability of each possible yield s is $P_{tsi} = n_{ts}$ /(6t), where n_{ts} is the number of times yield s has been observed as an outcome for seed i up through round t.

First-1 learning: Under the first-1 learning rule, the individual only pays attention to the first round, and she ignores all observations obtained subsequently.[12] First-1 learning is appropriate for individuals that form strong and persistent beliefs and/or find learning too difficult and thus ignore later information. In first-1 learning, the associated subjective probabilities are $P_t = R_1$ for the drawing game, and $P_{tsi} = \begin{Bmatrix} n_{1s}/6 \\ 0 \end{Bmatrix}$ when $\begin{Bmatrix} s \in S_1 \\ s \notin S_1 \end{Bmatrix}$ for the seed game, S_1 being the set of yields observed in round 1. Note that Bayesian learning and first-1 learning are the same in the first round, and only become distinct thereafter.

Last-1 learning: Under the last-1 learning rule, we assume that the individual only remembers the immediately preceding round. Last-1 learning is appropriate if individuals either have short memories or choose to focus on less information given the difficulty in calculating

[12] We also considered the more general case of first-n learning, where the individual pays attention only to observations from the first n rounds. We found that choosing n = 1 generated the best explanatory power.

probabilities from more complete learning rules. In last-1 learning, the corresponding subjective probabilities for drawing red chips are $P_t = R_t$ for the drawing game, and $P_{tsi} = \begin{Bmatrix} n_{ts}/6 \\ 0 \end{Bmatrix}$ when $\begin{Bmatrix} s \in S_t \\ s \notin S_t \end{Bmatrix}$ for the seed game, S_t being the set of yields observed in round t. Again, note that this rule becomes distinct from both Bayesian learning and first-1 learning only after the first round.

Collectively, these three rules provide a balanced framework for analysis. They identify different weightings schemes on observations: equal weighting of all observations under Bayesian learning; overweighting of initial information under first-1 learning; and overweighting of recent information under last-1 learning.

Evaluating the Models:

As in Gans, Knox, and Croson (2007) we calculate the log-likelihood for each learning rule and for each individual across all ten decisions and evaluate the Bayesian Information Criterion (BIC): BIC= -2 *LL* where *LL* is the standard logit log-likelihood function.[13] This estimate provides a basis to determine which learning rule provides the best fit for each individual.

While the BIC tells us which learning rule is the best fit, we use a likelihood-ratio (LR) based test to determine whether or not that rule is significantly better at estimating the true decision making process. Vuong (1989) developed the LR-based "Vuong statistic" which can be used to test whether two models perform equivalently well or whether one performs better than

[13] Usually the formula is BIC= -2**LL* + *k**ln(*n*) where *k* is the number of parameters and *n* is the number of observations. Note that our analysis of individual learning rules does not involve the estimation of any parameters so in our setting *k*=0.

the other. By using the Vuong statistic, we are able to compare each pair-wise combination of learning rules within each learning game to determine whether one rule dominates the other two, whether two rules dominate a third rule but not each other, and whether all rules perform equally well. For example, if Bayes is shown to out-perform both of the first-1 and last-1 learning rules, then we classify a farmer as a Bayesian learner. If both Bayes and last-1 out-perform the first-1 rule, but neither Bayes nor last-1 significantly outperforms each other, then we classify a farmer as being a Bayesian/last-1 learner.

5. Learning Rule Results

The results in Table 3 reveal how many farmers are classified in each learning rule assuming that farmers' risk preferences exhibit constant relative risk aversion, with the CRRA parameter for each individual estimated from the risk game. The sample includes the 151 farmers for whom we were able to estimate CRRA measures.[14] Focusing first on the Vuong results, Table 3 shows that Bayesian learning performs poorly relative to the other rules. No farmers can be classified as being a pure Bayesian learner in either game according to the Vuong method. The last-1 rule performs the best in both games, with 36 last-1 learners (24%) in the drawing game and 19 (13%) in the seed game. There are also a large number of farmers for whom Bayesian and last-1 learning jointly perform the best. This is true for 15 farmers (10%) in the drawing game and 42 farmers (28%) in the seed game. Overall, these results indicate that Bayesian learning is unlikely to accurately describe many people and, instead, provide evidence that individuals tend to overweight recent information and discount older information rather than equally weighting all information sources.

[14] This reduces to 147 in the drawing game due to difficulties of calculating utility when payoffs are 0.

Table 3

The Vuong statistic, however, does not provide definitive evidence on specific individual learning rules. Indeed, over half of the farmers in either game are estimated to have no single dominant rule.[15] While it may be the case that additional learning rules could describe many of these farmers, we tested alternative learning rules (including various simple rules of thumb, hot-hand rules, and both first-*n* and last-*n* rules with *n* values larger than one) and found consistent evidence that these alternative rules did not perform particularly well. In other words, by including more rules, it became even more difficult to significantly predict best learning rules. As noted earlier, we only have ten decisions per farmer in each game, which makes it more challenging to significantly differentiate the learning rules if we consider too many potential learning rules at the same time. Still, it is interesting to note that our general results are consistent with Gans, Knox, and Croson (2007) in showing that rules which are simpler and more myopic than Bayesian updating are the most common in both games.[16]

Looking at the BIC numbers in Table 3, we find similar results. Again, Bayes performs relatively poorly (with 17 farmers (12%) in the drawing game and 45 farmers (30%) in the seed game) while last-1 performs the best (with 89 farmers (60%) in the drawing game and 95 farmers (63%) in the seed game).

Table 4

[15] Remember that the Vuong method tests if one of the rules performs significantly better than the others for each individual. The BIC method assigns each individual to the rule which fits him best, whether or not it fits him statistically better than any of the other rules. Thus, using the BIC method, each farmer is assigned to one, and only one, rule.

[16] In addition to analyzing individual learning rules, we pooled farmers and calculated the weight associated with each learning rule. These results provided some evidence that last-1 is the most important learning style, but large standard errors indicate significant unobservable heterogeneity and provided relatively little additional information.

We cross-tabulate the individual learning rules in the two games in Tables 4a and 4b, and the results show that outcomes are generally not consistent across games. Focusing initially on the BIC rankings, only two farmers are classified as Bayesian learners in both games, and no farmers are classified as first-1 learners in both games. Last-1, however, is a slightly more consistent learning style with 59 of the 147 following this rule in both games.

Combining the BIC and Vuong comparisons, we find strong evidence that significant heterogeneity occurs both within and across games. Learning styles are difficult to classify and these results indicate that individual learning styles may also shift as environments change. These complexities related to learning styles pose a particular challenge for researchers using experimental learning evidence to explain real-life decisions. This issue is explored in the next section where we attempt to incorporate these estimates of learning styles into econometric models of GM adoption.

Although learning styles are difficult to determine, it could be that additional information can help predict learning styles. For example, we might predict that individuals who perform better on cognitive ability tests or who have higher levels of education would be more likely to be Bayesian learners. In order to analyze the connection between learning styles and both cognitive ability and demographic information, we used multinomial logits to test whether or not these variables are significantly related to learning styles. These results are presented in Appendix Tables A1 and A2 for the drawing and seed games, respectively.

We do not find any variable which consistently and significantly predicts learning style. There is weak evidence that individuals with higher cognitive ability are more likely to be Bayesian learners and less likely to be last-1 learners, especially in the seed game. Overall, these results imply that it is difficult to predict individual learning styles, even when cognitive and demographic information are available. This may be due to the complexity of human learning and the presence of unobserved heterogeneity in the determinants of individual learning styles across agents. Given such high levels of heterogeneity, much larger sample sizes might help in gaining some traction on these questions.

6. Technology Adoption and Learning Results

In this final empirical section, we use data on the year of adoption of GM seeds to estimate survival models that predict the probability that someone who has not yet adopted then decides to adopt in each time period. 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 $\lambda(.)$. Different specifications of the hazard rate have been proposed in the literature. We use the Weibull distribution with $\lambda(z,t) = e^{-z\beta} k \left[e^{-z\beta} t\right]^{k-1}$ because this allows the probability of adoption to either 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. Evidence that *k* is greater than 1 implies that the probability of adopting increases with time.

In our analysis, *t* represents years in which a farmer could have adopted GM technologies. In our sample, the first farmers using GM technologies started adopting in 1996. And yet, a few farmers were not yet farming in 1996. For those who were already farming by 1996, we set the earliest possible year of GM adoption to be 1996. For those who began farming after 1996, their first year making decisions on a farm was treated as the earliest possible adoption year. Because the adoption of GM technologies started slowly in the first few years and then increased rapidly in later years, we include dummies for calendar year. We also include crop reporting district dummies to control for local agro-climatic conditions that may influence the adoption decision.

In our application of the survival model, we measure the probability of adopting in any year, with a higher value reflecting earlier adoption. 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. We present several model specifications. In the first specification, we include only learning rules, using the first-1 rule as the base case. Next, we include learning rules while controlling for risk preferences as well as additional cognitive and demographic variables. Also, to compare with Barham et al. (2014), we include ambiguity preferences to see how the addition of learning style estimates might affect the result that ambiguity aversion hastens the adoption of GM corn. Each of these models is estimated using learning rules from the drawing and seed games, and the survival analysis is applied separately to the adoption decisions of GM corn and GM soybean.[17] Due to the high number of ties between learning rules when using the Vuong analysis, we utilize the BIC-based learning rules in this section.[18] We analyze whether or not learning styles impact the timing of adoption. The results of our adoption estimations are reported in Tables 5 and 6 for GM corn and soy, respectively.

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[17] Our econometric investigation of technology adoption makes use of the coefficient of relative risk aversion and the learning rules estimated in earlier stages of our analysis. To the extent that each prior stage generated consistent estimates, this consistency property applies to the estimation of parameters in our adoption model. Dealing with possible measurement errors associated with the estimates from prior stages is more complex: it would require assessing the distribution of these measurement errors. In our case, this appears to be a difficult task.
[18] The advantage of using the BIC criterion is that it does not allow ties. When the analysis is conducted using the Vuong categories (as shown in Appendix Tables A3 and A4), our results are similarly inconclusive.

Table 5

Corn results:

In Table 5 learning styles are not significantly related to the timing of GM corn adoption. Regardless of whether learning rules from the drawing or seed game are analyzed, there is no significant connection to adoption. Learning about new GM corn seeds is arguably difficult due to the many available GM traits (Useche et al. 2009) including the specific uncertainty associated with pest populations and control. Because of this, we might expect adoption of GM corn seed to be closely related to learning. However, we find that learning rules are not significantly correlated with the adoption of GM corn. Perhaps our estimated learning rules are too simple to accurately analyze complex adoption decisions that involve both individual learning (e.g., from experimentation) and social learning. Alternatively, the complexity of human learning may make it difficult to uncover simple relationships between learning and decision making.

The coefficient estimates provide some evidence that cognitive ability – as measured by the digit-span exercise – enables faster adoption of GM corn. However, education level is unrelated to adoption, thus providing inconclusive evidence overall with regards to how cognitive ability, as represented by these alternative measures, influences adoption.

Other estimation results are what we would expect from previous work on technology adoption (Aldana et al., 2011). Full time farmers and farmers cultivating more acreage adopt more quickly. We also find evidence that the time trend *k* is greater than one, implying that the probability of adoption increases over time. In regressions where we include risk and ambiguity aversion preferences, we find evidence confirming Barham et al. (2014) that more ambiguity-averse farmers are faster adopters of GM corn.

Table 6

Soybean results:

As with GM corn, we find no significant relationship between learning styles and the timing of soybean adoption in Table 6. Again, we see evidence that farmers on large farms are the early adopters and that *k* is greater than one, implying that the probability of adopting GM soybeans increases with time. In contrast to the GM corn results, we find evidence that farmers with higher digit spans are not faster adopters, full-time farmers are not faster adopters, farmers who have been making decisions for longer may be slower adopters, and ambiguity preferences are not significant in the soybean regression. This last result is also consistent with the findings in Barham et al. (2014). Incorporating learning style measures does not alter significantly our previous results which omitted these measures.

7. Conclusion

We combine data from economic experiments on learning and risk preferences with survey data on biotechnology adoption among corn and soybean farmers in Minnesota and Wisconsin. Learning and risk seem to both be central aspects of technology adoption and this paper integrates the two.

We provide strong evidence against Bayesian learning, and in favor of a heuristic based on more recent information; but primarily we find a great deal of heterogeneity in learning styles, consistent with the results of previous authors (Cheung and Friedman, 1997; Gans, Knox, and Croson, 2007). Even with detailed information on education and cognitive ability, we find it difficult to predict what learning style an individual will utilize.

We then link learning styles with technology adoption. Learning provides an important pathway for reducing risk and determining the benefits of alternative technologies. However, we do not find much evidence connecting the learning styles of individuals with the timing of adoption. There are several possible explanations for this non-result.

First, given that each farmer only made ten decisions in each game, it may have been difficult to accurately calculate the best learning rule for each individual. Similarly, with only 150 farmers and significant heterogeneity, we may not have enough power to get significant results in our adoption regressions.

Second, assuming the learning rules are accurately calculated within games, we provide evidence that learning styles differ across games and, by extension, may also differ when making real-life decisions. This poses a unique challenge for experimental researchers using learning games to explain real-life decisions.

Third, even if consistent learning rules were defined for individuals, learning styles may influence adoption in different directions. For example, first-1 learners form strong and persistent beliefs. If they hold strong positive beliefs about conventional seeds they will be unlikely to adopt new seeds. However, if they form strong positive initial beliefs about GM seeds, they may be faster adopters. Thus, we might need much more specific information about priors and learning experiences than was captured in our experimental games.

Fourth, our learning rules explain how individuals process new information, but this is only part of the story about how learning drives technology adoption. Farmers may also differ with regards to the types of information that they seek and how they learn in social situations. If farmers are not Bayesian learners and the order of information matters, then an accurate adoption analysis would require much more precision on the information available to farmers and when this information became available and from whom.

Together, these factors create a context in which unobservable heterogeneity remains important in adoption decisions and, even with our experimental evidence, it remains difficult to relate learning styles and technology adoption. Our analysis indicates that individual learning styles are complex and may well vary across situations, thus offering a possible explanation for the difficulties in predicting learning behavior.

This paper is, to the best of our knowledge, the first to integrate an analysis of learning styles with technology adoption using both experimental and survey data. While this paper provides compelling evidence against Bayesian learning, calling into question many theoretical and some recent empirical analyses of technology adoption, we mostly find that this line of research requires stronger data. This would include more information about individual learning as well as social learning.

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Table 1: Risk Experiments

Decision	Sure payoff	Risky prospect		CRRA (relative risk aversion parameter)
		Red chip	Black chip	
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
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	0.4
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

Table 2: Summary Statistics

Variables	Obs	Mean	Min	Max
Uncertainty, Risk, and Ambiguity Aversion				
Uncertainty aversion	131	0.79	-0.09	3.76
Risk aversion	151	0.77	-0.09	3.76
Ambiguity aversion=uncertainty - risk	123	0.06	-1.34	3.11
Individual Characteristics				
Age	191	53.2	20	80
Gender: Female	191	6.3%	0	1
Education				
High school or less	191	31.9%	0	1
No degree or 2-year college	191	35.6%	0	1
4-year college degree	191	20.4%	0	1
Some graduate school	191	12.0%	0	1
Family size	191	2.7	1	7
Household Income before taxes 2009 (Thousands)				
Under $20	191	9.9%	0	1
$20 - $59	191	33.5%	0	1
$60 - $99	191	27.7%	0	1
$100 or more	191	28.8%	0	1
Requested computer training	191	18.8%	0	1
Cognitive Measures				
Digit-span: digit memory	189	7.3	3	11
Figures	191	7.1	0	12
Cognitive Reflection Test (CRT)	191	1.1	0	3
Farming Characteristics				
Farming is not the principal occupation	191	16.2%	0	1
Acres of cropland operated 2009	191	600.2	10	8000
Share of dairy sales	187	25.8%	0%	99%
Years farmer has made decisions on farm	191	28.3	2	72
Corn				
Have never planted corn	191	2.1%	0	1
Planted conventional but not GM corn	191	10.5%	0	1
Have planted GM corn	191	87.4%	0	1
Years planting GM corn[1]	187	7.1	0	15
Soybean				
Have never planted soybeans	191	18.8%	0	1
Planted conventional but not GM soy	191	6.3%	0	1
Have planted GM soybeans	191	74.9%	0	1
Years planting GM soybeans[1]	155	8.4	0	15

1 Excludes those farmers who have not planted corn or soybeans respectively.

Table 3: Learning Rules

	Vuong Method[1]				BIC Method			
	Drawing Game		Seed Game		Drawing Game		Seed Game	
	Number	Percent	Number	Percent	Number	Percent	Number	Percent
No Best Rule	75	51	86	57				
Bayes	0	0	0	0	17	12	45	30
First-1	16	11	3	2	41	28	11	7
Last-1	36	24	19	13	89	60	95	63
Bayes/First-1	3	2	1	1				
Bayes/Last-1	15	10	42	28				
First-1/Last-1	2	1	0	0				
Total:	147	100	151	100	147	100	151	100

1 Using 10% significance level

Table 4a: Drawing and Seed Game Learning Rules - BIC Rankings

Drawing Game Learning Rules	Seed Game Learning Rules: Bayes	Firstn1	Lastn1	Total
Bayes	2	5	10	17
Firstn1	19	0	22	41
Lastn1	24	6	59	89
Total	45	11	91	147

Table 4b: Drawing and Seed Game Learning Rules - Vuong Tests

Drawing Game Learning Rules	Seed Game Learning Rules: No Best Rule	Bayes	First-1	Last-1	Bayes/First-1	Bayes/Last-1	First-1/Last-1	Total:
No Best Rule	44	0	2	9	1	19	0	75
Bayes	0	0	0	0	0	0	0	0
First-1	7	0	0	2	0	7	0	16
Last-1	18	0	1	5	0	12	0	36
Bayes/First-1	2	0	0	0	0	1	0	3
Bayes/Last-1	11	0	0	1	0	3	0	15
First-1/Last-1	2	0	0	0	0	0	0	2
Total:	84	0	3	17	1	42	0	147

Table 5: Hazard ratios, survival model for GM corn adoption

	Drawing Game Learning Rules		Seed Game Learning Rules	
	(1)	(2)	(3)	(4)
Learning rules, risk, and ambiguity				
Bayes learner (= 1)	0.698	0.824	0.876	0.822
	[0.241]	[0.305]	[0.297]	[0.339]
Last-1 learner (= 1)	1.192	1.149	0.904	0.88
	[0.227]	[0.267]	[0.273]	[0.300]
Risk aversion		0.975		1.016
		[0.151]		[0.159]
Ambiguity aversion		2.15		2.014
		[0.420]***		[0.438]***
Individual characteristics				
Age		0.988		0.988
		[0.020]		[0.020]
Gender: Female		0.813		0.814
		[0.294]		[0.301]
Education: No degree or 2-year college		1.235		1.222
		[0.355]		[0.370]
Education: 4-year college degree		1.383		1.373
		[0.362]		[0.364]
Education: Some graduate school		1.194		1.209
		[0.461]		[0.460]
Acres of cropland operated '09 (thousands)		1.391		1.371
		[0.155]***		[0.161]***
Farming is not principal occupation		0.435		0.441
		[0.147]**		[0.139]***
Years farmer has made decisions on farm		1.001		1
		[0.020]		[0.021]
Received computer training		0.879		0.894
		[0.256]		[0.243]
Longest number of digits right (out of 11)		1.218		1.216
		[0.098]**		[0.097]**
Observations	144	119	148	120
k	1.22	1.63	1.22	1.64
	[0.154]	[0.255]***	[0.153]	[0.270]***
Log-likelihood	-137.8	-89.83	-142.99	-93.28

All regressions assume a Weibull survival distribution and include year and crop-reporting district fixed effects as controls.
Excluded learning rule is First-1. Excluded education level is high school or less.
Learning rules determined using BIC rankings.
Robust standard errors in brackets.
* significant at 10%; ** significant at 5%; *** significant at 1%.

Table 6: Hazard ratios, survival model for GM soybean adoption

	Drawing Game Learning Rules		Seed Game Learning Rules	
	(1)	(2)	(3)	(4)
Learning rules, risk, and ambiguity				
Bayes learner (= 1)	0.933	1.113	1.668	1.67
	[0.334]	[0.458]	[0.568]	[0.834]
Last-1 learner (= 1)	1.118	0.761	1.428	1.026
	[0.311]	[0.258]	[0.447]	[0.467]
Risk aversion		1.491		1.252
		[0.278]**		[0.230]
Ambiguity aversion		1.401		1.378
		[0.299]		[0.292]
Individual characteristics				
Age		1.001		1.004
		[0.022]		[0.022]
Gender: Female		1.122		0.979
		[0.748]		[0.574]
Education: No degree or 2-year college		1.082		0.894
		[0.430]		[0.359]
Education: 4-year college degree		1.021		0.845
		[0.388]		[0.326]
Education: Some graduate school		1.86		1.748
		[0.894]		[0.784]
Acres of cropland operated '09 (thousands)		1.439		1.44
		[0.250]**		[0.229]**
Farming is not principal occupation		0.802		0.702
		[0.279]		[0.225]
Years farmer has made decisions on farm		0.962		0.967
		[0.018]**		[0.018]*
Received computer training		1.101		0.923
		[0.518]		[0.450]
Longest number of digits right (out of 11)		0.925		0.944
		[0.118]		[0.120]
Observations	119	99	122	100
k	1.02	1.61	1.06	1.6
	[0.109]	[0.239]***	[0.113]	[0.217]***
Log-likelihood	-145.85	-104.93	-148.87	-106.44

All regressions assume a Weibull survival distribution and include year and crop-reporting district fixed effects as controls.
Excluded learning rule is First-1. Excluded education level is high school or less.
Learning rules determined using BIC rankings.
Robust standard errors in brackets.
* significant at 10%; ** significant at 5%; *** significant at 1%.

Appendix Table A1: Odds ratios from multinomial logit of drawing game rules

	Bayes				First-1			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Individual cognitive measures								
General questions	1.26	1.45	1.56	1.14	1.20	1.15	0.97	1.32
Longest number of digits right (out of 11)	0.82	0.87	0.84	0.86	1.08	1.10	1.04	1.10
Figures	0.91	1.05	0.87	0.91	0.99	0.85	0.96	0.93
Individual characteristics								
Age		1.00	0.99			0.98	0.97	
Gender: Female		1.21	0.00			2.71	2.19	
Education: No degree or 2-year college		1.86	2.96			0.88	0.55	
Education: 4-year college degree		1.18	2.41			1.08	1.25	
Education: Some graduate school		1.92	3.60			1.38	1.13	
Acres of cropland operated '09 (thousands)		0.83	0.77			0.72	0.86	
Farming is not principal occupation		0.53	0.70			0.82	1.03	
Years farmer has made decisions on farm		1.04	1.03			0.97	0.98	
Received computer training		2.58	2.21			1.88	0.40	
Risk and ambiguity								
Risk aversion			0.19				0.82	
Ambiguity aversion			0.65				0.85	
Session fixed effects	No	No	No	Yes	No	No	No	Yes
Observations	145	145	121	145				
Log-likelihood	-130.8	-122.49	-93.78	-96.78				

Excluded learning rule is Last-1.

* significant at 10%; ** significant at 5%; *** significant at 1%.

Appendix Table A2: Odds ratios from multinomial logit of seed game rules

	Bayes					First-1				
	(1)	(2)	(3)	(4)	(5)	(1)	(2)	(3)	(4)	(5)
Individual cognitive measures										
General questions	1.39*	1.46*	1.30	1.54*	1.67**	1.07	1.40	2.82*	1.14	2.51*
Longest number of digits right (out of 11)	1.18	1.25	1.12	1.18	1.25	0.86	0.93	0.93	0.84	0.72
Figures	1.18	1.15	1.00	1.17	1.16	1.02	1.17	1.58	1.02	2.07**
Individual characteristics										
Age		0.98	1.00		0.97		0.96	0.76		0.94
Gender: Female		2.20	2.04		2.05		5.12	92.59*		6.30
Education: No degree or 2-year college		1.13	1.42		1.30		2.17	1.69		3.62
Education: 4-year college degree		0.74	1.14		0.61		0.46	0.44		0.05
Education: Some graduate school		1.85	2.05		1.85		0.00	0.00		0.00
Acres of cropland operated '09 (thousands)		0.81	0.84		0.78		1.40	0.40		1.86*
Farming is not principal occupation		0.88	1.06		0.69		0.78	3.04		3.21
Years farmer has made decisions on farm		0.99	0.96		1.00		1.09	1.33		1.23*
Received computer training		3.00	1.24		2.90		1.78	39.65		20.61
Risk and ambiguity										
Risk aversion			0.99					0.01**		
Ambiguity aversion			0.62					0.03		
Session fixed effects	No	No	No	Yes	Yes	No	No	No	Yes	Yes
Observations	149	149	122	149	149					
Log-likelihood	-120.1	-110.83	-81.86	-101.24	-89.5					

Excluded learning rule is Last-1.

* significant at 10%; ** significant at 5%; *** significant at 1%.

Appendix Table A3: Hazard ratios, survival model for GM corn adoption using Vuong statistic-based learning rules

	Drawing Game Learning Rules		Seed Game Learning Rules	
	(1)	(2)	(3)	(4)
Learning rules, risk, and ambiguity				
Bayes learner	2.24	5.947	1.39	0.458
	[1.385]	[5.005]**	[0.960]	[0.299]
Last-1 learner	1.066	1.319	3.729	1.206
	[0.321]	[0.477]	[1.806]***	[0.673]
Risk aversion		1.037		0.993
		[0.162]		[0.149]
Ambiguity aversion		2.326		2.008
		[0.434]***		[0.390]***
Individual characteristics				
Age		0.988		0.992
		[0.020]		[0.020]
Gender: Female		1.039		0.838
		[0.392]		[0.319]
Education: No degree or 2-year college		1.157		1.196
		[0.339]		[0.350]
Education: 4-year college degree		1.384		1.304
		[0.383]		[0.354]
Education: Some graduate school		1.32		1.186
		[0.498]		[0.461]
Acres of cropland operated '09 (thousands)		1.506		1.41
		[0.185]***		[0.153]***
Farming is not principal occupation		0.474		0.448
		[0.165]**		[0.141]**
Years farmer has made decisions on farm		1		0.999
		[0.021]		[0.020]
Received computer training		0.708		0.869
		[0.227]		[0.251]
Longest number of digits right (out of 11)		1.229		1.223
		[0.097]***		[0.108]**
Observations	144	119	148	120
k	1.2	1.67	1.28	1.66
	[0.153]	[0.255]***	[0.163]*	[0.264]***
Log-likelihood	-138.5	-87.34	-139.16	-92.46

All regressions assume a Weibull survival distribution and include year and crop-reporting district fixed effects as controls.
Excluded learning rule is First-1. Excluded education level is high school or less.
Learning rules determined using Vuong significance tests.
Robust standard errors in brackets.
* significant at 10%; ** significant at 5%; *** significant at 1%.

The learning rule variables equal 1 if a farmer is classified as being that type of learner. In the case of ties between two rules, the learning rule variables are set to 1/2. In the case of ties between all three rules, then each learning rule variables takes a value of 1/3.

Appendix Table A4: Hazard ratios, survival model for GM soybean adoption using Vuong statistic-based learning rules

	Drawing Game Learning Rules		Seed Game Learning Rules	
	(1)	(2)	(3)	(4)
Learning rules, risk, and ambiguity				
Bayes learner	1.646	2.311	2.517	0.759
	[1.346]	[2.948]	[1.812]	[0.883]
Last-1 learner	1.751	5.585	4.025	1.619
	[0.752]	[3.699]***	[2.141]***	[1.135]
Risk aversion		1.313		1.358
		[0.218]		[0.231]*
Ambiguity aversion		1.513		1.29
		[0.325]*		[0.281]
Individual characteristics				
Age		1.014		0.996
		[0.023]		[0.021]
Gender: Female		0.916		1.13
		[0.573]		[0.726]
Education: No degree or 2-year college		1.051		1.075
		[0.448]		[0.423]
Education: 4-year college degree		1.007		1.023
		[0.403]		[0.415]
Education: Some graduate school		2.003		1.809
		[1.026]		[0.909]
Acres of cropland operated '09 (thousands)		1.363		1.38
		[0.226]*		[0.236]*
Farming is not principal occupation		0.404		0.737
		[0.189]*		[0.261]
Years farmer has made decisions on farm		0.95		0.969
		[0.019]**		[0.018]*
Received computer training		0.775		1.055
		[0.432]		[0.487]
Longest number of digits right (out of 11)		0.919		0.935
		[0.119]		[0.134]
Observations	119	99	122	100
k	1.01	1.64	1.05	1.58
	[0.109]	[0.247]***	[0.109]	[0.235]***
Log-likelihood	-145.04	-101.15	-146.19	-107.33

All regressions assume a Weibull survival distribution and include year and crop-reporting district fixed effects as controls.
Excluded learning rule is First-1. Excluded education level is high school or less.
Learning rules determined using Vuong significance tests.
Robust standard errors in brackets.
* significant at 10%; ** significant at 5%; *** significant at 1%.

The learning rule variables equal 1 if a farmer is classified as being that type of learner. In the case of ties between two rules, the learning rule variables are set to 1/2. In the case of ties between all three rules, then each learning rule variables takes a value of 1/3.