Advice Taking, Learning, and Technology Adoption: Results from an Economic Experiment with Farmers[1]

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Abstract: This paper examines the complementarities between advice taking and individual learning in technology adoption. We run an economic experiment with US farmers measuring their learning ability and their propensity to take advice. We then compare the decisions they make in the experiments with their real-world adoption of genetically modified (GM) corn and soy seeds. The first adopters are those who are both quite able cognitively and disinclined to take advice. We find evidence that learning ability and advice taking are substitutes rather than complements in the technology adoption decision-making process.

Keywords: technology adoption, learning, advice taking, education, cognitive ability, economic experiments, genetically modified (GM) seeds.

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1. Introduction

The diffusion of new technologies is a key contributor to economic growth, and differences in technology use account for much of cross-country inequality (Klenow and Rodríguez-Clare, 1997; Comin and Hobijn, 2010). Understanding why some individuals or businesses adopt while others do not and what constraints they face can help in understanding the evolution of productivity, growth, and inequality. Broad, rapid patterns of diffusion can enhance productivity, growth, and equity (Feder et al., 1985; Garicano and Rossi-Hansberg, 2015). How efficiently economic agents respond to the availability of better technologies depends on their learning ability and willingness to internalize information. Early adopters may be faster learners (Foster and Rosenzweig, 1995), while the adoption propensity of those following them is likely to depend both on their willingness to incorporate advice from others as well as their ability to process that information.

In a context of full access to information, the breadth and pace of technology diffusion depends on the degree to which individual learning capacity and willingness to take advice are substitutes or complements. If they are complements, then small differences in learning ability will be magnified as low ability agents find the adoption process too daunting. If learning capacity and willingness to take advice are instead substitutes, then both able learners and willing advice takers will be relatively early adopters, and the pattern of diffusion will be quicker and less narrow, leading to higher aggregate productivity growth and lower inequality. In addition, if learning capacity and willingness to take advice are substitutes, there is room for governments to aid in the flow of information and advice, generating broader growth in the economy.

This paper presents experimental evidence from US farmers regarding the relationship between individual learning ability and the propensity for advice taking, with a focus on the adoption of new technologies. We examine the factors affecting the timing of adoption of new seed varieties among farmers. The most important findings are that individual ability and receptiveness to externally-provided information are substitutes rather than complements. We document that advice taking plays a significant role in speeding up technology adoption, contributing to increased productivity and reduced inequality.

Schooling and cognitive ability are commonly found to be positively correlated with technology adoption (Feder et al., 1985; Foster and Rosenzweig, 2010). How individuals and businesses take in new information and interpret it to make decisions is important in many settings including agriculture, manufacturing, finance, and health. For example, Ryan (2015) randomly gives Indian factories energy audits with specific suggestions for profitable investments. These energy audits lead to no increase in investment in environmental technologies and no decrease in electricity bills. Determining who is receptive to information and how this might interact with other key factors such as education and ability is paramount for optimizing the provision of such information.

A non-experimental literature explores whether knowledgeable investors are more likely to use financial advisors than are less knowledgeable investors but they find mixed results. Chalmers and Reuter (2014) find that less financially sophisticated individuals are more likely to use a financial advisor, while Hackethal et al. (2012) find the opposite. Bhattacharya et al. (2012) find that financial sophisticates are most willing to receive advice, but very few of them actually follow the advice after receiving it. Thus, there is conflicting evidence regarding whether the people who most need advice are more or less likely to seek it out, and even less evidence regarding whether they then make use of the advice. Even if consistent results were found using data from the financial sector, it could be difficult to transfer that knowledge to other settings because, in contrast to many advice-sharing relationships, the financial advisor and the investor often have opposing interests.[2]

As explained in Rogers' (1962) seminal work, potential adopters of a new technology can be thought of as starting with no information about a new technology. They then gradually gain more information, either from their own experimentation or from advice garnered from external sources. Individuals who decide not to adopt in one period revisit their decision in subsequent periods as more information comes to light. For research purposes, focusing on the timing of adoption for a technology which, ex-post, was found to be obviously superior for virtually all decision-makers is an ideal setting for studying the complementarity or substitutability between individual intelligence and external information sources.

In the United States, genetically modified (GM) corn and soy fit that description. Since the introduction of GM seeds in 1996, they have been almost universally adopted by US corn and soy farmers (Fernandez-Cornejo, 2014) and there has been almost no disadoption. GM

[2] Anagol et al. (2013) find that financial advisors give worse advice to less sophisticated individuals, taking advantage of their lack of sophistication to earn higher commissions.

technology has contributed substantively to agricultural productivity, increasing mean yields and reducing variability (Qaim, 2009; Shi et al., 2013; Chavas et al., 2014). It has also reduced time and management costs associated with pest and weed control. Given that GM technology generated significant improvements over traditional seeds, it remains an open question why some farmers jumped in immediately yet others waited years to adopt.

Farmers get information from a myriad of sources including agricultural extension agents, seed dealers, and their peers. Birkhaeuser et al. (1991) review the impacts of agricultural extension agents (which are usually publicly provided by the state) and find mixed but generally positive impacts (though the endogeneity of engaging with extension makes many of the results hard to interpret). A later review by Picciotto and Anderson (1997) encourages increasing the role of private sources of information. Other papers find that individuals learn from peers in the adoption and management of new technologies (Foster and Rosenzweig, 1995; Miguel and Kremer, 2007; Conley and Udry, 2010; Banerjee et al, 2013; Dupas, 2014). Genius et al. (2014) find that extension services and learning from peers are complements.

In addition to external sources, farmers also get information from their own experimentation. Foster and Rosenzweig (1995) look at learning by doing in agriculture. More recently, Aldana et al (2011) find evidence that early individual experiences adopting simple single-trait GM technologies make farmers more likely to adopt more complex stacked GM seeds thereafter. They also show that more educated farmers learn more quickly from their own experiences. But, none of the aforementioned papers look at potential complementarities between individual learning and on the one hand and externally provided recommendations on the other.

Whether taking advice from external sources and individual education and cognitive ability are complements or substitutes remains an open question. An older literature fit county-level production functions and found that farmer schooling and agricultural extension are substitutes (Huffman, 1977; Huffman, 1981; Huffman and Evenson, 2006). Jamison and Lau (1982) review eight articles which look for an interaction between schooling and agricultural extension using farm-level data from the developing world. They find inconclusive and usually insignificant results. In most of the papers mentioned above, the source of variation in extension services is unknown and likely endogenous to the outcomes under study.

We look anew at the same questions and offer three main contributions. First, we use farm-level data from the developed world where education levels are higher. As individuals in all countries are reaching higher levels of education, this will become the more relevant setting for looking at potential complementarities between intellectual ability and external informational recommendations. Second, we do not focus on any one source of information, but instead look generally at how farmers incorporate externally provided information. Given the modern information era, focusing on any single information source can be unnecessarily limiting. Finally, instead of studying how endogenous choices such as conversations with seed dealers or placement of extension agents impact adoption, we avoid that class of endogeneity problems by looking at farmers' underlying receptiveness to advice.

Ben Yishay and Mobarak (2014) and Maertens (2014) both ask: from whom are farmers most likely to take advice and learn? We focus on the converse of this question: which farmers are more likely to take advice? Furthermore, how does this interact with their intellectual ability, and does this interaction affect actual adoption outcomes? We only know of one paper looking at which farmers are most likely to seek out and subsequently use advice. Cole and Fernando (2012) find that more educated Indian farmers are more likely to seek out advice from a mobile-phone based agricultural consulting service. They take this as evidence of a digital divide since it may be easier for more educated farmers to navigate the service. They find evidence that farmers change their behavior after receiving the consulting services, but observed changes in behavior do not vary with education. The fact that more educated individuals are more likely to use the service but no more likely to actually change their behavior may suggest that, conditional on using the service, less educated individuals are more likely to change their behavior. This substitutability between education and advice-taking is in accord with what we find here.

As in Liu's (2013) research on GM cotton diffusion in China, we combine experimental evidence gathered from farmers with survey data on their technology adoption practices. We designed an experiment that allows us to estimate the importance of both learning ability and advice taking. This experiment is a variant of a typical advice-taking experiment found in the psychology literature (and from where we also borrow the term "advice taking"). We ran this experiment with US farmers who, over the last two decades, have been faced with the decision of whether to adopt GM corn and soybean seeds.

Our analysis progresses in three stages. First, we estimate learning ability for each farmer. We find that our measure of learning is correlated with both education and the digit-span measure of cognitive ability. Second, we find that better learners (those who have figured out the game the best on their own, as well as the better educated and those who perform better on the digit span) are less likely to take advice regarding play in the game, while worse learners are more likely to take advice in the game.

Third, we investigate the linkages between learning ability in the experiment and the timing of GM seed adoption in the real world. Better individual learners, with higher education levels and higher levels of cognitive ability, are earlier adopters. We also uncover evidence that advice takers are later adopters. The most important finding relates to the interaction between individual learning and learning from external sources. The earliest adopters are strong private learners who do not take advice from others. For strong private learners, being an advice taker actually slows adoption. On the other hand, for farmers who are not as good at learning on their own, being an advice taker speeds up adoption. This suggests that individual learning ability and advice taking are substitutes rather than complements. It also supports the conclusion that the broad, rapid diffusion of GM seed technology in the US has micro-foundations in the learning and advice-taking behavior of farmers. By encouraging technology adoption among late adopters, advice taking is found to play a significant role in stimulating productivity and reducing inequality.

The paper is organized as follows. Section 2 lays out the intuition behind the model driving the substitutability between learning and advice taking. Section 3 presents the GM technologies, field experiment, and survey data. Section 4 discusses the measurement of both learning ability and advice taking in our experiment. Section 5 analyzes the link between learning ability and advice taking in the game and actual adoption decisions made by the farmers on their farms. Section 6 probes correlations between experimental measures of advice taking and answers to survey questions regarding information use. Finally, section 7 concludes.

2. Intuitive Framework

Here we present the intuition behind the mechanism which would cause learning ability and advice taking to be substitutes. Specifically, this framework predicts that having a high propensity to take advice will slow adoption for good learners, but speed adoption for less able learners. Imagine that there is a new technology and farmers receive signals regarding the profitability of the technology and how best to implement it.

There are two sources of signals. Farmers receive their own individual signal (e.g., from their own research) and they receive externally provided signals (e.g., from crop consultants and peers). The individual signal received by good learners is more informative, having a lower variance, than that received by bad learners. Farmers with a high propensity to take advice receive externally provided signals more frequently than those with a low propensity to take advice. This may be because farmers with a low propensity to take advice are more prone to ignore incoming advice.[3]

We first explore the decisions of farmers with high learning ability. Good learners with a low propensity to take advice are confident in their beliefs (have low variance around their individual signal) and they know they are unlikely to receive more external signals. Because they have a relatively clear idea regarding how to use the technology, and know that new information will be slow to come by, they jump in early. On the other hand, good learners with a high propensity to take advice know that they will receive many external signals very quickly, and so wait to learn more about the idiosyncrasies of the technology before adopting. Thus, for good learners being an advice taker slows adoption.

For farmers with low learning ability, the result is the opposite. Bad learners with a low propensity to take advice begin with very imprecise beliefs about the new crop due to the low information content of their individual signal. Because they get external signals very rarely, they don't update their beliefs very often and so they learn very little about the crop and are late adopters. On the other hand, bad learners who are willing to take advice start out with imprecise priors from their individual signal, but they receive external signals relatively frequently and so gain information regarding the crop more quickly. For bad learners, being an advice taker speeds adoption.

3. The Setting, Experiment, and Survey

Experimental and survey data were collected from corn and soybean farmers in Wisconsin in early 2012. In January, 54 interested attendees at Wisconsin Corn and Soybean

[3] One could similarly conceive a model such that farmers with a low propensity to take advice receive a similar quantity of external signals compared to farmers with a high propensity to take advice, but that they perceive this advice to be less informative.

Conferences participated in our experiments. In February, 95 farmers participated during the Corn/Soy Expo in the Wisconsin Dells. Using the list of participants invited to and/or signed up for these events, we recruited farmers through the mail and with phone calls. The Corn and Soybean Conferences are half-day events conducted by UW Extension in locations across the state. The Corn/Soy Expo is a two-day event sponsored by the Wisconsin Soybean Association and the Wisconsin Corn Growers' Association and conducted in the Wisconsin Dells. Farmers come from across the state and may bring their family to enjoy a vacation as well as the educational opportunities and the industry trade show.

The farmers in our sample are more likely to be full time farmers than the average Wisconsin farmer and they manage more acres of cropland than the average. This is likely due to the fact that these farmers were recruited at events put on by extension agents and growers' associations to keep farmers up-to-date about corn and soy. Although one may question the external validity of results from our sample to the general population of Wisconsin farmers, which includes a large share of part-time farmers, our participants are representative of the full-time commercial farmers who dominate acreage and production and whose decisions are most important when we consider adoption and total output from US agriculture.

Before showing the summary statistics of our sample in section 3.4, we discuss GM corn and soy technologies in section 3.1, the experiment in section 3.2, and the survey in section 3.3.

3.1. GM Technologies

As mentioned above, after their commercial release in 1996, GM corn and soybean seeds have been almost universally adopted by US farmers. As measured by area planted, the US adoption rate for GM corn was 25 percent in 2000, 52 percent in 2005, and is estimated at 93 percent in 2014. Meanwhile, the US adoption rate for GM soybeans was more rapid, as it reached 54 percent in 2000, 87 percent in 2005, and 94 percent in 2014 (Fernandez-Cornejo, 2014).

GM corn involves both herbicide tolerance (HT) and insect resistance (IR) technologies while GM soy involves only HT technology. HT technologies introduce 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.

IR traits involve the insertion of transgenes using genetic material from a bacterium (Bacillus thuringiensis, or Bt) that can limit the impacts of two major pests, the European corn borer and root worms, and thus limit the need to use pesticides. Shi et al. (2013) find that the IR traits in GM corn lead to a decrease in the variance of corn yields and also increase skewness (decreasing downside risk) and decrease kurtosis (thinner tails). Qaim (2009) reviews the literature and finds IR traits also increase yields. On the other hand, Qaim's (2009) review finds that HT technology reduces production costs due to lower spending on herbicides, labor, machinery, and fuel (although seed prices are higher) but finds no impact on mean yields.

Although it is difficult to know exactly what information was available to farmers when GM seeds first became available twenty years ago, Joe Lauer, an agronomy professor at UW Madison, has been one of the premier experts on corn seed performance in the state since that time. He offered regular analyses of GM and traditional varieties in the informational newsletters he shared with farmers. These are available at http://corn.agronomy.wisc.edu/Pubs/Default.aspx.

A review of his newsletters reveals that discussions of GM corn in the early years (the second half of the 1990's) were purely informational and not easily construed as advising adoption. In the early 2000s, his write-ups on GM corn become more directive, encouraging farmers to try GM varieties.[4] For example, the February 12, 2003 newsletter states: "Bt corn continues to perform as well and possibly even better than normal elite commercial hybrids available in Wisconsin (see the last issue of the *Wisconsin Crop Manager*). It is a technology that improves yield and quality and helps farmers control damaging insect pests including European corn borer."

Surveys of Wisconsin farmers undertaken in 2001 and 2003 by researchers at the Program on Agricultural Technology Study (PATS) provide complementary evidence on farmers' views of the HT and IR soy and corn technologies at the time (Chen et al., 2001, Merrill

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[4] Newsletters which address GM corn of the earlier style include http://corn.agronomy.wisc.edu/AA/A005.aspx (1995), http://corn.agronomy.wisc.edu/AA/A010.aspx (1997), http://corn.agronomy.wisc.edu/WCM/W065.aspx (1999). Newsletters of the later style include http://corn.agronomy.wisc.edu/WCM/W097.aspx (2002), http://corn.agronomy.wisc.edu/WCM/W101.aspx (2002), http://corn.agronomy.wisc.edu/WCM/W114.aspx (2003), http://corn.agronomy.wisc.edu/WCM/W155.aspx (2004), and http://corn.agronomy.wisc.edu/WCM/W184.aspx (2006).

et al., 2005). Adopters were asked why they adopted and could check off as many reasons as they felt applied to them. Adopting farmers reported that yield gains; reduced pesticide, herbicide, and labor costs; and improved pest and weed management were the key motivations for adopting GM seeds. Recommendations from seed dealers, consultants, neighbors, and extension agents were also cited as reasons for adopting, though these reasons were cited less often.

Although there is some negative opinion towards GM among consumers, this is not the case among our sample of producers. In our survey we asked farmers to rate their agreement with the following statement on a Likert scale from 1 to 5: “Agricultural biotechnology makes most farm families better off.” 93% agreed somewhat or strongly with the statement and only 7% said they neither agree nor disagree. Not a single individual disagreed somewhat or strongly.

Of course this is what they say now, but what might be more relevant is what they thought in the second half of the 90’s when these technologies first became available. The first and only year we found this concern discussed in newsletters is 1999. In one newsletter from April 1999[5] Joe Lauer mentions that there is concern among farmers as to whether GM corn will be sellable. He then lists 11 GM corn varieties and shows that all are approved in the US, 7 in Japan, 5 in the EU, and 9 in Canada. Another newsletter from May 1999[6] revisits this issue and discusses that all GM varieties can be used as feed and are accepted in the US but not all are acceptable for export, and thus some elevators may not be accepting GM corn. This marketing concern was not commonly cited in the aforementioned newsletters after 2001.

In the 2001 and 2003 PATS surveys, non-adopters were asked reasons they didn’t adopt and could again check off as many reasons as they liked. The most common reasons farmers reported for not adopting GM varieties were the high price of the seeds, and not anticipating having problems with pests or weeds. Lack of familiarity with the seeds, and difficulties marketing GM seeds were mentioned by some farmers, but were not listed as major reasons for non-adoption, in part because in this region much grain serves as feed for livestock. Thus, for this study, we assume that the adoption decision made by farmers is based on production/profit considerations and does not involve anti-GM sentiment or concerns.

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[5] http://corn.agronomy.wisc.edu/WCM/W061.aspx

[6] http://corn.agronomy.wisc.edu/WCM/W063.aspx

3.2. Experimental Games

All participating farmers attended a session consisting of two parts. First was the experiment itself, with a series of games measuring risk aversion, ambiguity aversion, learning ability, and advice taking. Here we focus on the learning and advice-taking games. The farmers also completed a digit span exercise to measure cognitive ability. This part of the session was conducted on computers programmed with the software z-Tree (Fischbacher, 2007). The second part was a pen and paper survey on demographic and farm characteristics and a history of technology choices with respect to GM seed use. The session generally took less than 2 hours to complete and farmers earned an average of $51 in addition to reimbursement for travel costs.

Upon arrival at the experiment site, the 10% 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 responses to questions. During the sessions, instructions were read aloud and also appeared on the farmers' computer screens. Payoffs were determined after the completion of all of the games.

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.

Individuals often use learning rules that differ from Bayesian learning for both individual learning (Cheung and Friedman, 1997; Barham et al. 2015) as well as social learning (Stone and Zafar, 2014). Given the wide variability in how individuals understand and update probabilities, our investigation does not rely on probability assessments. Rather, we rely on simple measurements of how each individual learns and acquires information over time.

For the learning game, we built upon a game designed by psychologists Harvey and Fisher (1997). We first ran an individual learning game before introducing the opinion of an advisor in order to study advice taking. Screen shots can be found in Appendix A. As in Harvey and Fisher (1997), we framed the game by stating that there is a disease outbreak killing cattle. We focus on cattle because it is something with which the farmers will be familiar, while also not being too close to the crop-based focus of our survey. We stated that in order to provide adequate compensation to farmers, the government requires accurate estimates of the severity of the disease outbreak. Farmers were told that the severity of the outbreak depended on the color and size of a circle presented on the screen.

In the first round, the farmers knew nothing about how the number of dead cattle was determined other than the ranking of the three colors from least to most dangerous. Based on each circle, farmers provided a guess of the number of cattle they thought would die and after each round the farmer was told how many cattle actually died. In this way the farmer could learn more about how the disease worked.[7]

Participants were not informed of the underlying algorithm but were able to improve their estimates based on the feedback. This was repeated for 25 rounds, which provided sufficient opportunity for learning. Figures shown in Harvey and Fischer (1997) suggest that the rate of learning significantly decreases after the third block of ten rounds. Our results (shown later) suggest that learning significantly slows after ten rounds. The faster learning in our games is most likely due to the fact that we told the players the ordering of the colors from most to least severe. It may also be due to differences in screen quality, familiarity with computers, and the specific circles chosen.

The experiment was incentivized and one of the 25 rounds was chosen to count for payoffs. The payoffs were such that a correct estimate earned $50 while an incorrect estimate earned $50 divided by the absolute difference between the estimate and the truth. The farmer was told this equation at the beginning of the game, and after each round the farmer was shown the correct number of cattle that perished and the payoffs he would receive if that round were chosen. The average winnings in this game were $11.50 and ranged from 57¢ to $50. Without any initial information about the relationship between the circle and the number of dead cattle, numbers entered in the first round were uninformed guesses and, as a result, we focus our analysis on rounds 2 through 25.

Following this individual learning game, we completed an advice-taking game that utilized the same context and algorithm while introducing a recommendation from an advisor in order to enable the measurement of advice taking. These "advice-taking" experiments originate in the industrial and organizational psychology literature, and we adopt the term advice-taking from that literature. Bonaccio and Dalal (2006) offer a review of this class of experiments. Many

[7] The equation is $Dead\ Cattle = Color * \pi r^2$ where $Color = 2, 1, 0.5$ if the circle is red, green, or blue, respectively and r is the radius of the circle. The farmers were not told that the number of dead cattle is a linear function of the area of the circle.

papers study how experimental variations shape the propensity of participants to take advice. The advisor's level of experience, the advisor's level of confidence, the number of advisors, the incentives associated with the decision, and whether the participant solicited the advice all shape the degree to which advice is taken.

Other studies show that this willingness is shaped by personality traits such as agreeableness and dependency (Dalal and Bonaccio, 2010), expressivity (Feng and MacGeorge, 2006), and autonomy (Koestner et al, 1999). These findings suggest that willingness to take advice has intrinsic features that can be taken as given in a context where all participants receive the same advice in the same setting. The finding of others (and us below) that women are more receptive to advice than men (Dalal and Bonaccio, 2010; Feng and MacGeorge, 2006) is also supportive of the notion that the propensity to take advice has a substantive 'fixed' component. Accordingly, we expose all participants to the same experimental setting and measure the trait of 'propensity to take advice' as in the psychology literature.

In our experiment, participants were told the following: "In this second part of the game, you will use your training to make forecasts of how many cattle will die in current outbreaks. Obviously you can receive no information about the accuracy of these assessments because cattle are still dying. However, after making your assessment, you will be told the views of someone who participated in a similar experiment with us on an earlier day, but who received 100 rounds of training with this type of exercise rather than the 25 rounds of training you received. After getting this information, you will be given the opportunity to revise your original forecast. Do not feel obliged to make use of this information. It is up to you whether you take it into account."

Thus, in this advice-taking game, a different circle was again presented at the start of each round, individuals made an initial guess regarding how many cattle they thought died, the advisor's guess regarding how many cattle they think died for that specific circle was offered, and individuals made a final guess in which they could either enter the same guess or modify their guess if they so desired. This was again repeated for 25 rounds but the correct answers were no longer provided, meaning that there was no further learning during these rounds. The screen shots shown in Appendix A may help clarify how the game worked. In this second game the average winnings were $17.44 and ranged from 5¢ to $50.

We did not tell the participants any additional details about the individual whose advice we showed them. We had twenty faculty, staff, and graduate students play this game for 100 rounds in which they were told the correct answers, and then a subsequent 25 rounds in which they were not. The circles the farmers saw were those used in the final 25 rounds. The advice given to the farmers came from the individual who performed best on average across the 25 circles. We later show evidence that, on average, no farmer outperforms the advisor. The advice in the experiment was not intended to mimic real-world advice which comes specifically from an expert (e.g., a crop consultant or extension agent) or from a peer (e.g., a neighboring farmer). Instead, it was meant to mimic externally provided advice from any source.

Despite recruiting 149 farmers, computer problems resulted in some of their results being unusable. In two sessions, the individual learning game was interrupted in either round 1 or round 24, thus disrupting the learning process for 36 farmers. Furthermore, one farmer failed to complete the advice-taking game as a result of slow progress. We remove these farmers from our analysis and are left with 112 farmers.

Before the learning and advice-taking games, the farmers participated in a multiple-price list experiment measuring risk aversion. Though this is not the focus of our paper, we do include risk aversion as a control in the regressions since it has often been hypothesized to be a determinant of technology adoption. Every farmer had to make 10 decisions between a sure payoff and a lottery. These decisions were made all at once rather than sequentially. The sure thing involved a certain payoff of $10 while the payoff for the lottery depended on the color of chip drawn out of a bag. Only one decision per game affected their earnings and that decision was determined at the end of the experimental session.

3.3. Survey and Cognitive Ability Data

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

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).

3.4. Summary Statistics

Table 1 provides summary statistics of the survey and cognitive information among the farmers in our final sample.[8] All of these farmers have planted corn and all but four have planted soybeans. Conditional on planting the crop, 96% of corn farmers have planted GM corn and 92% of soy farmers have planted GM soy. These adoption rates (at the farmer level) are comparable to state averages (at the acreage level), which in 2011 were 86% for corn and 91% for soy (Fernandez-Cornejo, 2014). In 2011, farmers in our sample had planted GM corn for an average of 10.4 years and GM soybeans for 10.7 years.

There has been almost no disadoption. In our sample there are only three individuals who had previously adopted GM corn and yet planted only non-GM corn in 2011 and three individuals who had previously adopted GM soy and yet planted only non-GM soy in 2011. We do not know if this is a permanent disadoption, or if this is a temporary choice due to crop rotation since we only ask about the most recent year (2011) and the first year of adoption.

Farmers in our sample operate an average of 1009 acres of cropland; 17% of those surveyed report that farming is not their principal occupation; and the average years that participants have made decisions on the farm is 25.[9] The average age of our participants is 50, there are 3 females, and the average household size is 3. A quarter of participants (26%) received a high school degree or less and went no further. The average digit span is 7.6 with a standard deviation of 1.6, which is on-par with Miller's (1956) findings that an average adult has a digit-span of seven (plus or minus two).

[8] One farmer cheated on the digit span, writing down the numbers on a piece of paper by his side, and is dropped in regressions when digit span is included.

[9] For comparison, in the 2012 Wisconsin Census of Agriculture, 50% of farmers report that farming is not their principal occupation and the average cropland among all farmers is 131 acres.

4. Assessing Information and Learning

Learning is at the heart of the process of technology adoption. Before a new technology is available, individuals have no or scant information. As time goes on and more individuals adopt, they learn about the new technology. As noted above, there are two main avenues for learning: individual learning where individuals conduct their own research regarding the new technology (for example reading publications by seed companies regarding the performance of new seeds), and social learning by which they can take advice from extension agents and other farmers.

In general, the prospects for social learning and advice taking improve over time. Late adopters have more opportunities to learn from early adopters as the technology diffuses. This indicates that, when choosing whether or not to adopt a new technology, individuals will take into account their ability to process information as well as the availability of sources from which to take advice.

Significant heterogeneity in learning styles across individuals makes it challenging to evaluate the role of human learning in technology adoption. This issue is compounded by the fact that assessing probabilities can be particularly difficult in the early stages of adoption of a new technology. Given these issues, we make use of simple measurements of how each individual acquires information and do not attempt to construct probabilistic estimates.

In the following subsections of section 4 we will first discuss issues of measurement: how we measure individual learning and advice taking. Next we will look at how individual learning and advice taking are related to one another and to survey measures of education and cognitive ability. In section 5 we will look at how the two correlate with real-world technology adoption of GM corn and soy.

4.1. Individual Learning

First we write down a simple model of learning to help guide us in creating a measure of farmer learning ability. In each round the farmer learns more about the equation which determines, given circle area *x*, how many cattle died, *Y*. In each round *t*, the farmer's prediction is determined by: $\widehat{Y_t} = \widehat{\beta_t} * x + \epsilon_t$. With each subsequent round the farmer learns more about the value of the true β. In each round there is an error, ϵ, for example because the farmer sees the circle incorrectly. If we assume that $\hat{\beta}$ and ϵ are uncorrelated, which seems reasonable, then: $\text{var}(\hat{Y}) = x^2\text{var}(\hat{\beta}) + \text{var}(\epsilon)$. As the farmer learns more, $x^2\text{var}(\hat{\beta})$ will go to 0 and so after enough periods the variance in the prediction will equal the variance of the error term ($\mathrm{var}(\hat{Y}) = \mathrm{var}(\epsilon)$). Thus the variance of the prediction error after learning has ceased would summarize farmer learning ability according to the model.

In line with Harvey and Fisher (1997), to measure the accuracy of predictions we focus on the absolute percentage error (APE). This is the absolute difference between the prediction and the truth, divided by the truth. This measure will be highly correlated with the variance of the prediction error, while having the benefit of a meaningful zero (the APE will equal zero when the prediction is correct) and being unit-free. One could instead focus on the amount of money won in each round. But, because the amount won was not scaled by the number of cattle which died, winnings are much lower for circles corresponding with greater cattle death.[10]

In Harvey and Fisher, after practice the participants reach an average APE of approximately 30%. Our farmers do better, with an average APE of around 20% after the tenth round. Again, although we used the same formula as they did to determine the number of cattle deaths; our experiment was slightly easier than theirs because we informed the players of the ordering of the danger of the colors. Figure 1 depicts the average APE among all farmers for each round.[11] As expected, we see that the average APE decreases through the initial rounds as farmers learn the game and improve their guesses. After approximately fifteen rounds, learning appears to plateau.

We calculate our measure of learning as the farmers' average APE in the last ten rounds of the learning experiment, after they have ceased learning. In a previous version of the paper, we additionally looked at farmer heterogeneity in terms of how fast learning occurred (the slope of the decrease in APE), and the round at which learning ceased and the APE plateaued. Neither the slope nor the round at which learning ceased was ever significant in any of our regressions, and so we focus here on the farmers' final level of ability. Table 1 provides a summary of this individual learning measure. The average APE in the last ten rounds is 0.20 and is distributed as shown in Figure 2a where lower APEs signify better learners. To avoid confusion, we should

[10] The formulas for the two measures are: APE=|prediction – truth|/truth, and winnings=50/|prediction – truth| (or 50 if the farmer's prediction equaled the truth). The two are reciprocals of one another but with slightly different scaling.

[11] Figure 1 excludes round 1 of the individual learning game due to the fact that individuals had no information before this round and so guesses were pure noise. The uptick in round 25 is probably due to the fact that the circle in round 25 was the largest which appeared over the course of the entire 50 rounds but for the least dangerous color, and a handful of individuals performed extremely badly.

note that our measure of learning ability does not link up with Bayesian learning. It is a more general measure of cognitive ability. We consider being a good learner and having high cognitive ability to be similar concepts.

4.2. Advice Taking

We use the advice-taking game to calculate a measure of advice taking for each individual. By comparing the initial guess, the advice, and the final guess, we are able to calculate how much each farmer responds to advice. But, before we do that, we first show that the advice is better than the farmers' initial guesses and farmers would be well-served by taking the advice. The average APE over all players and over all 25 rounds before receiving advice is 0.20, and after receiving advice is 0.10. The advisor's average APE over all 25 rounds is 0.06. While some individuals outperform the advisor in certain rounds, no individual's initial guess APE mean is lower than that of the advisor. Thus, on average, before receiving advice, no individual performs better than the advisor. However, after taking advice, 11 individuals do achieve lower average APEs than the advisor. Appendix Figure 1 shows the APEs for each of the 25 rounds for the advice itself, for the farmers before advice, and for the farmers after advice. Collectively, this provides strong evidence that the advisor is worth paying attention to and that individuals stand to improve their performance if they take advice.

To estimate advice-taking measures for participants, we focus on a regression-based approach similar to that employed by Lim and O'Connor (1995).[12] For this estimation, we make a 25 round panel for each participant and we regress the final estimate (*F*) on the initial estimate (*I*) and the advice (*A*):

$$F_t = \propto_I I_t + \propto_A A_t + \varepsilon_t$$

where *t* denotes rounds and α_I and α_A capture the weight on initial guesses and advice respectively. We restrict α_I and α_A to sum to 1 and to each be between 0 and 1.

[12] We also calculated formula-based measures, such as the percentage shift, weight of advice, and weight of own estimate, as described in Bonaccio and Dalal (2006). In general, our results are robust to these alternative measures; however, we prefer to utilize the regression-based approach. Bonaccio and Dalal (2006) state that regression-based measures are preferable since formula-based measures take ratios of differences, which are susceptible to measurement problems. Bonaccio and Dalal (2006) also describe several papers that utilize regression-based models in similar contexts, including Phillips (1999) and Brehmer and Hagafors (1986).

In the remaining analysis, we focus on α_A, which we call the advice weight. Higher values indicate that an individual is more responsive to advice. Participants never learn the correct value in this game so they cannot learn whether the advisor's advice is of good quality. Still, their perception of the advice might change over the 25 rounds. We explore whether the weight the respondent put on the advice increases or decreases over time and find that for 48% of the people the weight decreases and for 52% of the people it increases over time. When combining all individuals, the slope is positive but very far from significant. Thus, we assume that individuals' perceptions of the quality of advice does not change over time, and just look at their average weighting of advice.

Table 1 summarizes the advice-taking measure. The average advice weight is 0.62, indicating that individuals place slightly more weight on the advice than their own initial guesses. Certain individuals place all weight on their initial guesses while other place all weight on the advice, as shown in Table 1 and Figure 2b which presents a histogram of the advice weight.

Strong learners may be disinclined to follow advice if they are confident in their own abilities. According to Bayesian updating, individuals will combine their prior (*I*) with the signal (*A*) to get their posterior (*F*). The weight placed on the signal would depend on the individuals' beliefs regarding the precision of his prior relative to the precision of the advice. Those farmers who performed better at the individual learning task should rationally put a lower weight on the advisor's advice and a higher weight on their own initial guess. This is part of the reason why, when we later look at the impact of advice taking on technology adoption we always simultaneously control for the farmer's APE in the last 10 rounds of the individual learning game which should be a proxy for the precision he places on his prior.

4.3. Linking Individual Learning and Advice Taking

We now evaluate the correlates of individual learning and advice taking. We start in columns (1) and (2) of Table 2 by looking at the correlation of individual learning in the experiment with our survey based measures of education and cognitive ability. Those farmers who have not attended any college have an absolute percentage error (APE) which is 2.7 percentage points (0.30 standard deviations) higher than those who have attended at least one year of college, although this correlation is not significant at traditional levels. Farmers who perform better in the digit span exercise also perform significantly better in the individual learning experiment, with a one standard deviation increase in the digit span leading to a 0.25 standard deviation decrease in the average APE in the last 10 rounds. In column (3) we add many additional control variables including demographics, land size, and risk aversion and find that none of the control variables are significantly correlated with our individual learning measure, and none of them detract from the significant correlation between digit span and our learning measure.

These results suggest that our measure of individual learning from the experiment can be thought of as a measure of cognitive ability. This also suggests that, at least for Wisconsin farmers, schooling is not as useful a measure of ability as are more specific measures of cognitive ability. In fact, in results not shown here we have tried other measures of education including having a two-year college degree, having a four-year college degree, and having received some post-graduate education. The education variable we show here (an indicator variable for having a high school diploma or less) is the one which comes closest to being significantly correlated with learning ability and, later, with technology adoption. While many papers in a developing country context find that education is correlated with ability and technology adoption (Foster and Rosenzweig, 2010), this correlation may be less strong in developed countries where education is both of higher quality and more common.

In columns (4) through (6) we look at correlates of our measure of advice taking. Again we first look for correlations with our measures of education and cognitive ability. Although not significant at traditional levels, in column (4) the coefficient on having a high school diploma or less has a *p*-value of 13% while the coefficient on digit span in column (5) has a *p*-value of 11%. This gives suggestive evidence that advice and learning ability are substitutes rather than complements. Once controlling for other variables these coefficients become much less significant. We do find evidence that women appear more likely to take advice, a finding which matches the psychology literature mentioned previously (though one should remember our sample includes only three women). There is some evidence that older individuals are more likely to take advice, with an increase in age of ten years leading to a 0.23 standard deviation increase in advice taking, though this is usually not significant at traditional significance levels. What may be most noticeable about columns (4) through (6) is how few of the control variables are significantly correlated with advice taking.

In column (7), we regress advice taking on learning ability while including controls such as education levels. Strong learners may be disinclined to follow advice if they are confident in their own abilities. If individuals are Bayesian updaters, then those who performed better at the individual learning task should rationally put a lower weight on the advisor's advice and a higher weight on their own initial guess.[13] However, learning and advice taking are independent aspects of decision making. Depending on an individual's perception of his own ability and how much he trusts the advisor's advice, individuals can choose to weight advice very differently.

We find evidence that poor learners, those who finish the game at a higher error level, are more willing to take advice. The magnitude is such that a one standard deviation decrease in learning ability leads to a 0.24 standard deviation increase in advice taking. This gives suggestive evidence that better learners trust their own guesses more than poor learners and, as a result, better learners are less inclined to take advice.[14] It is in accord with Schiebener et al.'s (2014) result that those who perform worse on an experimental task, and those with lower levels of working memory and executive functioning, are the most likely to accept advice on that task.

As a final set of experimental variables, we categorize individuals as being either good or poor individual learners (good learners are those whose APE in the last 10 rounds is less than or equal to the median value of 0.20) and advice takers or non-advice takers (advice takers are those whose advice weight is greater than or equal to 0.67 which is the median). These categorizations will be useful for us when analyzing real-world technology adoption. Summary statistics in Table 1 show that it is slightly more common for people to excel in one area, i.e. to be either a good individual learner or an advice taker (60% of the population), though it is also quite common for individuals to either excel at both or at neither (40% of the population).

5. Learning and Technology Adoption

Effective technology adoption relies on learning. Specifically, individuals must combine their own experience and expertise with advice from various sources in order to make initial adoption decisions and to improve their utilization of new technologies through time. However,

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[13] Because of the natural correlation between ability and propensity to take advice suggested by Bayesian updating and evidenced in the data, when we look at how advice taking impacts technology adoption, we simultaneously control for learning ability.

[14] This may be some consolation to those who have been passengers in a car with a driver who insists he knows the directions to get to the destination.

researchers are limited in their ability to analyze the impact of learning on technology adoption since learning is highly individualized and difficult to observe (Barham et al., 2015). By combining experimental measures of individual learning and advice taking with survey data on real-life decisions, this paper provides an important contribution.

We link our measures of learning and advice taking to technology adoption to test the hypotheses which come from our intuitive model. First, more able learners may be earlier adopters if they know that they can quickly learn how to utilize new technologies. Second, good learners who are also advice takers will be slower adopters than good learners who are non-advice takers, since the former can learn quickly but are also inclined to wait to utilize advice in their decision making. Third, less able learners who are also advice takers will adopt more quickly than non-advice takers, since they will learn more about the technology in a shorter time span.

5.1. Survival Model

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 subsequently decides to adopt in each time period. The hazard function, $\lambda(z,t)$, measures the adoption rate at time *t* conditional on not having adopted before time *t*. Different specifications of the hazard function have been proposed in the literature. We use the Weibull distribution with $\lambda(z,t) = e^{-z\beta} k \left[e^{-z\beta} t \right]^{k-1}$ where β is a vector of parameters capturing the effects of *z* on the hazard rate. We choose this specific function because it 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. The first farmers using GM technologies adopted in 1996 yet a few of the younger farmers in our sample were not yet farming at that time. 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. The survival analysis takes into account that the data are censored, in that not all farmers have adopted by 2012, since it estimates a probability of adoption in each year. We include fixed effects for calendar year to control for climactic events and news which came out about the seeds at different points in time. We also include crop reporting district (CRD) fixed effects to control for local agro-climatic conditions that may influence the adoption decision. Standard errors are robust to heteroskedasticity.

In our application of the survival model we measure the probability of adopting in any year, with a higher value reflecting earlier adoption. A hazard ratio greater than one signifies that the variable hastens adoption, while a hazard ratio of less than one is associated with slower adoption. We present several model specifications in Table 3 for corn and Table 4 for soy. In columns (1) and (2), we include only the survey measures of cognitive ability: education and digit span. In column (3) we control for the two experimental measures: the APE in the last 10 rounds and the advice weight, to capture the impact of an individual's willingness to take advice and his own learning ability. We then re-run these estimations in column (4) using standard covariates in adoption models such as individual demographic variables, farm size, and risk aversion. We also look into the interplay between advice taking and ability by looking at the interaction of the two continuous variables in columns (5) and (6), or by categorizing each individual based on his individual learning and advice-taking group in columns (7) and (8).

5.2. Results

Table 3 provides evidence linking farmer learning characteristics to the timing of the adoption of GM corn. Individuals with higher schooling and cognitive ability are earlier adopters. Those with a high school diploma or less are likely to adopt later (*p*-value of 10.3% in column (1)) and a higher digit span increases the probability of adoption (*p*-value of 7.2% in column (2)). Once we control for the experimental measures of learning ability and advice taking, the survey measures lose significance. There is robust evidence that both individual learning and advice taking are determinants of the timing of GM corn adoption, with both worse individual learners (measured by higher APEs) and advice takers (higher advice weight) being later adopters. To interpret the magnitude of the hazard ratios shown in Table 3, imagine two farmers who have not yet adopted GM corn. According to the estimates in column (3), if one farmer's learning ability is one standard deviation lower than that of the other, his likelihood of adopting will be 20% lower. If one farmer's propensity to take advice is one standard deviation higher than the other, his likelihood of adopting will be 21% lower. Thus, the two variables have impacts of similar magnitudes.

In columns (5) and (6) we interact the two variables and show that both the two original variables as well as their interaction are significant. Because it is difficult to interpret coefficients on interactions of continuous variables, we show the relationship graphically in Figure 3. There one can see the impact of the advice weight on the hazard ratio of adopting for three different values of the asymptote: the fifth percentile (0.1), the fiftieth percentile (0.2), and the ninety-fifth percentile (0.4). The figure shows that the advice weight has a negative impact on adoption for the very good learners. Good individual learners who are not advice takers have the highest probability of adopting. Among non-advice takers (advice weight=0), those with the best skill (APE = 0.1) are approximately 3 times as likely to adopt in any period as those with average skill (APE = 0.2). Among the highly skilled (APE = 0.1), non-advice takers (advice weight = 0) are approximately 3 times as likely to adopt in any period as those who place a 50% weight on the advice.

To look at the interaction between these two variables in a simpler manner, in Columns (7) and (8) we instead include indicator variables for different categories of individuals. Here we see the same qualitative results as when using the interaction, but in an easier to interpret format. These columns provide evidence that good individual learners who do not take advice are the earliest adopters. All bad individual learners, as well as good individual learners who do take advice are later adopters, with much smaller differences in adoption probability amongst themselves. If one were to look at learning and advice taking in isolation, ignoring the interaction, one would miss the fact that it is specifically those good learners who choose not to take advice who are the earliest adopters. Individual learning and social learning do not appear to be complements.

Next we analyze GM soybean adoption. For those 99 individuals in our sample who have adopted both GM corn and GM soy, the correlation in year of adoption between the two is 56%, suggesting that, although they are highly correlated, there is still a fair amount of variation in year of adoption between the two. It is not obvious that the correlates of GM corn and soy adoption will be the same. In fact, Barham et al. (2014) discuss differences between the two technologies and show evidence that farmer ambiguity aversion affects adoption of the two crops in a significantly different manner.

Columns (1) through (4) of Table 4 show results for soy with the same sign as those for corn, with worse learners being slower adopters of GM soybeans and advice takers being quicker adopters, but these coefficients are not significant. However, when advice taking and learning are interacted in Columns (5) through (8), there is again strong and robust evidence that the earliest adopters are good individual learners who do not take advice. Figure 4 shows the impact of the interaction graphically, and the soy results look quite similar to the case of corn. The result that those individuals who are good learners but not willing to take advice are the earliest adopters is strong and robust across both technologies.

The results for adoption of both GM corn and GM soy show the substitutability between cognitive ability and advice taking. Figures 3 and 4 show that for those farmers with high learning ability (APE of 0.1) the line is downward sloping, implying that more advice taking leads to slower adoption. For those farmers with low learning ability (APE of 0.4) more advice taking instead leads to quicker adoption. Similarly tables 3 and 4 show that the fastest adopters are those who are good individual learners but don't take advice. The next speediest adopters are those who are bad individual learners but do take advice. The slowest adopters are those who either are both good learners and good advice takers, or bad learners and bad advice takers.

For both the GM corn and soy adoption regressions, one might wonder whether the individual who responded to the survey is the one who has the power to make adoption decisions. We asked the respondents their role on their farm and 65% claimed to be the primary farm operator, 31% claimed to be a joint operator, partner, or one of several key decision makers, 1% claimed to be the spouse of the key decision maker, and 3% claimed to be a hired farm manager with no ownership interest. The qualitative results (not shown) do not change if one excludes the 4% in the last two categories, or if one limits the analysis to the 65% in the first category. The small sample size makes it difficult to delve more deeply into heterogeneity on this dimension. Future researchers may want to explicitly consider differences between sole and joint decision-making processes.

There are two main advantages of modeling the adoption timing decision as a survival analysis. First, survival analysis takes into account the fact that not all farmers in our sample had begun making decisions by 1996 when GM technologies first became available. Second, survival analysis takes into account the fact that not all farmers had adopted GM technologies by the time we collected data, after the 2011 harvest.

As a robustness check (results not shown here) we can drop the 29% of farmers who began making decisions after 1996 and run OLS where the dependent variable is having adopted GM no later than 1998. Another option is to additionally drop those who never adopt, and run an OLS regression in which the dependent variable is year of adoption. When we do either of these analyses for corn or soy, evidence regarding the substitutability between individual ability and advice taking remains strong. The fastest adopters are still those who are either good individual learners or good advice takers, but not both. The distinction between those who are only good learners or only good advice takers is still there but becomes less pronounced.

A few caveats regarding the results are in order. First, one might worry about reverse causality. Our analysis uses advice taking in 2012 to explain adoption decisions made up to 16 years earlier. A story could be told such that the timing of adoption of GM seed caused farmers to realize that it is good (or bad) to take advice, thus influencing their future propensity to take advice. We think it is unlikely that the experience of adopting GM corn would lead farmers to change their propensity to take advice in this experimental setting, but we cannot prove this with our current data.

Second, although there is always a potential for omitted variable bias, we control for farm and farmer characteristics that are commonly incorporated in adoption models as well as several additional experimental variables. We find that our results are robust to their inclusion. We also explored relevant variables which are less standard in the adoption literature such as trust. One concern is that participants who are more trusting in general or who trust us and extension agents more might be more willing to take advice since they may believe we stacked the advice in their favor. When we control for a survey-based measure of confidence in external sources of information in Section 6, the results do not change. Thus, our key findings are found to be robust to the inclusion of a variety of variables.

Additionally, we might think that heterogeneity in the profitability of GM would affect timing of adoption. (This is similar in spirit to what is found by Suri (2011) for fertilizer in India.) We don't have a measure of heterogeneous GM profitability per se, though we do control for crop-reporting district fixed effects which should take care of much geographic variation. Farm size might proxy for expected profits per acre from GM corn which varies at the farmer level, for example if there is a fixed cost to learning about the new technology. Still, Table 2 shows that farm size is not correlated with receptiveness to advice or learning ability, which suggests that this source of omitted variable bias should not impact the coefficient on those variables in the adoption regressions.

6. **Identifying Advice Taking**

We have found that our two experimental measures are highly correlated with timing of adoption. Our experimental measure of learning ability is correlated with schooling and digit span, and so seems to be a proxy for cognitive ability. On the other hand, our experimental measure of advice taking was not found to be correlated with any of the common demographic variables we included. Are there survey measures of advice taking which correlate with this experimental measure?

Looking to the survey, in one question, farmers were asked to "check all of the information sources that you use for learning about seeds for your crops" with six fixed options in addition to a line for "Other (specify)." The options listed included both experts (such as extension agents) and non-experts (such as other growers). Some farmers in essence dismissed the survey, which listed only external sources of information, and instead wrote in that they relied on their own experiments as a source of information. We classify them as "self-reliant."

Next, farmers were asked to rate their confidence in the same six fixed sources of information. The options ranged from 1 to 4 with 1 signifying "no confidence at all" and 4 signifying "a great deal of confidence." Every farmer rated at least one of the six sources with a 3 or higher. We create a measure of the farmer's confidence in external sources which equals 1 if his highest confidence level is a 4 and a 0 if his highest confidence level is a 3.[15] [16]

Appendix Table 1 shows that each of these measures is significantly correlated with the advice weight in the direction that we would predict when no other control variables are included. Self-reliant farmers are less likely to take advice (column (1)) and farmers with more confidence in external information sources are more likely to take advice (column (4)). The other

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[15] We have also looked at other measures such as the average rating, which behaves similarly. Whether the average or the maximum is a more appropriate measure depends on whether we believe farmers weight all sources of information and advice equally or rely on their most trusted source of information. Given that we believe farmers rely on their most trusted sources, and due to the non-cardinality of the ratings, we prefer the indicator variable discussed above to the average.

[16] The sources of information were: a) Other growers or producers; b) Extension agents or state specialists; c) Farm supply or chemical dealer, crop consultant, or advisor; d) Growers' association; e) Print and electronic information sources (internet, newspapers, etc.); and f) Special events, demonstration projects, or F.I.R.S.T. plots.

columns in that table add in progressively more control variables. Confidence continues to significantly predict our experimental advice-taking measure, with higher confidence in external sources associated with higher advice weights. Self-reliance is not significantly correlated at traditional levels of significance once other controls are included.

Self-reliance is associated with significantly faster adoption of both GM corn and GM soy when no controls are included. Confidence in external sources is associated with significantly slower adoption of GM soy, but the effect on corn is not significant. If one conducts a horse-race, including both the survey measures and the experimental measures in the technology adoption survival analysis, the experimental measures do not lose significance. Self-reliance remains significant if one does not include other demographic controls, but confidence does not.

Overall, we find that advice taking as measured in the experiments is correlated with measures of real-world agricultural advice taking collected in a survey. These measures of real-world advice taking are correlated with adoption, and so may be helpful in cases when it is not possible to run advice-taking experiments with individuals. But, the experimental measures perform better than the survey measures when including both at the same time. While the experimental measures perform best, it may be possible to collect similarly simple variables in surveys to measure individuals' receptiveness to advice.

7. **Conclusion**

New technologies come online continually and profitable individuals are those who can respond most efficiently to these new advances. Individuals can either choose to adopt based on their own perceptions and research; or they can rely on advice gathered from external sources such as their peers or extension agents. These decisions shape the productivity, growth rate, and income distribution of an economy.

We combine experimental evidence on learning ability and receptiveness to advice with survey evidence on the timing of adoption of GM seed technologies. Survey measures of education and cognitive ability (having studied past high school, and score on the digit span exercise) are correlated with farmers performing better on the experimental learning task. These variables are also correlated with farmers being earlier adopters of new GM technologies. This confirms the generally accepted evidence that better educated farmers and farmers with higher cognitive ability tend to be early adopters.

The earliest adopters are those who are both good individual learners and also unwilling to take advice. It is the interaction of these two characteristics which is most important, compared to the isolated impact of either characteristic alone. The slowest adopters are those who either are both good learners and good advice takers, or both bad learners and bad advice takers. We also find that better learners do seem to be less willing to take advice, or conversely that worse learners are more willing to take advice.

Huffman (1981) finds that differential access to education and information explains most of the differential productivity between black and white-owned farms in the 1960's in the U.S. South. Our results that that learning ability and receptiveness to externally provided information are substitutes rather than complements suggest that government interventions aimed at providing advice can help alleviate, rather than increase, inequality. Advice-taking may play a significant role in stimulating productivity and reducing inequality.

Maertens (2014) finds that people learn most from progressive farmers who adopt immediately, in the first period the technology is available, without waiting to see what their peers do. This begs the question of who are these progressive farmers who adopt without waiting to take advice or learn from others' experiences. Our results suggest they are individuals who are good at learning on their own and who have a low propensity to take advice. This is in accord with Läpple and Van Rensburg (2011) who find that early adopters ("pioneers") of organic farming in Ireland are less likely to use advisory information sources and have less interest in gathering information than do late adopters ("laggards").

In the case of GM seeds, the early adopters happened to have been correct and were early adopters of a technology which turned out to be undeniably advantageous. It is hard to know what we would have found if we were looking at a new technology which was less positive. Perhaps these farmers would have figured out not to jump in early, or perhaps they would have adopted and then disadopted quickly. It would be interesting in future research to look at a wider array of technologies and to study both the adoption and disadoption decisions for technologies which are less desirable. We also hope that in the future theorists will extend models of learning to include heterogeneous propensities to take advice. Finally, our experiment focuses on advice taking when advice is given out freely and participants have no choice but to receive it. We do not look at advice seeking, which may be another fruitful avenue for future research.

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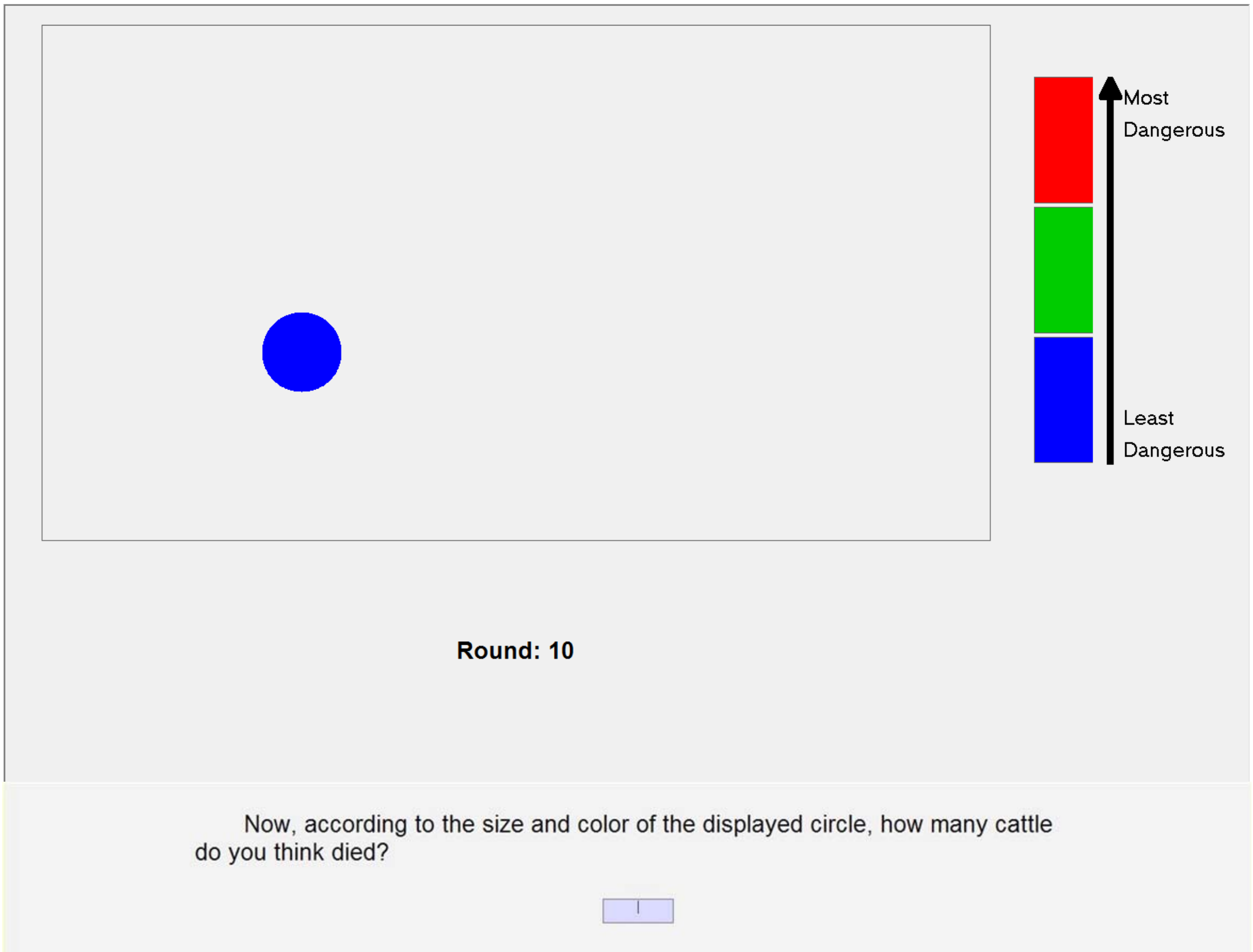
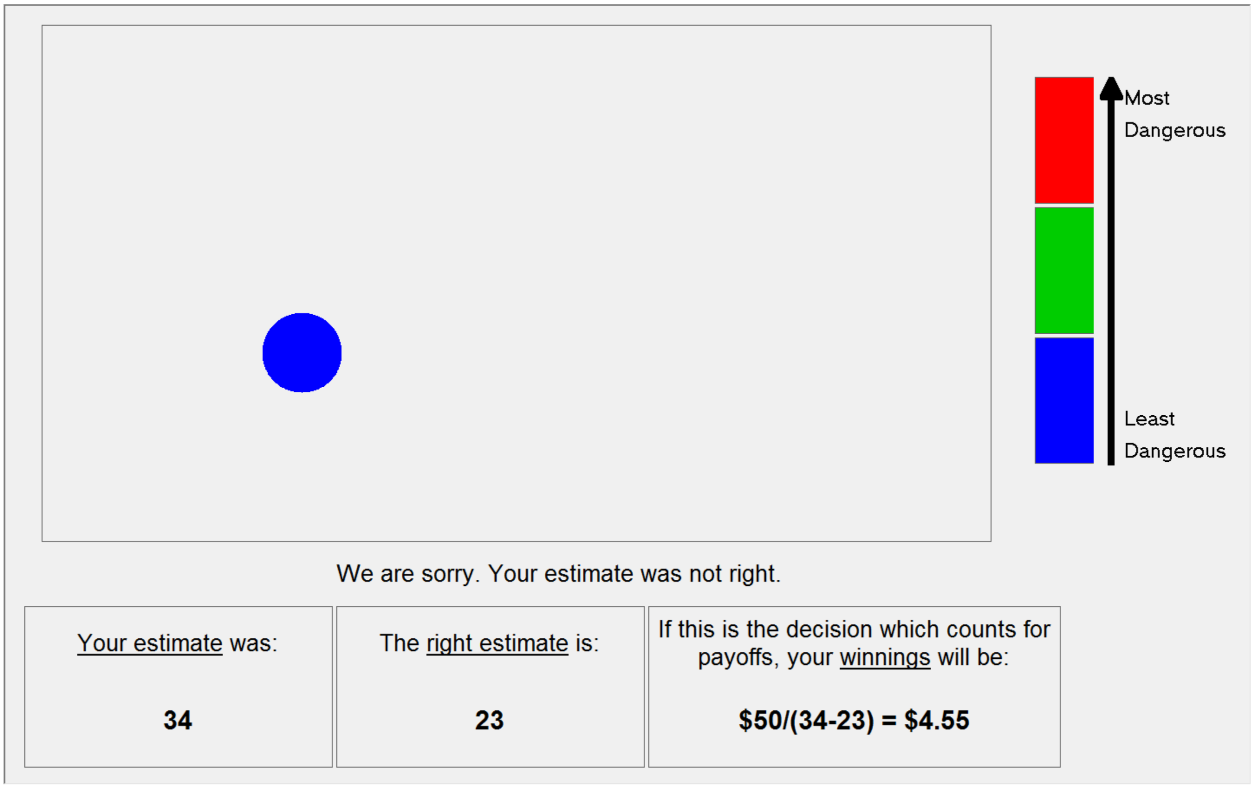
Appendix A: Screen Shots from the Learning Games

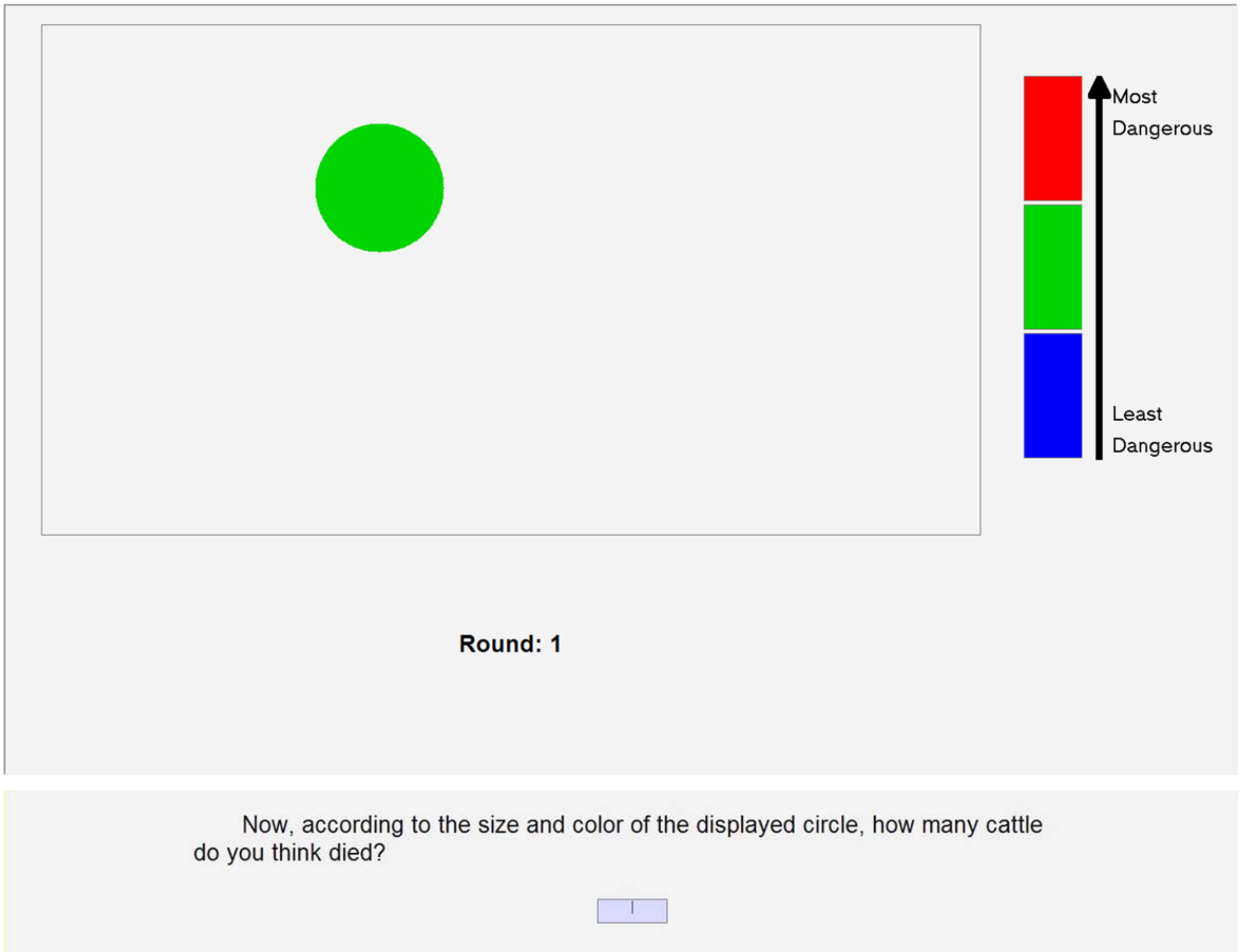
1. Screen that participants see when making their guess in the individual learning game:



2. Screen that participants see when being told how their answer compares to the correct answer in the individual learning game:



3. Screen for participants to give their initial estimate in the advice-taking game:



4. Screen that participants see when given a chance to revise their estimate in the advice-taking game:

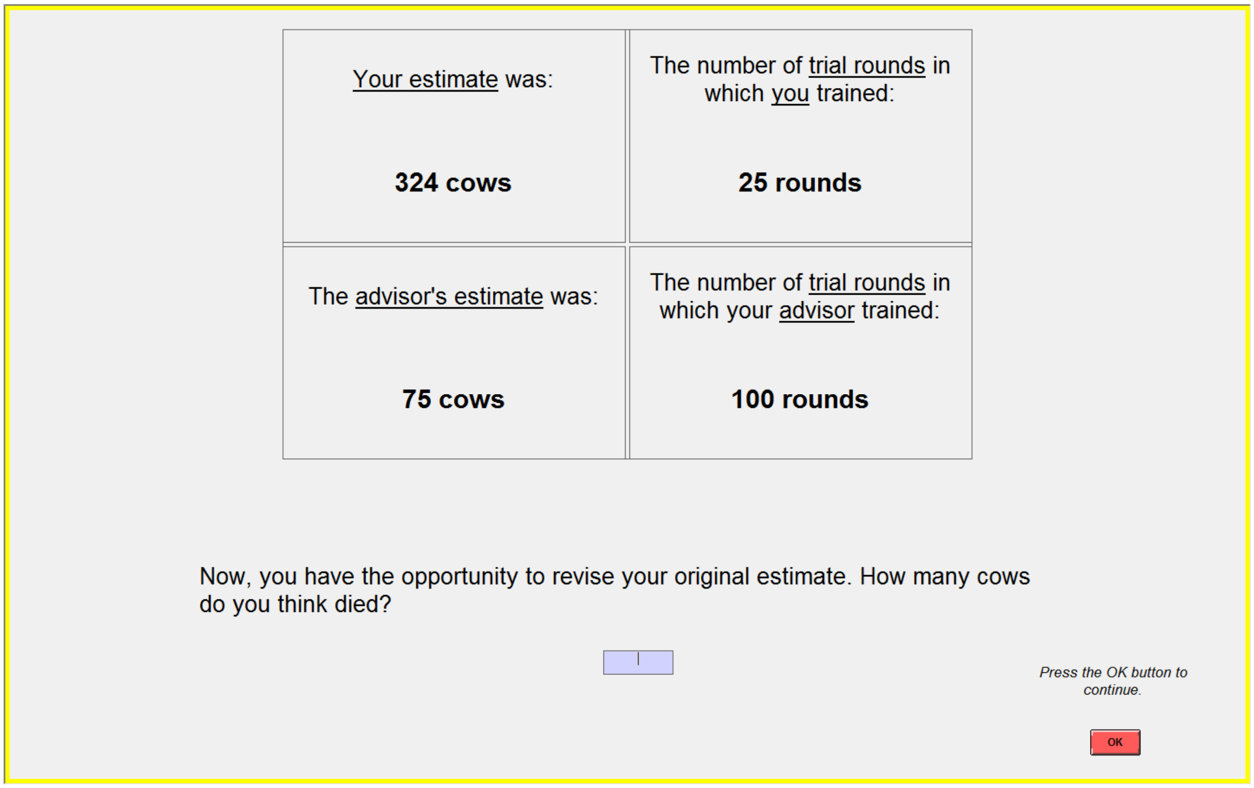


Table 1: Summary Statistics

Variables	Obs	Mean	Std. Dev.	Min	Max
Demographic Characteristics					
Age	112	50.36	15.10	22	83
Gender: Female	112	2.7%			
Household size	112	2.86	1.29	1	7
Household Income before taxes 2011 (Thousands)					
Under $80	112	34.8%			
$80 - $139	112	33.0%			
$140 or more	112	32.1%			
Requested computer training	112	9.8%			
Cognitive Characteristics					
High school diploma or less	112	25.9%			
Digit span	111	7.63	1.57	4	11
Number of risky choices	112	5.06	2.74	0	10
Farming Characteristics					
Farming is not the principal occupation	112	17.0%			
Acres of cropland operated 2011	112	1009	1070	30	6500
Years farmer has made decisions on farm	112	25.13	15.14	2	57
Corn					
Have never planted corn	112	0.0%			
Planted conventional but not GM corn	112	4.5%			
Have planted GM corn	112	95.5%			
Years planting GM corn (up through 2011)	112	10.36	4.51	0	16
Soybean					
Have never planted soybeans	112	3.6%			
Planted conventional but not GM soy	112	6.3%			
Have planted GM soybeans	112	90.2%			
Years planting GM soy (up through 2011)[1]	108	10.66	5.06	0	16
Experimentally-Measured Characteristics					
Learning - APE in last 10 rounds	112	0.20	0.09	0.02	0.58
Advice weight	112	0.62	0.23	0	1
Good learner - non advice taker	112	30.0%			
Bad learner - advice taker	112	30.0%			
Good learner - advice taker	112	20.0%			
Bad learner - non advice taker	112	20.0%			
Survey-Measured Characteristics					
Self-reliant	112	4.5%			
Maximum confidence	112	60.7%			

1 Excludes those farmers who have not planted soybeans. Equals zero for farmers who have only ever planted conventional soybeans.

Table 2: Advice Taking Regressions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
VARIABLES		APE in Last 10 Rounds * 100				Advice Weight * 100	
APE in last 10 rounds							0.62**
							[0.25]
High school diploma or less	2.66		1.36	7.71		4.64	3.79
	[1.91]		[2.15]	[4.99]		[5.60]	[5.47]
Digit span		-1.41***	-1.25**		-2.25	-1.24	-0.46
		[0.53]	[0.59]		[1.41]	[1.54]	[1.54]
Age			0.10			0.54	0.48
			[0.13]			[0.35]	[0.34]
Female			-2.33			30.92**	32.37**
			[5.39]			[14.01]	[13.68]
Acres operated (1000's)			-0.32			0.78	0.98
			[0.87]			[2.27]	[2.21]
Farming not principal occupation			-0.20			4.09	4.22
			[2.52]			[6.55]	[6.39]
Years making decisions on farm			-0.13			-0.38	-0.30
			[0.13]			[0.35]	[0.34]
Received computer refresher			2.97			4.11	2.26
			[3.42]			[8.90]	[8.71]
Number of risky choices			0.12			0.23	0.15
			[0.33]			[0.85]	[0.83]
Constant	19.76***	31.21***	27.39***	60.45***	79.44***	49.00**	31.93
	[0.97]	[4.11]	[7.23]	[2.54]	[10.95]	[18.79]	[19.59]
Observations	112	111	111	112	111	111	111
R-squared	0.017	0.062	0.087	0.021	0.023	0.096	0.148

Standard errors in brackets. *** p<0.01, ** p<0.05, * p<0.1

Table 3: Hazard Ratios, Survival Model for GM Corn Adoption

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
High school diploma or less	0.667			1.094		1.005		1.034
	[0.166]			[0.304]		[0.291]		[0.284]
Digit span		1.128*		0.990		1.004		1.077
		[0.075]		[0.077]		[0.073]		[0.086]
APE in last 10 rounds			0.777*	0.740**	0.382***	0.230***		
			[0.108]	[0.112]	[0.123]	[0.095]		
Advice weight			0.904**	0.891**	0.737***	0.643***		
			[0.041]	[0.048]	[0.073]	[0.080]		
Advice weight x APE in last 10 rounds					1.114**	1.192***		
					[0.053]	[0.077]		
Good individual learner / Non-advice taker							1.804*	2.473**
							[0.569]	[0.937]
Bad individual learner / Advice taker							1.132	1.736
							[0.378]	[0.714]
Bad individual learner / Non-advice taker							0.977	0.946
							[0.340]	[0.357]
Age				0.994		0.997		1.008
				[0.020]		[0.020]		[0.019]
Female				0.962		1.113		1.186
				[0.293]		[0.396]		[0.515]
Acres operated (1000's)				1.469***		1.505***		1.656***
				[0.169]		[0.176]		[0.206]
Farming not principal occupation				0.587		0.483*		0.635
				[0.230]		[0.213]		[0.252]
Years making decisions on farm				0.977		0.977		0.980
				[0.022]		[0.021]		[0.020]
Received computer refresher				0.988		0.853		0.759
				[0.469]		[0.403]		[0.336]
Number of risky choices				0.946		0.945		0.937*
				[0.035]		[0.033]		[0.036]
k	1.223**	1.252***	1.234***	1.579***	1.273***	1.667***	1.241**	1.557***
	[0.100]	[0.103]	[0.098]	[0.124]	[0.102]	[0.147]	[0.104]	[0.126]
Number of farmers	112	111	112	111	112	111	112	111

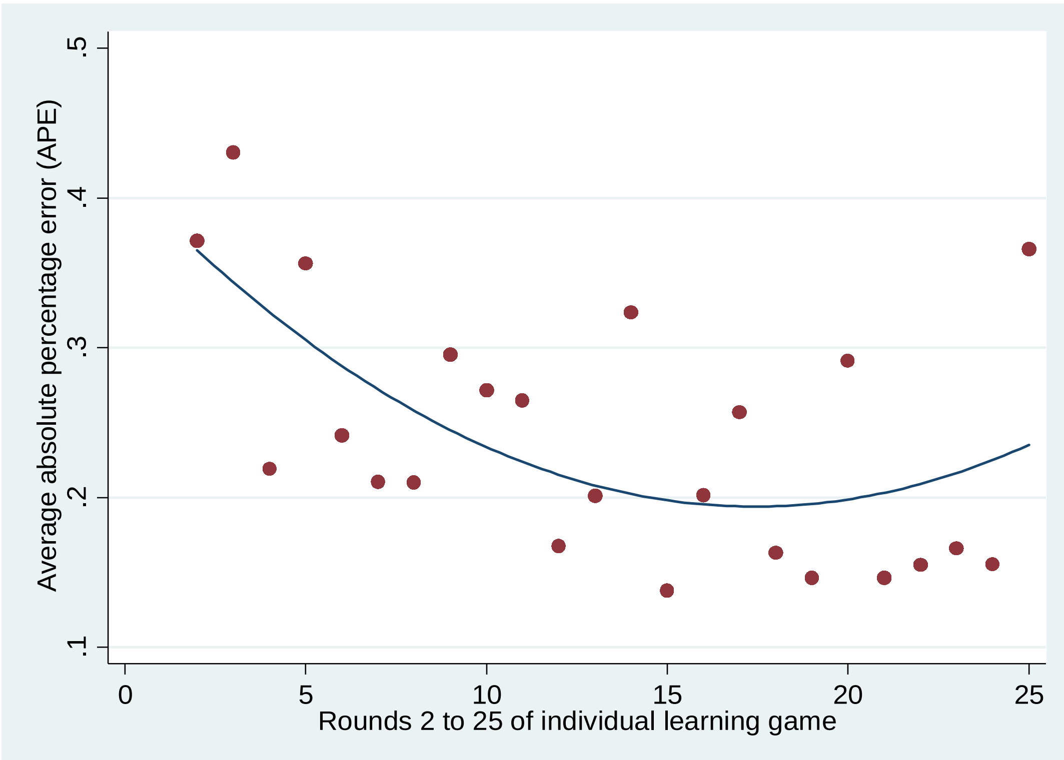
All regressions assume a Weibull survival distribution and include year and crop-reporting district fixed effects. In Columns 7 and 8, "good individual learner / advice taker" is the excluded category. The APE and advice weight are both scaled up by a factor of 10. Robust standard errors in brackets. Significantly different from 1 at * – 10%, ** – 5%, and *** – 1% levels.

Table 4: Hazard Ratios, Survival Model for GM Soybean Adoption

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
High school diploma or less	0.795			0.878		0.844		1.060
	[0.203]			[0.268]		[0.258]		[0.300]
Digit span		1.098		1.065		1.060		1.09
		[0.087]		[0.095]		[0.093]		[0.096]
APE in last 10 rounds			0.885	0.888	0.324**	0.326**		
			[0.138]	[0.126]	[0.160]	[0.158]		
Advice weight			0.971	0.965	0.718***	0.718**		
			[0.050]	[0.060]	[0.090]	[0.095]		
Advice weight x APE in last 10 rounds					1.170**	1.167**		
					[0.077]	[0.081]		
Good individual learner / Non-advice taker							3.580***	4.053***
							[1.269]	[1.775]
Bad individual learner / Advice taker							2.298**	2.512**
							[0.885]	[1.099]
Bad individual learner / Non-advice taker							1.279	1.184
							[0.586]	[0.592]
Age				1.004		1.008		1.024
				[0.022]		[0.023]		[0.023]
Female				1.732		1.928		2.396*
				[0.733]		[0.842]		[1.087]
Acres operated (1000's)				1.078		1.094		1.246**
				[0.118]		[0.126]		[0.135]
Farming not principal occupation				0.479		0.409*		0.515
				[0.218]		[0.199]		[0.239]
Years making decisions on farm				0.954**		0.956**		0.950**
				[0.020]		[0.020]		[0.021]
Received computer refresher				2.526*		2.103		2.335*
				[1.393]		[1.132]		[1.159]
Number of risky choices				1.040		1.048		1.033
				[0.047]		[0.045]		[0.041]
k	1.153	1.186	1.154	1.479***	1.221**	1.536***	1.256**	1.561***
	[0.117]	[0.124]	[0.114]	[0.147]	[0.129]	[0.171]	[0.125]	[0.175]
Number of farmers	108	107	108	107	108	107	108	107

All regressions assume a Weibull survival distribution and include year and crop-recording district fixed effects. In Columns 7 and 8, "good individual learner / advice taker" is the excluded category. The APE and advice weight are both scaled up by a factor of 10. Robust standard errors in brackets. Significantly different from 1 at * – 10%, ** – 5%, and *** – 1% levels.

Figure 1: Average APE over Time



This figure depicts the average absolute percentage error (APE) over all farmers in each round except the first. It is overlaid with a quadratic fit line.

Figure 2a: Learning - Average APE in Last 10 Rounds

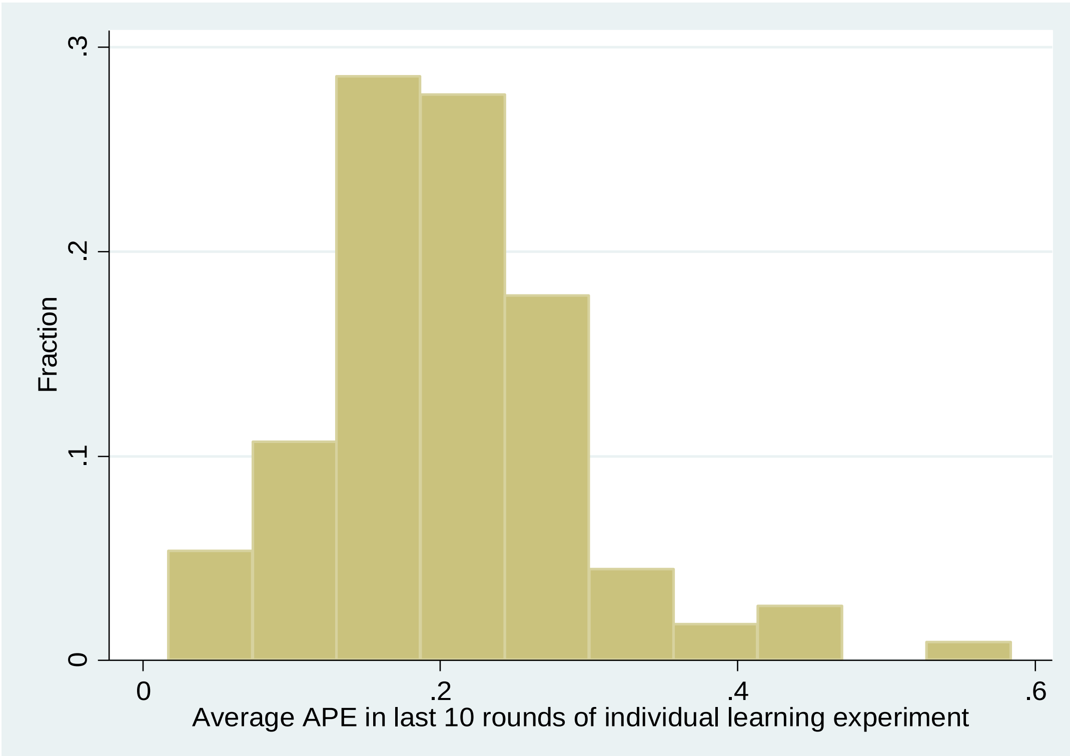


Figure 2b: Advice Weight

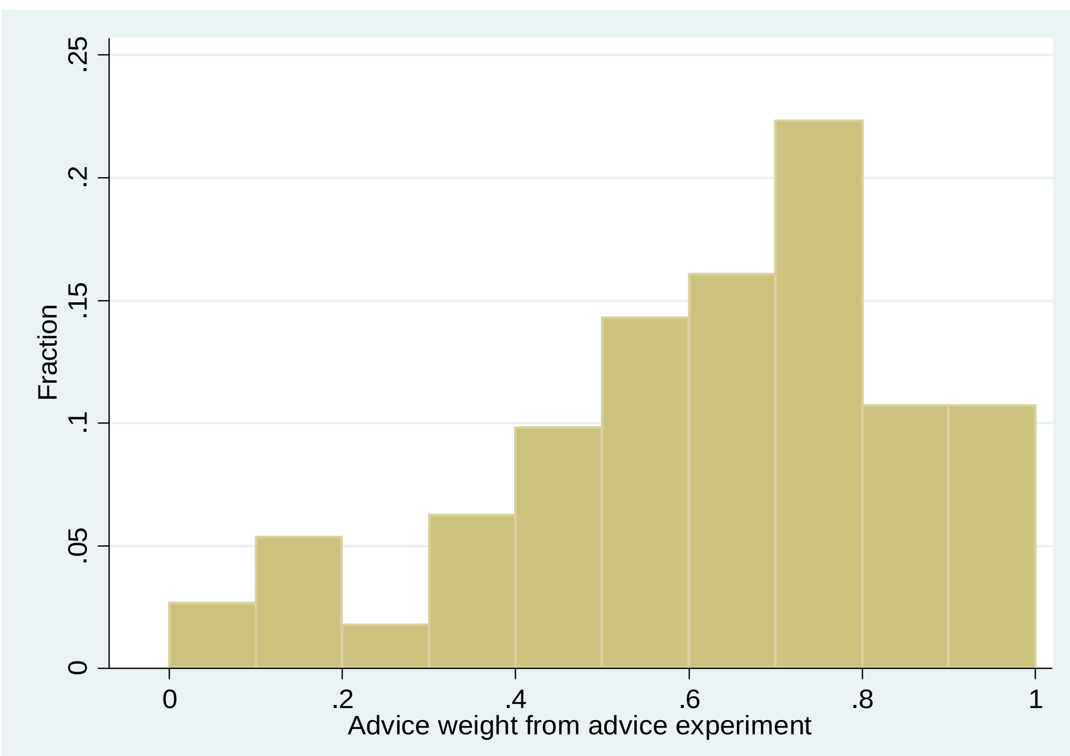


Figure 3: Corn Adoption

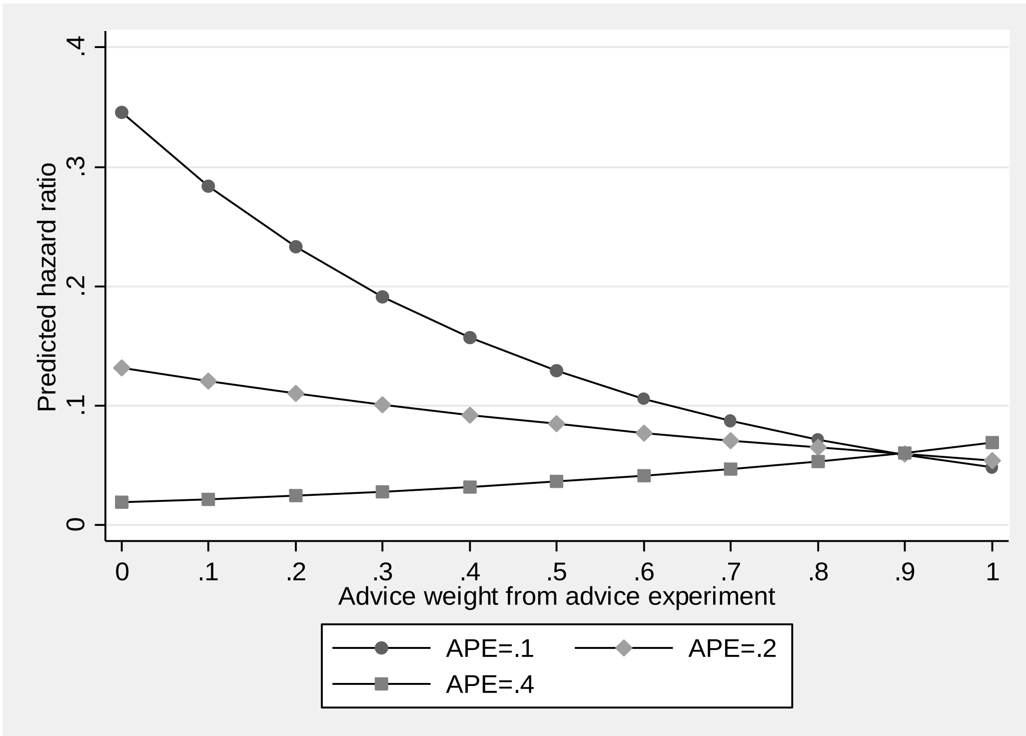
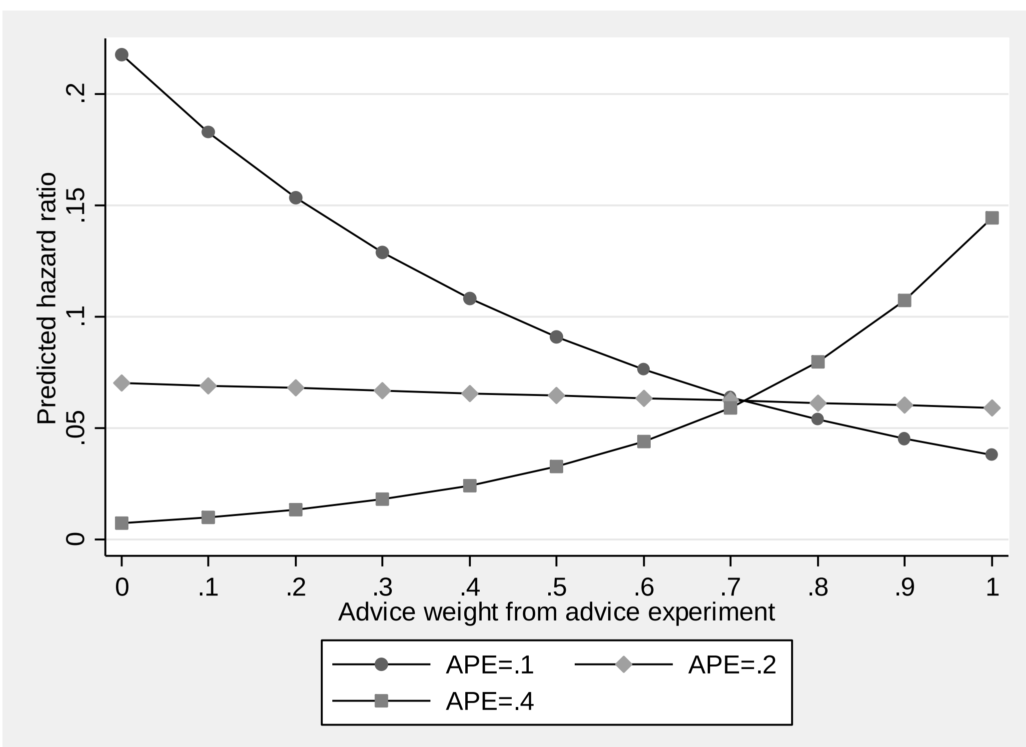


Figure 4: Soy Adoption



Appendix Table 1: Regressing Experimental Advice Taking on Survey Questions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
VARIABLES				Advice Weight * 100			
Self-reliant	-19.05*	-16.74	-15.96				-15.79
	[10.55]	[11.59]	[11.32]				[11.18]
Confidence in external sources				11.75***	9.45**	8.37*	8.32*
				[4.39]	[4.54]	[4.48]	[4.45]
High school diploma or less		3.79	2.99		4.89	4.08	3.29
		[5.60]	[5.47]		[5.51]	[5.41]	[5.41]
Digit span		-1.11	-0.35		-1.17	-0.46	-0.35
		[1.54]	[1.53]		[1.52]	[1.52]	[1.51]
APE in last 10 rounds * 100			0.61**			0.57**	0.56**
			[0.25]			[0.25]	[0.25]
Age		0.53	0.47		0.43	0.38	0.38
		[0.35]	[0.34]		[0.35]	[0.34]	[0.34]
Female		29.36**	30.86**		26.66*	28.48**	27.01**
		[13.97]	[13.65]		[13.93]	[13.67]	[13.64]
Acres operated (1000's)		1.97	2.11		0.43	0.65	1.78
		[2.40]	[2.34]		[2.24]	[2.19]	[2.32]
Farming not principal occupation		3.78	3.92		3.87	4.01	3.71
		[6.51]	[6.36]		[6.44]	[6.31]	[6.28]
Years making decisions on farm		-0.39	-0.31		-0.26	-0.20	-0.21
		[0.35]	[0.34]		[0.35]	[0.34]	[0.34]
Received computer refresher		5.09	3.22		2.32	0.82	1.78
		[8.87]	[8.70]		[8.79]	[8.64]	[8.62]
Number of risky choices		0.08	0.01		0.21	0.14	0.00
		[0.85]	[0.83]		[0.83]	[0.82]	[0.82]
Constant	63.30***	49.21**	32.42	55.32***	46.28**	30.87	31.35
	[2.23]	[18.69]	[19.50]	[3.42]	[18.53]	[19.36]	[19.27]
Observations	112	111	111	112	111	111	111
R-squared	0.029	0.114	0.165	0.061	0.133	0.177	0.193

Standard errors in brackets. *** p<01, ** p<05, * p<1

Appendix Figure 1: Farmer and Advice-Giver APEs in the Advice-Taking Game